

**Role of Moisture Content in Governing The Physical Properties, Flowability, and
Fluidization Behavior of Pine Residues, Waste Coal and Organic Fraction Municipal Solid
Waste Blends**

By

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Abstract

Fossil fuels have been the dominant source of energy and chemicals for over 150 years but have significantly contributed to global warming. Biomass has emerged as a promising renewable alternative because it can be converted into electricity, fuels, and chemicals while being considered carbon neutral, as the CO₂ released during conversion is balanced by that absorbed during plant growth. The United States possesses abundant biomass resources; however, their direct utilization is limited by high moisture content, low bulk density, and low energy density. Blending biomass with waste coal (WC) and the organic fraction of municipal solid waste (OFMSW) offers a promising approach to improve fuel quality while enhancing energy security, reducing greenhouse gas emissions, and diverting waste from landfills. Nevertheless, biomass moisture, often exceeding 50% in freshly harvested materials, adversely affects physical properties, flowability, fluidization behavior, and overall processing. These effects become more complex in blended systems, and comprehensive studies on moisture effects remain limited.

This study investigated ten blends of pine residues (PR), WC, and OFMSW with moisture contents ranging from 10–40% (wet basis). Results showed that moisture content and OFMSW proportion were the primary factors governing the physical and flow behavior of the blends. Increasing moisture increased bulk density but reduced particle density and flowability by increasing cohesion, adhesion, angle of internal friction, and angle of wall friction. Machine learning models successfully predicted these properties with coefficients of determination (R^2) between 0.83 and 0.96.

Thermogravimetric analysis (TGA), Fourier-transform infrared spectroscopy (FTIR), and differential scanning calorimetry (DSC) were used to characterize thermal behavior and

drying energy. PR and OFMSW exhibited greater water affinity because of abundant oxygen-containing functional groups, whereas WC showed lower affinity due to its aromatic carbon structure. Although drying energy of the blends increased slightly with moisture, it remained lower than that of the individual materials, indicating synergistic interactions. Statistical analysis confirmed that drying energy was governed mainly by blend composition and component interactions rather than moisture alone.

Moisture content showed the strongest positive correlation with minimum fluidization velocity (U_{mf}), while PR had a weaker positive influence and WC and OFMSW slightly reduced U_{mf} . WC strongly increased bed pressure drop, whereas PR and OFMSW reduced it. A modified Ergun equation incorporating moisture effects significantly improved predictions of pressure drop and U_{mf} , with new coefficients determined for PR and OFMSW. Finally, CFD simulations demonstrated that the Syamlal–O'Brien and Gidaspow drag models provided the closest agreement with experimental pressure-drop data and accurately predicted fluidization behavior for PR and WC, whereas OFMSW exhibited larger prediction errors. Solid volume fraction contours further showed that PR and WC experienced greater bed expansion and solids circulation, while the EMMS model predicted denser bubbling beds.

Artificial Intelligence (AI) Use Disclosure Statement

In the preparation of this dissertation, the following Artificial Intelligence (AI) tools were used: Copilot, ChatGPT, Gemini, Quill Bot, and Liner. These tools were used primarily to paraphrase, summarize texts, and explanation of some complex contexts. The author acknowledges full responsibility for the intellectual content of this work and has ensured that all AI-assisted sections have been reviewed and revised for accuracy and appropriate academic style. All AI-generated content was reviewed and validated for relevance, appropriateness, and accuracy before incorporation into the final document to maintain the scholarly integrity of this research.

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Table of Contents

Abstract	2
Artificial Intelligence (AI) Use Disclosure Statement	4
Digital Accessibility Disclosure Statement	5
Acknowledgments	6
Table of Contents	8
List of Tables.....	16
List of Figures	19
List of Abbreviations	28
Chapter 1. Introduction	30
1.1. Motivation of the research	33
1.2. Research hypothesis	34
1.3. References	36
Chapter 2. Background.....	41
2.1. Types of feedstock residues	42
2.1.1. Forest residues	42
2.1.2. Municipal solid waste	43
2.1.3. Waste coal.....	44
2.2. Waste conversion processes.....	45
2.3. Introduction to Fluidized bed systems	51

2.3.1. Bubbling fluidized bed	52
2.3.2. Fixed bed and moving bed.....	53
2.3.3. Circulating fluidized beds	53
2.4. Fluidization regimes	54
2.4.1. Measurement of minimum fluidization velocity (U_{mf})	56
2.4.2. Determination of the pressure drop in a fluidized bed	56
2.4.3. Bed expansion	57
2.5. Challenges in the determination of the U_{mf} and pressure drop of multicomponent heterogeneous mixtures	58
2.6. Material properties that influence the fluidization of multicomponent biomass coal systems	59
2.6.1. Particle size.....	60
2.6.2. Particle shape.....	63
2.6.3. Particle density	64
2.6.4. Bulk density	65
2.6.5. Moisture content.....	67
2.7. Empirical and modeling approaches for determining minimum fluidization velocity of multicomponent systems.....	70
2.7.1. Pressure drop approach	71
2.7.2. Empirical model approaches.....	73
2.7.3. CFD modeling approach.....	74

2.8. Summary.....	85
2.9. References	87
Chapter 3. Investigating moisture and blend ratio effects on rheological properties of waste coal, pine residues, and organic fraction municipal solid waste: statistical and machine learning methods	
	123
3.1. Abstract	123
3.2. Introduction.....	125
3.3. Material and method	130
3.3.1. Sample preparation	130
3.3.2. Proximate and ultimate analysis of the samples	131
3.3.3. Physical properties measurement.....	132
3.3.4. Preparation of the blends and moisture adjustments.....	132
3.3.5. Flow properties measurement.....	136
3.3.6. Statistical analysis	137
3.3.7. Machine learning analysis.....	138
3.4. Results and discussion.....	139
3.4.1. Physical properties	139
3.4.2. Flow properties.....	142
3.4.3. Statistical prediction of the physical and low probability of the blends	148
3.4.4. Correlation matrix of physical and flow properties of the blends.....	152
3.4.5. Model performance of machine learning	153

3.4.6. SHAP analysis of the key factors influencing rheological properties of the blends	154
3.4.7. Conclusion	159
3.4.8. References	161
Chapter 4. Thermal Behavior of Blended Biomass Feedstocks	167
4.1. Abstract	167
4.2. Introduction	169
4.3. Material and method	172
4.3.1. Sample preparation	172
4.3.2. Proximate and ultimate analysis of the samples	172
4.4. Result and discussion	176
4.4.1. Physicochemical characterisation	176
4.4.2. Thermogravimetric analysis (TGA)	178
4.4.3. Fourier transform infrared (FTIR) analysis	180
4.4.4. Correlation of BET Surface Area, Surface Energy, and FTIR Functional Groups with Moisture Retention and Drying Behavior	182
4.5. Drying energy requirement	184
4.5.1. Response Surface Analysis of Drying Energy	189
4.5.2. Approximate predictive models for the drying energy requirement of the blends	191
4.6. Conclusion	195
4.7. References	197

Chapter 5. Moisture effect on the fluidization behavior of waste coal, pine residues, and organic fraction municipal solid waste blends	201
5.1. Abstract	201
5.2. Introduction.....	203
5.3. Material and method	206
5.3.1. Sample preparation	206
5.3.2. Physical properties measurement.....	207
5.3.3. Fluidized bed system and fluidization experiment	211
5.3.4. Statistical analysis	212
5.4. Results and discussion.....	213
5.4.1. Effect of moisture content on the particle size distribution	213
5.4.2. Effect of moisture content on the particle size of the blends	216
5.4.3. Geldart classification of particles.....	216
5.4.4. Effect of moisture content on the porosity of the blends	218
5.4.5. Effect of moisture content on the sphericity of the blends	219
5.4.6. Fluidization behavior of waste coal, pine residues and organic fraction municipal solid waste blends	221
5.4.7. Fluidization behaviors of waste coal, pine residues, and organic fraction municipal solid waste	222
5.4.8. Effect of moisture on the pressure drop vs superficial gas velocity profile	229
5.4.9. Effect of moisture content on fluidization quality	232

5.4.10. Effect of moisture content on the minimum fluidization velocity	236
5.4.11. Effect of moisture content of the bed pressure drop at the point of fluidization	240
5.4.12. Statistical and machine learning analysis of the key parameter influencing the minimum fluidization velocity and pressure drop	241
5.4.13. Correlation for minimum fluidization velocity of waste coal, pine residues organic fraction organic fraction municipal solid waste and blends	246
5.5. Conclusion	254
5.6. References	256
Chapter 6. Estimation of the pressure drop in a packed bed of pine residues and organic fraction municipal solid waste using the revised Ergun correlation.....	262
6.1. Abstract	262
6.2. Introduction.....	263
6.3. Material and method	266
6.4. Statistical analysis	266
6.5. Discussion.....	267
6.5.1. Physical characteristics of pine residues and organic fraction municipal solid waste at various moisture contents	267
6.5.2. Expression of the pressure drop and flow rate relationship through packed bed of pine residues and organic fraction municipal solid waste.....	269
6.5.3. Conclusion	287
6.6. References	288

Chapter 7. CFD modeling of fluidized bed of coal, pine residues, and OFMSW blends	291
7.1. Abstract	291
7.2. Introduction	293
7.3. Methodology	299
7.3.1. Fluidized bed geometry and meshing	299
7.3.2. Model description and simulation settings	300
7.3.3. Simulation setup and boundary conditions	306
7.4. Results and discussion	311
7.4.1. Mesh sensitivity analysis	311
7.4.2. Effect of the drag model on the fluidized bed hydrodynamic	316
7.4.3. Prediction of the distribution of solid particles along the fluidized bed	322
7.4.4. Effect of drag model on pressure drop profile	331
7.4.5. Comparison of the CFD simulation and experimental results	337
7.5. Conclusion	350
7.6. References	352
Chapter 8. Conclusion and recommendation	359
8.1. Conclusions	359
8.2. Original contributions	362
8.3. Future recommendations	362

Appendix 1	364
Appendix 2:	366

List of Tables

Table 2.1: Recent studies on CFD simulation of biomass and coal systems	81
Table 3.1: Proximate analysis of waste coal (WC), pine residues (PR), and the organic fraction of municipal solid waste (OFMSW), dry basis.....	131
Table 3.2: Ultimate analysis of waste coal (WC), Pine residues (PR), and the organic fraction of municipal solid waste (OFMSW).....	131
Table 3.3: Blend nomenclature (mass ratio).....	133
Table 3.4: Actual moisture content of blends (wet basis)	133
Table 3.5: Statistical prediction of the physical and low probability of the blends	150
Table 4.1: Physicochemical characterization of waste coal (WC), pine residues (PR) and organic fraction municipal solid waste (OFMSW)	173
Table 4.2: Metal content analysis of waste coal (WC), pine residues (PR) and organic fraction municipal solid waste (OFMSW).....	173
Table 4.3: Actual moisture content of the blend after moisture adjustment (%wb).....	174
Table 4.4: Latent heat of vaporization of WC, PR, and OFMSW at different moisture levels (wb)	187
Table 4.5: Experimental drying energy of the blends	188
Table 4.6: Predictive models for the drying energy requirement per unit mass of water of WC, PR, and OFMSW.....	192
Table 4.7: Calculated drying energy requirement (kJ/kg water removed) for the blended samples.....	193
Table 4.8: %Mean relative deviation of experimental and predicted draying energy	194
Table 5.1: Blend nomenclature (mass ratio).....	208

Table 5.2: Actual moisture content of blends (wb)	209
Table 5.3: Surface volume diameter (mm) of the blends at different moisture content	216
Table 5.4: Geldart classification of the blends as affected by the moisture content and the blend ratios.....	217
Table 5.5: Effect of moisture content on the porosity of the blends	219
Table 5.6: Effect of moisture content on the blend sphericity	220
Table 5.7: Summary of the fluidization index of the blends at various moisture contents: (values were taken after the U_{mf})	235
Table 5.8: Model fitting test for U_{mf} and pressure drop	244
Table 5.9: Coefficient of variation of the blends at various moisture content (Wet basis) ...	248
Table 5.10: Effective particle diameter of the blends at various moisture content (wet basis)	249
Table 5.11: The estimated values of the coefficient k and α for the blends and their respective R^2 value.....	251
Table 5.12: Parameters for model verification	252
Table 6.1: Physical properties of PR at different moisture content.....	268
Table 6.2: Physical properties of OFMSW at different moisture content.....	268
Table 6.3: Estimation of the slope and intercept parameters for PR at different moisture content	272
Table 6.4: Estimation of the slope and intercept parameters for OFMSW at different moisture content	273
Table 6.5: Comparison of k_1 and k_2 values between this study and existing literature.....	280
Table 6.6: % Mean relative deviation of U_{mf} between experimental and the modified Ergun equation for PR	285

Table 6.7: Mean relative deviation of U_{mf} between experimental and the modified Ergun equation for OFMSW	285
Table 7.1: Phases properties and operating conditions for fluidized bed simulation.....	307
Table 7.2: Other parameters for boundary conditions	307
Table 7.3: Solution Methods.....	309
Table 7.4: Mesh independence assessment	312
Table 7.5: % Mean relative error between experimental and simulated pressure drop for pine residues using Syamlal O'Brien, Gidaspow, and EMMS drag models	340
Table 7.6: % Mean relative error between experimental and simulated pressure drops for coal using Syamlal O'Brien, Gidaspow and EMMS drag model.....	340
Table 7.7: % Mean relative error between experimental and simulated pressure drop for OFMSW using Syamlal O'Brien, and Gidaspow drag model	341
Table 7.8: Comparison of static and expanded bed heights (%increase in bed height).....	346
Table 7.9: %MRD between experimental and predicted bed height for pine residues	347
Table 7.10: %MRD between experimental and predicted bed height for waste coal	348
Table 7.11: %MRD between experimental and predicted bed height for OFMSW	349

List of Figures

Figure 2.1: Forest residues	43
Figure 2.2: Composition of municipal solid waste.....	44
Figure 2.3: waste coal or legacy coal.....	45
Figure 2.4: Fluidized bed.....	52
Figure 2.5: Fluidization regimes	55
Figure 2.6: Fluidization curve of two-component mixture, a) fully mixed, b) complete segregation, c) partially mixed/stratified.....	59
Figure 2.7: Geldart classification of particles	61
Figure 2.8: Multi-scale resolution of gas-solid interaction in the binary gas-solid flow	78
Figure 3.1. Pictures of sample preparation equipment: a) hammer mill, b) plastic granulator, c) Vibro screen separator	130
Figure 3.2: WC sample appearance with different moisture content: a) 2.3MC%, b) 6.5%MC, c) 22.2%MC, d) 35%MC.....	134
Figure 3.3: Flow function graph	137
Figure 3.4: Bulk density of the blends at various moisture content (%wb).....	140
Figure 3.5: Particle density of the blends at various moisture content (%wb).....	141
Figure 3.6: Tap density of the blends at various moisture content (%wb)	142
Figure 3.7: Effect of moisture content (%wb) on the flow index	144
Figure 3.8: Effect of moisture content (%wb) on the angle of internal friction (AIF)	145
Figure 3.9: Effect of moisture content (%wb) on cohesion	146
Figure 3.10: Effect of moisture content (%wb) on the angle of wall friction (AWF)	147

Figure 3.11: Effect of moisture content (%wb) on adhesion	148
Figure 3.12: Pearson correlation of physical and flow properties: each box has a value between -1 and +1, showing the effect of one variable on the other. Perfect correlation is given a value of +1, and perfect negative correlation is given a value of -1; 0 indicates no correlation between the variables.	153
Figure 3.13: Comparison of the predicted and actual values for the best-performing machine learning models in the dataset: each subset reveals the name of the best model using MAE, RMSE, and R^2 as performance metrics	154
Figure 3.14: SHAP analysis summary of the physical and flow properties of pine residues, organic fraction of municipal solid waste, and waste coal. The plot shows the variables ranked by their absolute SHAP value, indicating their relative impact on the outcome. The dots to the right represent increasing impact on the outcome, whereas the ones to the left indicate reduced impact on the outcome.	158
Figure 4.1: Thermogravimetric analysis of WC, PR, and OFMSW.....	180
Figure 4.2: FTIR spectra of a) waste WC (waste coal), b) PR (pine residue) and c) OFMSW (organic fraction municipal solid waste).....	182
Figure 4.3: Differentials scanning calorimetry of a) waste WC (waste coal), b) PR (pine residue) and c) OFMSW (organic fraction municipal solid waste).....	185
Figure 4.4: Heat of vaporization of per gram of sample for WC, PR and OFMSW at various moisture content (wb)	186
Figure 4.5: Response surface plot of the drying energy per kg of water removed of the blends	191
Figure 5.1: Pictures of sample preparation equipment: a) hammer mill, b) plastic granulator, c) Vibro screen separator	207

Figure 5.2: Schematic representation of the Fluidized bed used in this study: (1) Acrylic column, (2) pressure sensor point1, (3) U-tube manometer, 4) Pressure sensor point2, (5) distributor plate (6) column stand, (7) regulator valve, (8) camera, (9) air flow meter	212
Figure 5.3: Particle size distribution of WC (2.3%M)	214
Figure 5.4: WC sample appearance with different moisture content: a) 2.3MC%, cohesion: 0.15kPa; B) 6.5%MC, cohesion:0.55kPa, c) 22.2%MC, cohesion: 0.87kPa, d) 35%MC.....	215
Figure 5.5: Effect of moisture content (MC. %wet basis) on the particle size distribution of PR: *Control in the legend indicates that the sample was used as received, and moisture was not adjusted.....	215
Figure 5.6: Effect of moisture content (MC. %wet basis) on the particle size distribution of OFMSW: *Control in the legend indicates that the sample was used as received, and moisture was not adjusted.	215
Figure 5.7: Determination of the minimum fluidization velocity of sand particles	221
Figure 5.8: Fluidization behavior of pine residue (MC=7.4% wet basis)	224
Figure 5.9: Fluidization behavior of OFMSW (MC=6.7% wet basis)	224
Figure 5.10: Channeling formation during fluidization of a) blend4, 7.3%M; b) blend6, 6.7%MC)	226
Figure 5.11: Segregation during fluidization of blends: a) blend2, 5.8%M, b) blend7, 5.6%M, and c) blend4, 7.3%MC.....	227
Figure 5.12: Partial and intermittent fluidization behavior observed during fluidization of a) B5, 7.1%MC; b) B9, 5.8%MC	228
Figure 5.13: Plug flow during fluidization of a) WC, 18.2%MC; b) PR, 40%MC and, c) OFMSW, 40%MC	229

Figure 5.14: Variation in pressure drop and superficial gas velocity at different moisture content for WC	231
Figure 5.15: Variation in pressure drop and superficial gas velocity at different moisture content for PR.....	231
Figure 5.16: Variation in pressure drop and superficial gas velocity at different moisture content for OFMSW.....	232
Figure 5.17 : Variation in pressure drop and superficial gas velocity at different moisture content for B7.....	232
Figure 5.18: Fluidization characteristics curves for WC, PR, OFMSW and B7 at various moisture content	235
Figure 5.19: Minimum fluidization velocity of the WC (B1), PR (B4) and OFMSW (B6) at various moisture contents	238
Figure 5.20: Minimum fluidization velocity of B2, B3, and B5 with various moisture contents	239
Figure 5.21: Minimum fluidization velocity of B7, B8, B9 and B10 with various moisture	239
Figure 5.22: Effect of moisture content on pressure drop at minimum fluidization velocity for individual sample (WC, PR and OFMSW).....	240
Figure 5.23: Effect of moisture content on pressure drop at minimum fluidization velocity for binary blends (B2, B3 and B4)	241
Figure 5.24: Effect of moisture content on pressure drop at minimum fluidization velocity for ternary blends (B7, B8, B9 and B10)	241
Figure 5.25: Pearson correlation matrix between moisture content, components on the Umf and pressure drop.....	243

Figure 5.26: SHAP analysis on the key factors affecting the minimum fluidization velocity and the pressure drop	246
Figure 5.27: Effect of particle properties and moisture content on the Umf of B4	250
Figure 5.28: Effect of particle properties and moisture content on the Umf of B6	250
Figure 6.1: Linear form of the pressure gradient and the air flow rate for PR at various moisture content based on Eqn. 5.1	270
Figure 6.2: Linear form of the pressure gradient and the air flow rate for OFMSW at various moisture content based on Eqn. 6.1	271
Figure 6.3: Dependence of viscous (blue) and kinetic (orange) energy loss correlations on the porosity correlations at various moisture content used in the Ergun equation for PR	274
Figure 6.4: Dependence of viscous (blue) and kinetic (orange) energy loss correlations on the porosity correlations at various moisture content used in the Ergun equation for OFMSW ..	275
Figure 6.5: Dependence of kinetic energy loss on the modified porosity correlation for PR at different moisture content.....	276
Figure 6.6: Dependence of kinetic energy loss on the modified porosity correlation for OFMSW at different moisture content.....	276
Figure 6.7: Plot of the friction factor vs Reynold number using modified porosity correlation at different moisture content for PR	279
Figure 6.8: Plot of the friction factor vs Reynold number using modified porosity correlation at different moisture content for OFMSW	279
Figure 6.9: Pressure drop per unit length versus superficial gas velocity for PR at 6% moisture content (%wb).....	281
Figure 6.10: Pressure drop per unit length versus superficial gas velocity for PR at 9.9% moisture content (%wb).....	282

Figure 6.11: Pressure drop per unit length versus superficial gas velocity for PR at 20.3% moisture content (%wb).....	282
Figure 6.12: Pressure drop per unit length versus superficial gas velocity for PR at 29.5% moisture content (%wb).....	283
Figure 6.13: Pressure drop per unit length versus superficial gas velocity for PR at 40.3% moisture content (%wb).....	283
Figure 6.14: Pressure drop per unit length versus superficial gas velocity for OFMSW at 6.8% moisture content (%wb).....	283
Figure 6.15: Pressure drop per unit length versus superficial gas velocity for OFMSW at 10.2 % moisture content (%wb).....	284
Figure 6.16: Pressure drop per unit length versus superficial gas velocity for OFMSW at 28.6% moisture content (%wb).....	284
Figure 7.1: Schematic diagram and mesh display of the fluidized bed used for the simulation	300
Figure 7.2: SIMPLE algorithms to solve the multiphase model.....	310
Figure 7.3: CFD simulation workflow	311
Figure 7.4: Snapshot of time average solids volume fraction representing the bed hydrodynamics for different mesh resolutions	313
Figure 7.5: Effect of mesh size on the transient pressure drop, with pine residues particles at 4Umf using the Syamlal O'Brien drag model	314
Figure 7.6: Effect of mesh size on the pressure drop	315
Figure 7.7: Effect of mesh size on the bed expansion.....	316
Figure 7.8: Snapshot of the simulated time-averaged solid volume fraction contour of pine residues using the Syamlal O'Brien drag model at the gas velocity of 4Umf	318

Figure 7.9: Snapshot of the simulated time-averaged solid volume fraction contour of pine residues using the Gidaspow drag model at the gas velocity of $4U_{mf}$	319
Figure 7.10: Snapshot of the simulated time-averaged solid volume fraction contour of pine residues using the EMMS drag model at the gas velocity of $4U_{mf}$	319
Figure 7.11: Snapshot of the simulated time-averaged solid volume fraction contour of coal using the Syamlal O'Brien drag model at the gas velocity of $4U_{mf}$	320
Figure 7.12: Snapshot of the simulated axial time-averaged solid volume fraction contour of coal using the Gidaspow drag model at the gas velocity of $4U_{mf}$	320
Figure 7.13: Snapshot of the simulated time-averaged solid volume fraction contour of coal using the EMMS drag model at the gas velocity of $4U_{mf}$	321
Figure 7.14: Snapshot of the simulated time-averaged solid volume fraction contour of OFMSW using Syamlal O'Brien drag model at the gas velocity of $4U_{mf}$	321
Figure 7.15: Snapshot of the simulated time-averaged solid volume fraction contour of OFMSW using the Gidaspow drag model at the gas velocity of $4U_{mf}$	322
Figure 7.16: Axial average solid holdup for different drag models; a) Pine residues, b) waste coal, c) OFMSW at $4U_{mf}$	324
Figure 7.17: Relative position of pine residues particle in the radial direction using: (a) Syamlal Obrien, (b) Gidaspow, (c) EMMS drag models (y in m)	326
Figure 7.18: Relative position of waste coal particle in the radial direction using: (a) Syamlal Obrien, (b) Gidaspow, (c) EMMS drag models. (y in m)	327
Figure 7.19: Relative position of OFMSW particle in the radial direction using: (a) Syamlal Obrien, (b) Gidaspow, (c) EMMS drag models. (y in m)	327
Figure 7.20: Radial mean velocity magnitude of pine residues using various drag models: (a) Syamlal O'Brien, (b) Gidaspow, (c) EMMS	330

Figure 7.21: Radial mean velocity magnitude of waste coal using various drag models: (a) Syamlal O'Brien, (b) Gidaspow, (c) EMMS	331
Figure 7.22: Radial mean velocity magnitude of OFMSW using various drag models: (a) Syamlal O'Brien, (b) Gidaspow	331
Figure 7.23: Effect of drag model on transient fluidized bed pressure drop: (a) pine residues, (b) waste coal, (c) OFMSW at 2.5Umf.....	333
Figure 7.24: Snapshot of the transient pressure drop profile for pine residues using various drag models, at 4Umf: (a) Syamlal O'Brien, (b) Gidaspow, (c) EMMS	334
Figure 7.25: Snapshot of the transient pressure drop profile for waste coal using various drag models, at 4Umf: (a) Syamlal O'Brien, (b) Gidaspow, (c) EMMS.....	335
Figure 7.26: Snapshot of the transient pressure drop profile for OFMSW using various drag models, at 4Umf: (a) Syamlal O'Brien, (b) Gidaspow	335
Figure 7.27: Pressure drop distribution across the zx-plane bed height for Syamlal Obrien, Gidaspow and EMMS drag model at 4Umf: (a) pine residues, (b) waste coal, (c) OFMSW..	337
Figure 7.28: Effect of inlet air velocity on the pressure drop in fluidized bed of waste coal using various drag models	338
Figure 7.29: Effect of inlet air velocity on the pressure drop in fluidized bed of waste coal using various drag models	339
Figure 7.30: Effect of inlet air velocity of the fluidized bed pressure drop of OFMSW using different drag models	339
Figure 7.31: Snapshot of the pine residues bed evolution at different air velocity using Syamlal O'Brien, Gidaspow, and EMMS drag models	343
Figure 7.32: Snapshot of the coal bed evolution at different air velocity using Syamlal O'Brien, Gidaspow, and EMMS drag models.....	343

Figure 7.33: Snapshot of the OFMSW bed evolution at different air velocities using Syamlal O'Brien and Gidaspow drag models	344
Figure 7.34: Experimental visualization of the pine residues bed expansion at different inlet air velocity	345
Figure 7.35: Experimental visualization of the waste coal bed expansion at different inlet air velocity	345
Figure 7.36: Experimental visualization of the pine residues bed expansion at different inlet air velocity	345
Figure 7.37: Effect of inlet air velocity on the predicted bed height of pine residues using different drag models	347
Figure 7.38: Effect of inlet air velocity on the predicted bed height of waste coal using different drag models.....	348
Figure 7.39: Effect of inlet air velocity on the predicted bed height of pine residues using different drag models	349
Figure 8.1: Pressure drop versus superficial gas velocity at various moisture contents.....	364
Figure 8.2: Effect of moisture content on fluidization index.....	365
Figure 8.3: Coefficient for the Energy Minimization Multi-Scale model.....	366

List of Abbreviations

DC	Drag coefficient
ε_s	Void fraction of solid in dense phase
ε_g	Void fraction of gas in dense phase
ρ_g	Gas/ fluid density (kg m ⁻³)
ρ_s	Solid density (kg m ⁻³)
ρ_b	Particle density
ρ_t	Bulk density
ρ_p	Tap density
dp	Particle diameter (m)
U_g	Gas velocity (m/s)
f_f	Friction factor
U _{mf}	Minimum fluidization velocity (m/s)
Re	Reynold number based on solid fraction
$\overline{M}_{gs}$	Momentum exchange coefficient (kg m ⁻³ s ⁻¹)
μ_g	Viscosity of gas (Pa s)
φ	Sphericity
ΔP	Pressure drop (Pa)
W	Mass of particle (kg)
dt	Time step (s)
τ_g	Gas stress tensor (Pa)
τ_s	Solid stress tensor (Pa)
λ_s	Solid bulk viscosity (Pa s)

g	Gravitational acceleration (m/s^{-2})
FI	Fluidization index
FI	Flow index
d_{eff}	Effective particle diameter (m)
γ	Coefficient of variation
g	Fluid phase source term
H	Bed height
u_s	Solid velocity (m/s)
u_g	Gas velocity (m/s)
$\gamma_{\theta p}$	Collision dissipation energy
K_{gs}	Gas drag force
βg	Interphase drag force
ϕ_{pg}	Energy exchange between particles and fluid
Pp	Solid pressure
MC	Moisture content

Chapter 1. Introduction

There is an urgent need to encourage and improve the use of renewable energy sources for energy production. Among these energy sources, biomass waste, including forest residues, industrial solid waste like the organic fraction of municipal solid waste, emerges as the most relevant on a global scale, considering the impacts of the use of fossil fuels on the environment and global warming (Zinani et al., 2020). Fossil fuels have been identified as the major source of greenhouse gas (GHG) emissions, which are directly linked to rising temperatures and extreme weather conditions (Holechek et al., 2022). With continued reliance on fossil fuels as the primary energy source, a 3 °C or more temperature increase is predicted by the end of this century (Shah et al., 2013). In addition, beyond CO₂ emissions, it is forecasted that fossil fuels will experience a significant reduction of about 80% of their current availability around 2050 and beyond, which is a major energy concern for the ever-growing population (Dragan Burić¹, 2023; Hansen et al., 2017; Ripple et al., 2021). According to the IPCC Sixth Assessment Report (AR6), achieving the Paris Agreement goal of limiting global warming to 1.5°C necessitates rapid emissions reductions across all sectors, including a 43% reduction in global greenhouse gas emissions by 2030 (relative to 2019 levels) and net-zero CO₂ emissions by the early 2050s (Holechek et al., 2022; Dragan Burić¹, 2023). If the global temperature rises by 2 degrees or more compared to the pre-industrial period, irreversible and possibly large negative changes in natural and human systems can be expected according to the models. To achieve this goal, renewable energy production will need to be increased by up to 6-fold or 8-fold if energy demand is held constant at, or increased 50% from, the 2020 energy demand level (Legendre et al., 2026). In the US, biomass waste is available in various forms, including agricultural waste, forest waste residues, and industrial solid waste such as the organic fraction of municipal solid waste

(OFMSW). Biomass energy shared only 5% of the total primary energy consumption in the US in 2022 (US Energy Administration, 2024), and this value can considerably increase if biomass waste resources were used to their full potential. Converting biomass waste to energy production is also a way to reduce its negative impact on the environment. In an attempt to mitigate the climate issue, a goal was set by the Energy Independence and Security Act (EISA) of 2007 to enhance the production of clean, renewable fuels by producing 36 billion gallons of renewable fuel from biomass and fossil fuel blends, such as coal, by 2022 (US Congress, 2008). Due to the nature of the biomass feedstocks (non-uniform shape, large variability in size, low density), thermochemical conversion methods such as combustion, pyrolysis, and gasification through the process of fluidization are preferred methods for their conversion (Wang & Wu, 2023). Thermochemical conversion is a process in which heat, in the absence of or in a limited-oxygen environment, breaks down biomass into various products, such as syngas, biooil, and char (also called biochar). This process usually occurs in suitable vessels, called fluidized bed reactors, in which the particles are suspended in an upward-flowing fluid, usually hot air (Travieso et al., 2017). Fluidized bed reactors have emerged as a highly relevant thermochemical process equipment because they have good feeding flexibility, provide perfect mixing of gas and solid, good heat transfer rate, and homogeneous temperature distribution, which enhances conversion (Ren et al., 2019; Siedlecki et al., 2011 & Ren et al., 2019).

The importance of combining biomass and coal blends has been highlighted by numerous papers published in recent literature (Del et al., 2023; Let et al., 2023; Vasconcelos et al., 2023; Zinani et al., 2020). Jurado et al., (2017) presented experimental results of co-firing blends of biomass and coal in a retrofitted 100 kWth fluidized bed combustor and found that combining biomass with coal decreased SO₂ levels in the flue gas.

Similarly, Mun et al., (2016), investigated boiler and net plant efficiencies and combustion characteristics from blending biomass with coal in a 500 MWe fluidized bed coal-fired power plant. Both works revealed that incorporating biomass with coal has several advantages, such as a reduction in emissions of nitrogen oxide (NO_x), Sulphur oxide (SO_x), and carbon dioxide (CO₂), due to biomass carbon neutrality (Yek et al., 2024 & Chen et al., 2018). Incorporating coal into biomass energy will also provide reliable feedstocks for the continuous operation of integrated biorefineries (Chen et al., 2018).

The primary limitation of co-processing biomass with coal arises from their highly heterogeneous physical and flow properties such as non-uniform particle size and shape, high cohesiveness, low bulk density, and elevated moisture content combined with coal's inherently high particle density. These contrasting characteristics often promote particle segregation when the materials are mixed. The major drawback of combining biomass and coal is often associated with their heterogeneous physical and flow properties (non-uniform particle size and shape, high cohesiveness, low bulk density). These properties also affect their transportation, storage, and feeding equipment design. Low bulk density, for example, may result in high transportation and storage costs. Moreover, under fluidization conditions, particles may segregate due to the difference in density and size; lighter particles would move to the upper sections of the bed, whereas denser, larger, or sometimes smaller and denser particles remain in the bottom, which may alter the bed performance (Fotovat et al., 2013). Careful consideration of particle heterogeneity and segregation tendencies is essential when designing handling and feeding systems for biomass–coal mixtures. In fluidized bed operation, moisture-induced agglomeration and particle clustering can compromise bed uniformity, causing temperature instabilities and pronounced pressure fluctuations that increase the energy required to sustain fluidization, especially in biomass. (Motta et al.,

2018). Additionally, high moisture in biomass and coal mixture may affect the product's yields and the syngas heating values. Because moisture promotes particle agglomeration and increases the minimum fluidization velocity, maintaining low moisture levels is essential for stable fluidization. The specific moisture tolerance, however, is highly dependent on the physical properties of the biomass or coal feedstock. Modeling fluidized beds plays a crucial role in enhancing the feasibility of thermochemical conversion. While experimental studies remain valuable, they are often time-intensive and limit the ability to precisely monitor operational variables or predict particle behavior and flow dynamics within the system. By leveraging advanced computational methods and simulation tools, such as computational fluid dynamics (CFD), the efficiency and performance of fluidized beds can be significantly improved

1.1. Motivation of the research

The gasification of biomass, including pine residues, organic fraction municipal solid waste, and coal blends, is still in the developing stage on an industrial scale, mainly due to the complexity of pine residues and OFMSW's physical nature, which includes large size, extreme shape, high moisture content, and low bulk density. These differences are critical to designing handling and conversion systems such as fluidized bed reactors. During the fluidization of these blends, the hydrodynamic behavior, which comprises mixing and interaction between the particles and the fluid, is not fully understood. Most reported works on fluidization have been directed to a single biomass component or a binary mixture of biomass and an inert material such as sand (Cui & Grace, 2007a; Przywara et al., 2024; X. Wu et al., 2017; Del et al., 2023; Jing et al., 2019; Let et al., 2022; Si & Guo, 2008; Zhu et al., 2023). Several works have also been reported on the fluidization of biomass (single type) and coal mixture (Grove, 2023; Jurado et al., 2017; Królczyk et al., 2015; Mun et al., 2016; Wang et al., 2022; Wu et al.,

2017). However, there have been limited studies on the fluidization of multicomponent particles of heterogeneous species of biomass, such as pine residues, organic fractions of municipal solid waste (OFMSW), and waste coal. Various aspects of the bed dynamics, such as bed pressure drop, bed voidage, minimum fluidization velocity, bed expansion, and bed composition relating to binary mixtures (both homogeneous and heterogeneous) have been well investigated (Khawaja, 2016; Ma et al., 2017; Mu et al., 2020; Let et al., 2023; Reyes-urrutia et al., 2023; Travieso et al., 2024). However, this information is lacking for multiple component species, such as pine residues, waste coal, and OFMSW. Moreover, the high moisture content in the pine residues and OFMSW are detrimental to fluidization. High moisture content means a high cost of energy for drying pretreatment. Therefore, the selection of an economical and reasonable moisture range is equally important for the feasibility of fluidization operation.

1.2. Research hypothesis

The bed expansion, bed pressure drops, and the minimum fluidization velocity of pine residues, waste coal, and organic fraction municipal solid waste (OFMSW) are influenced by the respective component physical properties, their respective proportion in the mixture, and the moisture content. This study aims to investigate these parameters on the minimum fluidization velocity of these types of feedstocks.

To achieve this objective, the following sub-objectives will be investigated.

- 1) Characterizing the physical and flow properties of pine residues, waste coal, and organic fraction municipal solid waste blends at various levels of moisture contents (10%, 20%, 30%, and 40%).

- 2) Determine the energy required for drying the samples and their blends at various moisture content levels, to minimize the drying energy while maintaining the average blend moisture content.
- 3) Experimentally investigate the fluidization behavior of blends at different moisture contents (10%, 20%, 30%, and 40%). Include factors such as bed pressure drop, bed expansion, and minimum fluidization velocity for pine residues, waste coal, OFMSW, and their blends.
- 4) Develop and validate new correlations for multicomponent pine residues, waste coal, and OFMSW blends by modifying the existing Ergun equation to predict their fluidization behaviors.
- 5) Develop a 3D computational fluid dynamics (CFD) model to simulate the fluidization behavior of pine residues, OFMSW, and waste coal blends, using Ansys Fluent software.

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Chapter 2. Background

The global energy demand is increasing, and fossil fuel stocks cannot meet these growing needs. With an estimated population growth of about 9.2 billion by 2050, it is predicted that the energy demand and consumption will triple its current status (Jha et al., 2022). Fossil fuels have been the primary source of energy worldwide, and their consumption is connected to the emission of greenhouse gases (GHG) and pollutants into the atmosphere, the principal cause associated with climate change and human health risks (Lelieveld et al., 2019). The immediate solution to supply these growing needs requires diversifying energy sources by leveraging waste resources available, such as biomass resources, including agricultural waste, forest residues, municipal solid waste, and fossil fuel waste, such as waste coal. The advantages of these feedstocks are their abundance, their low cost, and they can be accessed in any part of the world in commercial quantities. For example, the United States has an annual production of 278 million dry tons of biomass from forestlands and 194 million dry tons annually from croplands, and about 254 million tons from municipal waste (DOE, 2011). Studies show that gathering about one billion tons of biomass from agriculture and forest resources in a sustainable manner can displace over 30% of the country's present petroleum consumption by the year 2030 (U.S. Department of Energy., 2005).

In this study, we will focus on forest residues, the organic fraction of municipal solid waste, and waste coal as energy sources. In the next section, we will provide an overview of these feedstocks and their conversion processes.

2.1. Types of feedstock residues

2.1.1. Forest residues

Biomass is geographically widespread and abundant; the global production exceeds 200 billion tons annually, sequestering more than 100 billion tons of CO₂ equivalent through photosynthesis (Ma et al., 2026). Biomass feedstocks are classified into five main categories: (i) lignocellulosic forestry residues (e.g., wood chips, bark, sawdust), (ii) agricultural residues (over 60 billion tons globally, and projected to be over 180 million tons in the US by 2030 (DOE, 2011b)), (iii) organic solid wastes (projected to reach 3.4 billion tons by 2050, (iv) livestock manure (over 100 billion tons globally, with potential for both energy recovery and nutrient cycling, and (v) aquatic biomass (e.g., microalgae with oil yields up to 30 times higher per unit area than conventional crops. Forestry residues (Fig 2.1) are considered a promising, environmentally friendly substitute feedstock for fossil-based fuels since they are available in large quantities but are not used to their full potential (Amezcuca-Alfieri & Mexicano, 2018; Carrasco-Diaz et al., 2019). In addition, differing from first-generation bioenergy resources derived from edible food crops, biomass residues do not compete with food; they are relatively cheap. Conventional biomass disposal methods exhibit significant drawbacks. In many regions, large volumes of this biomass are openly burned, causing resource loss and releasing pollutants, such as particulate matter (PM), SO₂, NO_x, and polycyclic aromatic hydrocarbons (PAHs) (Deepak et al., 2024). These emissions deteriorate air quality, harm human health, and contribute to haze formation. Landfilling of biomass further occupies significant land area and produces methane, a potent greenhouse gas with far greater warming potential than CO₂ (Pardo et al., 2024). Such practices waste valuable resources and exacerbate climate change.

The United States (US) leaves behind more than 36.2 million dry tons of logging residues generated from its various forestry activities each year (Manisha et al, 2024). These enormous feedstocks can contribute significantly to the nation's energy security goals while reducing the negative environmental impacts, such as wildfire, due to their carbon neutrality (Carrasco-Diaz et al., 2019). Studies showed that the recoverable residues from woody residues could generate 67.5 TWh of electricity annually, which could power more than 6.1 million homes in the US, considering that a household in the US uses about 11,000 kWh annually (Manisha et al, 2024). Energy produced from wood residues could displace 17.6 million tons of carbon emitted from coal-fuelled power plants (about 3% of total carbon emissions from US electricity (Gan & Smith, 2006).



Figure 2.1: Forest residues

2.1.2. Municipal solid waste

Municipal solid waste has received considerable attention due to its great potential to generate clean energy (Traven, 2024). Municipal solid waste (MSW), also known as trash or garbage, consists of everyday household and industrial items such as product packaging, grass clippings, furniture, clothing, bottles, food scraps, newspapers, and batteries (Mukherjee et al., 2020), as illustrated in Figure 2.2. It is forecasted that the amount of MSW generated worldwide will increase from the current amount of 2.1 billion tons per year to about 3.8 billion

tons by 2050, and this amount is expected to triple by 2100 (Waste & Outlook, 2024; Aliabadi et al., 2023). In the US, the amount of MSW generated in 2018 was 292.4 million tons, and this amount is subject to an increase in the years to come. MSW is considered one of the most renewable resources for energy generation (Traven, 2024). Studies revealed that over 250TWh of electricity could be produced from MSW per year, reflecting its potential as a substitute for fossil fuels (Carmen & Mart, 2020; Mondal & Rafizul, 2024; Waste & Outlook, 2024).

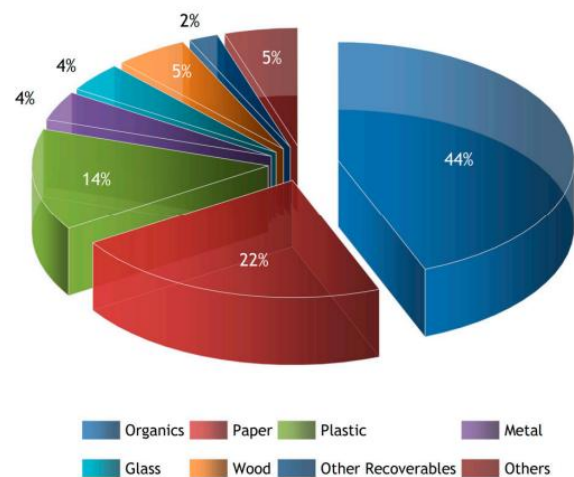


Figure 2.2: Composition of municipal solid waste

2.1.3. Waste coal

Coal has been a primary source of energy generation in the US. According to the US Department of the Interior, millions of Americans across the country live within just one mile of an abandoned coal mine. Waste coal, also known as legacy coal, is a byproduct generated during coal mining activities in the years 1800s until the 1970s (Kunstman et al., 2019). These mines cover over 188 million acres of land and host approximately 38,991 piles of waste coal abandoned in mine sites, mostly in landfills and waste ponds (Energy Justice.net, 2005). About 400 kg (880lb) of waste coal is generated for every tonne of hard coal mined and often contains some lost coal that is partially economically recoverable. It is different from the

byproducts of burning coal, such as fly ash. Waste coal is a mixture of coal, soil, and rocks with low energy content and high amounts of toxic metals such as mercury, chlorine, and Sulphur. These toxic chemicals leach into waterways and cause acid drainage, endangering aquatic life and human health (Kondracka et al., 2012). Given the considerable quantities of these low-grade wastes (pine residues, OFMSW, and waste coal) and their relative impact on the environment, they provide cheap and sustainable feedstock to integrated biorefineries. Therefore, exploring their conversion into value-added products such as energy and chemicals would not only contribute towards achieving the International Energy Agency's energy goal to reduce global warming by 1.5 °C and achieve a net-zero emission by 2050, but also provide cheap, clean fuel and a safe and clean environment to communities.



Figure 2.3: waste coal or legacy coal

In this section will explore various technology routes that are currently being used to convert these wastes into fuel products and chemicals.

2.2. Waste conversion processes

Although widely available, the utilization of these feedstocks is hindered by their distinct properties and complex structural composition. Biomass, for example, is Lignocellulosic material consisting of tightly intertwined components, including cellulose, highly crystalline linear β -1,4-glucan polymers (Ma et al., 2026), hemicellulose (branched

heteropolysaccharides), and lignin (amorphous aromatic polymers that provide structural rigidity)(Ma et al., 2026). This recalcitrant matrix requires substantial energy input for processing, thereby raising both technological and economic challenges. The OFMSW, on the other hand, is highly heterogeneous with high moisture and ash content, with very low heating value. Because of their inherent properties, these feedstocks necessitate adequate processing techniques for their conversion to value-added products. Biomass has been successfully converted into products such as methane, biogas, and ethanol via various methods, including biochemical/biological and thermochemical routes.

Biochemical/biological conversion uses bacterial microorganisms and enzymes to break down the structure of biomass through the process of fermentation. This usually leads to the production of alcohol such as methanol and ethanol (Ledakowicz, 2025). Anaerobic digestion is a biological conversion process in the absence of oxygen to give out methane, carbon dioxide, and hydrogen sulfide (Ledakowicz, 2025). Biological processes are less efficient in converting the complex structure of the biomass, on its only limited to wet biomass. Therefore, thermochemical conversion routes are preferred and have received considerable attention as they have proved to be suitable for these types of feedstocks (Alvarado-Flores et al., 2024; Khater et al., 2024; Soltes, 1983). The thermochemical conversion process consists of processes such as combustion, hydrothermal liquefaction, pyrolysis, and gasification. In these processes, heat, combined with chemicals or catalysis, breaks down the biomass into its byproducts, such as biochar, bio-oil, and gases, also known as syngas in specific equipment (Amezcuallieri & Mexicano, 2018).

Each of the thermochemical processes will be discussed in the subsequent sections. Direct combustion is the most common conversion method to derive heat and energy from waste biomass. It consists of burning the fuel in the presence of an excess of air to produce

heat, carbon dioxide, and water vapor, with ash. This energy is usually used in power plants as a source of heat to drive steam turbines for electricity production, mechanical power, or other applications, such as domestic heating systems (Mignogna & Ceci, 2024). However, this approach produces low energy efficiency and substantial global warming potential.

The biomass torrefaction process is generally carried out in the temperature range of 200 to 300 °C at slow heating rates, < 50 °C/min, in an oxygen-free space (Mignogna & Ceci, 2024). Torrefaction is also often referred to as mild pyrolysis and a pretreatment technology to improve biomass for solid fuel production. The main product of torrefaction is biochar, which has properties intermediate between precursor biomass and charcoal. In addition to the solid biomass, the volatile fraction represented by non-condensable gases (mainly CO₂ and CO, and in low concentrations also CH₄ and H₂) and some condensable gases or liquids (water, furfural, furans, phenols, and organics such as acetic acid, propionic acid, and formic acid) is also released (Niu et al., 2019). The intended use for torrefied biomass is as a solid fuel in power generation.

Hydrothermal liquefaction, also known as HTL, transforms wet biomass like algae sludge and agricultural waste into high-energy-value biocrude oil and byproducts like biochar, aqueous phase gas, using heat under high pressure with a catalyst. HTL temperature ranges from 280 to 370°C, and pressure in the range of 10 to 25MPa (Mignogna & Ceci, 2024). Bio grease/biooil is the renewable equivalent of petroleum, as it is a high-energy-density intermediate that can be upgraded to a variety of liquid fuels. The main advantage of the HTL process is the ability to directly process wet biomass, enabling the conversion of materials such as algae or slurry into biooil. The process saves a significant amount of energy as no dehydration/drying of feedstock is required, thus reducing costs and allowing the process to be conducted at relatively low temperatures. Biooil obtained from liquefaction has better fuel

quality than pyrolytic oil due to its reduced oxygen content, which increases its stability and facilitates its use as a fuel. However, HTL yield is low, between 20 and 55%wt with a low heating value (Parameters & Solvents, 2021).

Pyrolysis is a thermochemical process by which biomass is burned in the absence of oxygen at a temperature range of 300 to 550 °C with or without a catalyst at a pressure range between 5 and 20 bar. (Khater et al., 2024) to produce biochar, bio-oil, and producer gas or pyro-gas (Khandelwal et al., 2024). Depending on the operating temperature and the desired products, pyrolysis can be categorized into fast, slow, and flash pyrolysis. Fast pyrolysis is conducted at a high heating rate (10 – 200°C/s), and the temperature ranges between 400 and 700 °C (Peters et al., 2015). Slow pyrolysis takes place at a slow heating rate of 0.1 to 1 °C/s and the temperature is often between 300 and 500 °C. In flash pyrolysis, the temperature ranges between 800 and above 1000 °C, and the heating rate can be as high as 1000 °C/s (Roldi-Oliveira et al., 2022). The products generated are used in many industrial applications, such as agriculture: biochar can be used as fertilizer for soil amendment, and the products pyro gas and bio-oil can be used as energy resources. (Peters et al., 2015). The product yield of pyrolysis depends on the process conditions, the catalyst, and the type of biomass used (Singh et al., 2017). Pyrolysis is a cost-effective process that does not need pre-treatment of the biomass; however, the biooil produced is highly corrosive and has a low energy density due to the high oxygen content.

Gasification is the thermochemical conversion method that deconstructs biomass into syngas (hydrogen-rich gas), char, tar, ash, and other combustible products such as methane, CO, and CO₂ at temperatures above 800 °C, in a controlled oxygen environment with a catalyst (Mishra & Upadhyay, 2021; Puig-Arnavat et al., 2010) by the aid of a gasifying agent. Gasifying agents are oxidizing agents that initiate chemical reactions; these include air,

steam, carbon dioxide, or their mixtures. Gasification is divided into primary, secondary, and tertiary stages, based on the reaction chemistry and temperature, which often occur simultaneously. The primary stage is comprised of drying, the release of volatile compounds, and CO₂, usually at a temperature below 500°C; no chemical reaction occurs at this stage (Singh et al., 2017). The moisture content of the biomass (30–60%) is vaporized or evaporated to values below 15%.

In the secondary stage, also referred to as the decomposition stage, products such as CO, CO₂, H₂, water vapor, gaseous aromatics, and phenols are produced at around 700 to 850°C, leading to the formation of ash. During the final stage, liquid tar, polynuclear aromatics, and syngas are produced between 850 and 1000°C (Singh et al., 2017). The effectiveness of the gasification process can be influenced by the type of gasifier and its performance, biomass composition, and biomass size distribution. In addition, each reaction is strongly influenced by fuel characteristics and process variables such as gasifying agent, gasification temperature and pressure, heating rate, and residence time. All these are key criteria for the selection, design, and operation of a given gasification system.

Although biomass such as pine residues and the organic fraction of municipal solid waste (OFMSW) represent abundant renewable energy resources, the large-scale industrial application remains limited due to their relatively low calorific value and complex physical properties. The energy content of forest biomass typically ranges from 15 to 23 MJ/kg (Ioannis et al., 2016), while OFMSW exhibits lower values of approximately 8 to 17 MJ/kg, depending on its source and composition (Rabia et al., 2021). In addition, these biomasses are highly heterogeneous and often characterized by high moisture content, non-uniform particle size, wide particle size distributions, and strong cohesive and compressible behavior. These characteristics significantly complicate their handling, storage, and thermochemical

conversion. Also, the ability to continually feed biomass into conversion equipment remains a challenge.

To overcome these challenges, biomass is often blended with higher-energy and more homogeneous materials such as coal to enhance overall fuel quality. Co-gasification of biomass and coal has been shown to produce synergistic effects on reaction kinetics, including a reduction in activation energy. Furthermore, the inherent metal oxide content in biomass acts as a catalytic agent, improving gasification performance by increasing gas yield and reducing tar formation, thereby making the product gas more suitable for use in gas engines (Banik et al., 2025). This blending strategy also contributes to lower emissions of hazardous pollutants such as sulfur- and nitrogen-containing compounds, as well as heavy metals (Chinonso et al., 2024). Studies have shown that increasing the biomass fraction in coal-biomass blends improves combustion performance by accelerating reaction rates, lowering ignition temperatures, and enhancing burnout. This process also significantly reduces pollutant emissions, particularly NO (nitrogen oxides) and SO₂ (sulfur dioxide), due to the synergistic effects during co-combustion (Hu et al., 2025).

Blending biomass with coal or inert materials like sand (commonly silica sand) and glass beads or olivine significantly improves flow properties and fluidization in reactors. It mitigates issues like poor handling, bridging, and segregation, especially in fluidized beds, by managing particle density and reducing fluidization velocity (Travieso et al., 2017). These mixtures enhance process efficiency, reduce tar formation, and improve bed material stability. These materials also act as heat carriers and heat-transfer mediums to facilitate the combustion of biomass (Wesolowska et al., 2026). They also promote mixing and uniform temperature distribution within the bed.

Despite these environmental and performance advantages, the combined handling of biomass and coal remains challenging due to the contrasting physical and mechanical properties of the two materials. Moreover, unlike fossil fuels, which benefit from mature and well-established conversion technologies, the thermochemical conversion of biomass requires a deeper understanding of reactor design and operating conditions tailored to its unique physicochemical characteristics. To date, fluidized-bed reactors have proven to be among the most effective biomass and coal gasification systems.

The following section will provide a brief description of the different types of fluidized bed systems

2.3. Introduction to Fluidized bed systems

Fluidization finds its application in thermochemical conversion processes such as combustion, gasification, drying of solids, coating of particles, and many others (Cui & Grace, 2007; Jena et al., 2008a). Fluidization is a process by which a bed of particulate matter is conditioned to behave like a fluid by subjecting it to an upward flow of fluid (gas or liquid) through a perforated distribution plate. Fluidized beds are extremely preferred in the process industry for their specific features, which include perfect mixing of solids with the fluid medium, uniform temperature distribution within the bed, high rate of heat and mass transfer, and chemical reaction between the solid particles and the fluid, resulting in a high yield of the products (Fu et al., 2019; Jena et al., 2008a; Si & Guo, 2008). Fluidized bed types include bubbling or circulating fluidized beds, fixed beds, which can be classified as downdraft, updraft, and cross-draft, and entrained flow fluidized beds (Moharamian & Hossainpour, 2025). A fluidized bed usually consists of a plenum, a distributor, a bed region, and a freeboard region, as shown in Fig.2.4.

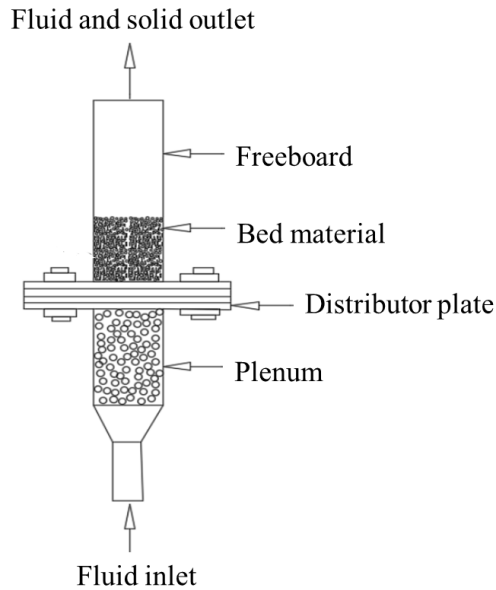


Figure 2.4: Fluidized bed

2.3.1. Bubbling fluidized bed

Bubbling fluidized bed gasification is the simplest and possibly the most cost-effective for biomass gasification and operates at a relatively low gas velocity ranging from 0.2 to 5m/s (Siedlecki et al., 2011; Ren et al., 2019). They are suitable for various types of biomasses with a wide range of particle sizes. The inert bed material is usually made of sand, silica dioxide, dolomite, etc. The gasification agent is introduced from the bottom through the distributor grid (Ren et al., 2019). This promotes uniform temperature distribution in the bed and high heating rate transfer between the bed materials and the biomass, resulting in uniform gas product. Some of the limitations of BFBG are the low solid conversion due to the back mixing in the bed, and the slow oxygen diffusion rate, which creates an oxidizing condition in the bed, hence reducing the gasification efficiency (Alauddin et al., 2010).

2.3.2. Fixed bed and moving bed

Fixed and moving bed gasifiers are the most commercially used gasifiers because of their simple design and easy operation (Mishra & Upadhyay, 2021). There are three types of fixed-bed gasifiers, namely updraft, downdraft, and cross-draft gasifiers, which are named based on the direction of the flow of the biomass and the gasifying agent gasifiers (Loha et al., 2018). They are suitable for small-scale applications up to 10 MW.

2.3.3. Circulating fluidized beds

The components of a circulating fluidized bed gasifier consist of a high-velocity riser, a cyclone, a downcomer, and a loop seal or an L-valve. Generally, the biomass particles are recirculated in the bed, leading to an increase in the residence time of the particles in the bed, enhancing the conversion efficiency. (Gómez-Barea & Leckner, 2010). CFBG has a higher superficial gas velocity in the range of 2 to 10m/s which allows the biomass to flow outside the reactor through a cyclone and be recycled back into the reactor (Gómez-Barea & Leckner, 2010)(Karl & Pröll, 2018; Sansaniwal et al., 2017), resulting in nearly complete carbon conversion, high gas yield, high heating value, and low tar content (Mishra & Upadhyay, 2021). Despite the simplicity of the setup, fluidized beds are complex systems, as they usually exhibit unstable conditions due to the bed's pressure fluctuation. The fluctuation within the bed is a result of the drag force exerted on the particles by the moving fluid, and also the collision between the particles (Lv et al., 2020). The transition of the particle from a fixed to a fluidized state takes place in various progressive stages, from fixed bed, bubbling, turbulent, fast fluidizations to pneumatic transport regimes with increased gas velocity as shown in Fig 4.

2.4. Fluidization regimes

When the fluid (gas or liquid) is uniformly passed through the bottom of a bed, it experiences some resistance due to the bed material's weight, particle shape, and size, which subsequently causes the bed pressure gradient to increase. As the fluid velocity increases, the pressure gradient across the bed rises proportionally until the drag force exerted by the fluid balances the weight of the bed, while the bed material remains in a stable condition (Fig 2.5a). This is due to the large friction that the fluid experiences when moving through the void space in the bed. This friction force is proportional to the bed weight and influenced by the particle properties such as the size, size distribution, the shape, and the moisture content.

As the gas velocity increases, the individual particles separate from each other, rearrange at the same time, and begin to move slowly in an upward movement. At this point, they become less resistant to the flow, marking the transition from fixed to fluidized bed (Fig 2.5b), and the velocity at this point is called the minimum fluidization velocity. At this fluid velocity, the pressure drop within the bed balances the weight of the particle per unit area of the bed (Cocco & Wei, 2023). Beyond this point, the pressure drop remains approximately constant even with further increases in velocity (Khawaja, 2016). The next stage is called the bubbling stage (Fig 2.5c). Two separate phases may appear at this stage, namely the continuous/emulsion phase and the discontinuous phase, also known as the bubbling phase. At much higher velocities, the frequency of bubble formation and breaking increases (Fig 2.5d). When the bubble passes through a relatively high-density fluidized bed, the system looks more like a boiling liquid, often referred to as a boiling bed. If the bubble diameter becomes equal to the tube diameter, slugging may occur. These slugs of gas may alternate with the slug of the fluidized solids that are carried upward and subsequently collapse, releasing the solids that fall back into the bed as shown in Fig 2.5e and 2.5f. At sufficiently high

velocity, the upper boundary of the bed becomes less distinct, the bed surface becomes diffused, and the upper surface of the bed disappears, as the bed becomes turbulent (Fig 2.5g). At this stage, further increase in the fluid velocity may result in the entrainment of particles, also known as pneumatic transport of solids requiring recycling.

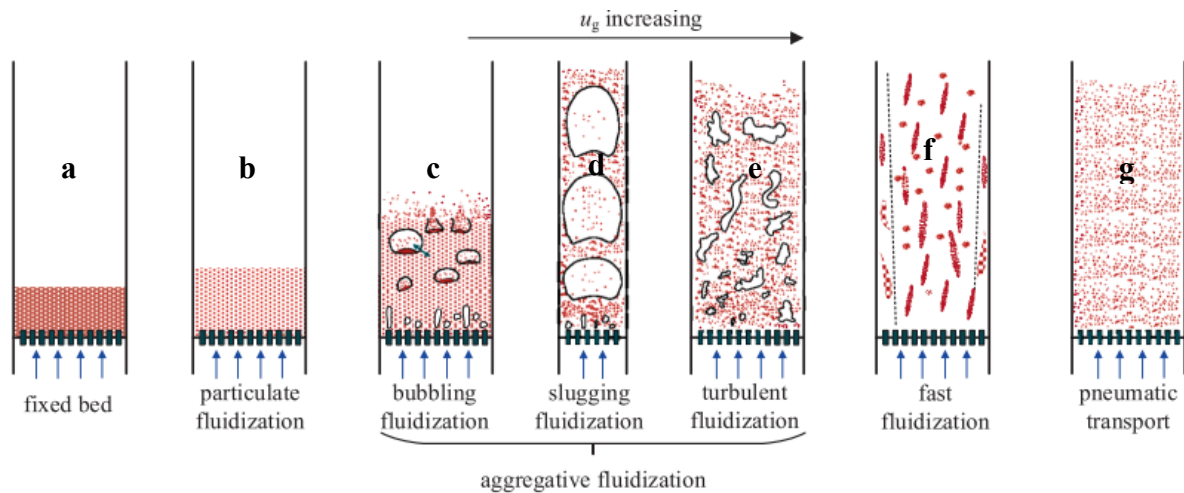


Figure 2.5: Fluidization regimes

The design and operation of fluidized-bed reactors are primarily governed by two key parameters: the minimum fluidization velocity (U_{mf}) and the pressure drop across the bed. The minimum fluidization velocity represents the superficial fluid velocity at which the drag force exerted by the fluid balances the weight of the bed particles, marking the transition from a fixed-bed regime to the onset of bubbling fluidization (Travieso et al., 2017). From the gas velocity, one can determine the fluidization regime in the bed. The pressure drop represents the drag force per unit area required to balance the weight of the bed material and achieve suspension of the particles within the fluid phase.

In the next section, we will elaborate on the U_{mf} and the pressure drop in the fluidized bed and address the impact of multicomponent material on these properties.

2.4.1. Measurement of minimum fluidization velocity (U_{mf})

The minimum fluidization velocity is defined as the superficial gas velocity at which the drag force of the upward-moving fluid is equal to the apparent weight of the particle in the bed (Fu et al., 2019; Janevski et al., 2018; Oliveira et al., 2013). The minimum fluidization velocity is experimentally determined from a pressure drop versus the superficial gas velocity curve at the point where the pressure drop becomes constant. The value is obtained at the intersection of the two extrapolated linear portions of the plot corresponding to the complete fluidized bed region and the fixed bed region, respectively (Toschi et al., 2021). The U_{mf} is important because it dictates the onset of fluidization and phenomena such as the extent of segregation or mixing in the bubbling fluidized beds (Janevski et al., 2018). The minimum fluidization velocity (U_{mf}) can also be determined using the voidage method, in which U_{mf} is identified as the superficial gas velocity at which the bed begins to expand (Fu et al., 2019; Huang et al., 2022; Zhang et al., 2021). However, this method is limited by the difficulty in precisely identifying the exact point at which bed expansion initiates. Another commonly used approach is the heat transfer method, where U_{mf} is defined as the gas velocity at which the heat transfer coefficient between the bed and a heat transfer surface increases sharply, reflecting the enhanced particle mixing and solid-fluid contact associated with the onset of fluidization (Let et al., 2022). The pressure drop method was used to identify the U_{mf} of the pine residues, municipal solid waste, and waste coal blend in this study.

2.4.2. Determination of the pressure drop in a fluidized bed

Pressure drop in fluidized beds is a critical parameter that strongly influences reactor performance, stability, and overall operational efficiency. In fluidized systems, pressure drop arises from a combination of particle-particle interactions, particle-gas momentum exchange, and particle-wall collisions (Bi, 2007). Experimentally, the pressure drop across a bed of

material is commonly measured using differential pressure transmitters or U-tube manometers connected between two vertical locations along the fluidized bed (Chauhan et al., 2023). Accurate measurement of pressure drop is essential for identifying key fluidization regimes, such as the onset of minimum fluidization, and for validating hydrodynamic models. Moreover, pressure-drop behavior provides valuable insight into bed expansion, solids holdup, and gas-solid interaction mechanisms under varying operating conditions.

2.4.3. Bed expansion

Bed expansion is one of the most important parameters in fluidized beds as it indicates the state of fluidization. As the bed expands the interparticle contact decreases, and the void fraction increases, which directly affects heat and mass transfer and reaction kinetics in the bed. It determines the flow regime and is directly related to the emulsion and the bubble phases, which are the main components of a fluidised bed (Fan & Zhou, 2021). Bed expansion is defined as the initial bed height to the height at the minimum fluidization velocity. The bed expansion ratio is commonly measured by visual observation of the expanded bed height, a U_{mf} , and calculated using the following formula:

$$H_{Expanded} = \frac{(H - H_{mf})}{H_{mf}} \quad (2.1)$$

Where $H_{expanded}$ is the expanded height

Bed expansion depends on the bed geometry, the inlet gas velocity, and the properties of the particle, such as the bulk density and particle size. According to the Geldart classification of powders, bed expansion for group B and D particles arises entirely from the volume occupied by bubbles. (Fan & Zhou, 2021) found that as the superficial gas velocity of Geldart B coal particles increased, the expansion rate of the emulsion phase first increased and then gradually stabilized, and the proportion of the bubbles phase increased at higher

superficial air velocity. Many studies (Fan & Zhou, 2021; Kai et al., 2024; Yang et al., 2017; Zhou et al., 2025) have reported that, in the fixed-bed regime where the superficial gas velocity (U) is less than the U_{mf} ($U < U_{mf}$), bed expansion is negligible. Slightly above U_{mf} , the bed height increases gradually with superficial gas velocity, whereas at higher velocities ($U \gg U_{mf}$) the expansion becomes nonlinear due to bubble formation and coalescence. At sufficiently high gas velocities, the bed height may approach a stable value. Larger bubbles increase the gas holdup, resulting in a higher bed voidage and expanded bed height.

2.5. Challenges in the determination of the U_{mf} and pressure drop of multicomponent heterogeneous mixtures

Biomass is commonly blended with sand or other inert materials, such as silicates, to improve its flowability due to its low density and high cohesiveness, and it is also co-mixed with coal to increase its overall energy density. However, capturing the behavior of these mixtures is challenging, due to the differences in their properties such as particle size and size distribution, density, (Fu et al., 2019; Stovall et al., 1986 & Yu & Standish, 1991). For example, a bed consisting of material of different densities, a lighter particle may fluidize earlier, while heavier particles may remain at the bottom of the bed, resulting in incomplete fluidization (Noda et al., 1986). Due to their different properties, factors such as mixing and segregation of the components may affect the estimation of the U_{mf} and the bed pressure drop. The behavior of particles in the bed of multicomponent systems was studied by Chiba et al., (1979). Different zones were captured depending on the particle properties and represented in Fig 2.6: a) complete mixing zone, composed of small particles having nearly the same size and densities, b) complete segregation, composed of particles with different sizes and densities, and c) partial mixing, which is intermediate between a and b (Noda et al., 1986).

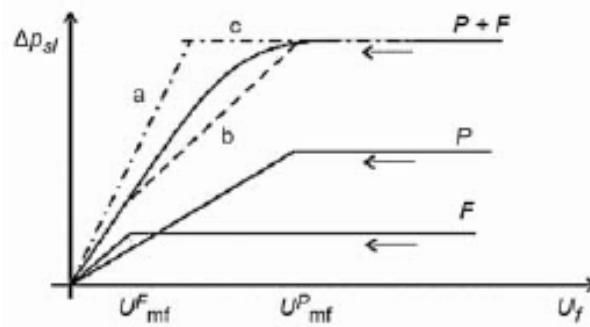


Figure 2.6: Fluidization curve of two-component mixture, a) fully mixed, b) complete segregation, c) partially mixed/stratified

Many authors have investigated the behavior of fluidized multicomponent materials and found that in the fluidized bed of a multi-material mixture, usually the fine particles occupy the space between the coarse particles in the bed, which causes the gas to struggle to flow and, in consequence, increase the bed pressure drop (Shao et al., 2016; Jena, G.K. Roy, 2008).

Moreover, researchers have studied specific factors that impact the minimum fluidization velocity and bed pressure drop. For example, Travieso et al. (2017) investigated the minimum fluidization velocity of mixtures of sugarcane bagasse and silica sand with varying mean particle diameter and mass fractions. They observed that the mass fraction of the component strongly affected the minimum fluidization velocity. Other works concluded that the fluidization velocity and the fluidization pattern of a binary mixture of biomass and sand are linked to the particle shape, size, and volume fraction, and partial fluidization due to channeling and spouting obtained at a high biomass loading rate (Emiola-sadiq et al., 2021).

2.6. Material properties that influence the fluidization of multicomponent biomass coal systems

To understand the principle of fluidization in multicomponent biomass and coal systems, it is imperative to identify factors that affect their fluidization behavior, especially the onset of particle motion.

2.6.1. Particle size

The behavior of the fluidized bed is strongly influenced by the bed material particle size. The Geldart classification (Fig 2.7) is a widely used method to categorize particles by their behavior during fluidization. Particles are demarcated into four groups, labelled A, B, C, and D, based on particle size (Sauter mean diameter) and the difference between particle density and the gas density ($\rho_s - \rho_g$) (Cocco, 2014; Cocco & Wei, 2023; Rovero et al., 2012). This classification is only valid when air is used as the fluidizing medium. Geldart has summarized the characteristics of each group as follows (Cáceres-martínez et al., 2023; Rovero et al., 2012; Yehuda & Kalman, 2020).

Geldart Group A, or aeratable, particles are generally preferred for fluidization due to their fine particle size, relatively small diameters, and moderate particle density (approximately $1400 \text{ kg}\cdot\text{m}^{-3}$). These characteristics promote smooth fluidization behavior and minimize particle agglomeration (Rovero et al., 2012). Group B or sand-like particles are coarser, ranging from 150μ to $1000 \mu\text{m}$ and densities from 1400 to $4000 \text{ kg}/\text{m}^3$. They tend to agglomerate more and may not require higher gas velocities to achieve fluidization as they bubble from the onset of fluidization (Cocco, 2014). Group C particles are fine powders with a mean diameter generally less than $50 \mu\text{m}$, which can be very difficult to fluidize as they exhibit strong interparticle forces. They are considered cohesive, leading to particle clustering, and may often require fluidization aids such as baffles, microjets, pulsing, and mechanical vibration. Group D particles are sometimes added to enhance fluidization (Cocco, 2014). Group D or spoutable are the largest particles within a broad density range; they are highly permeable, may result in high channeling and uneven gas distribution. Usually, large bubbles lead to slugging even in large gas velocity.

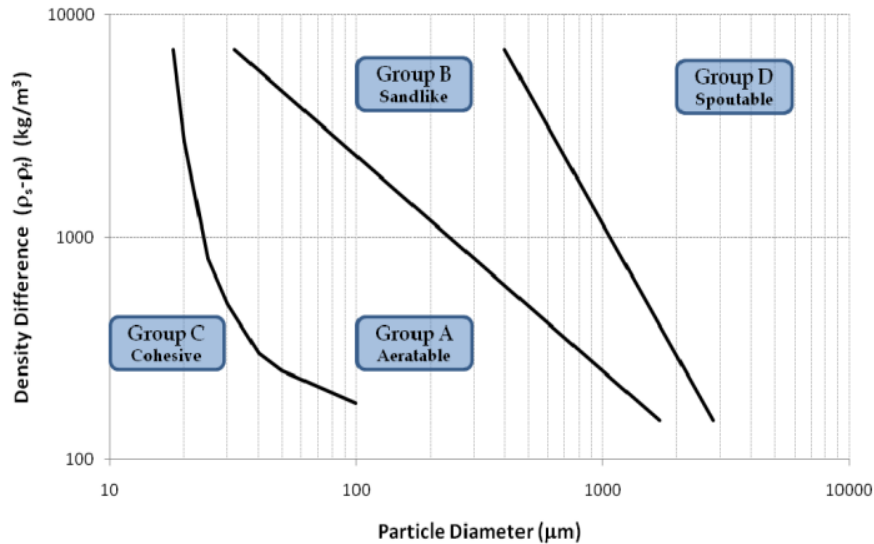


Figure 2.7: Geldart classification of particles

The Geldart classification of particles usually treats all particles of a given density and size as equivalent in terms of fluidization behavior. This concept underestimates the influence of multi-component bed materials, where particles are widely distributed in shape and size, and the mean diameter may not adequately quantify the size of all particles in the bed. For example, in polydisperse (non-uniform) systems, smaller particles ("flotsam") tend to rise, while larger particles ("jetsam") sink, a phenomenon governed by the balance of gravity and drag forces, rather than a single average particle size (Yu et al., 2024). This often results in a "bad quality" of fluidization, which can only be improved by considering the full PSD or adding fine particles to create a "lubricating effect" (Korkerd et al., 2020). Research shows that binary or multi-component mixtures do not fluidize exactly like single-component beds. For example, binary systems with different particle types show distinct fluidization patterns and different minimum fluidization velocities than would be predicted by a simple average size (Tanga et al., 2012; Li et al., 2021; Pandey et al., 2025; & Yu et al., 2024). Korkerd et al., (2020) studied the U_{mf} of five particle size distributions of silica sand, including narrow cut, Gaussian, Gaussian

with high standard deviation, negatively skewed, and positively skewed distributions, and found out that the U_{mf} values of particles with a wide PSD were lower than that of the narrow cut particles with the same diameter, and concluded that smaller particles improved the fluidization characteristics due to the lubricating effect of the smaller particles. The U_{mf} increased as the average particle diameter increased.

Furthermore, Cáceres-Martínez et al., (2023) studied the behavior of various biomass and sand mixtures including rice husk ground (215–2330 μm), coffee ground (698 – 4150 μm), poultry litter (117- 2970 μm), palm shell (1330-7830 μm), oil palm shell fiber (87 1090 μm), oil palm shell coarsely and finely ground (1120-33350 μm , 158-3960 μm) and coarsely and finely ground sugar bagasse (308-1940 μm , 460 – 3260 μm), the particle ranged between Geldart B and D classification, moisture content ranged from 7.5 to 14.9%. The U_{mf} was measured using the pressure drop method. The pressure drop and the bed height were also measured and concluded that apart from the mass fraction of the biomass, the size of the particle has a relevant effect on the fluidization behavior. The effect of particle size using monodispersed silica particles with diameters from 400 to 800 microns was analysed by Chandimal Bandara et al., (2017). It was observed that the U_{mf} increased as the particle diameter decreased. Furthermore, particles were mixed according to a predetermined proportion, giving a mean diameter of 600 microns. It was observed that the 600 microns showed the highest U_{mf} ; however, smaller particles (~200 microns) showed a strong drag effect, especially in the early fluidization. The pressure drop also showed significant variability due to the size difference, but it increased as the particle size decreased.

In summary, particle fluidization using a bed of particles with uniform size and density may seem easy. But when the fluidizing bed is comprised of non-uniform and non-spherical particles, as is typically the case for biomass particles, the behavior of particles at the various

fluidization regimes becomes difficult to determine because of the possibility of the occurrence of one or more regimes at a given airflow rate.

2.6.2. Particle shape

Raw biomass is usually physically processed into granular form before it can be used for thermochemical purposes. This process results in material with non-uniform shape and size. This poses additional complications in establishing accurate predictions of their behavior during applications since the non-spherical particle-particle interaction and particle-fluid interaction behave rather differently compared to spherical particles. The shape of a biomass particle can be described by two or more shape factors, namely form, roundness, irregularity, aspect ratio, and sphericity (Ulusoy, 2023). Shape factor is one of the important parameters used for non-spherical particles, and has been widely reported using a quantity from 0 to 1 (G. Olatunde et al., 2017). For instance, sphericities of $\phi < 0.5$ indicate extremely flat particles, $\phi > 0.5$ represent flat particles, and $\phi > \sim 0.8$ represent nearly spherical particles (Li et al., 2012). Similarly, Lucas et al. (1986) also classified sphericity of particles into three categories, namely, round ($0.8 \leq \phi \leq 1$), sharp ($0.5 \leq \phi \leq 0.8$), and others ($0.1 < \phi < 0.5$).

Experimental studies by Charan et al., (2023) have shown that non-spherical particles can have lower minimum fluidization velocities and higher bed expansion compared to spherical particles of the same size and density. This is because shape affects how particles pack, how they interact with gas, and how they respond to fluidization forces (Guo et al., 2012). Such a difference is mainly related to particle orientation and corresponding differences in particle stresses. For example, non-spherical particles with high surface-to-volume ratios can have 20 %- 120 % higher average shear particle stress than that of spheroidal particles. Non-spherical particles of large aspect ratio are difficult to fluidize due to the interlocking between particles (Zou et al., 2023). The U_{mf} of different biomass types was

studied by Zhong et al., (2008), and the effect of biomass aspect ratio was evaluated. It was reported that the minimum fluidization velocity of long thin biomass increases with an increasing diameter and aspect ratio of length/diameter, while long thin biomass with the aspect ratio over a certain value could not be fluidized. This was attributed to the increase in particle transections, leading to an increase in U_{mf} . Spherical or more uniform particles are usually used to assist the fluidization of non-spherical particles in typical industrial applications, although segregation might happen due to non-uniform mixing, a case observed by Salatino & Solimene (2017).

2.6.3. Particle density

Particle density is the ratio of the average mass to the average volume of particles that form the bulk solid, excluding the void spaces. Particle density is a fundamental physical property that dictates how particles interact with fluids, disperse within them, and settle over time, while also directly influencing the structure and packing efficiency of bulk solids (Lotfiman et al., 2022; Yang, 2026). When it comes to fluidization studies by Chandimal Bandara et al., (2017) revealed that the U_{mf} of Silica was proportional to the particle density. This is because a higher particle density results in greater gravitational forces, requiring a higher upward fluid velocity to suspend the particles.

Particle densities of several biological materials have been reported in the literature. For example, Gil et al. (2013) reported that the particle density of ground poplar varied between 1293 and 1457 kg.m^{-3} as particle size reduced from 5 mm to 2 mm. additionally, Hehar et al. (2014) reported the particle density of loblolly pine ground wood to be 1437.9, 1423.6, 1448.3, and 1443.6 kg/m^3 , which were classified into four categories, namely unfractionated ($< 420 \mu\text{m}$), coarse (180–420 μm), medium (90–180 μm), and fine ($< 90 \mu\text{m}$) respectively. Also, the particle density of different components of municipal solid waste

measured using a water pycnometer was reported by Yesiller et al., (2014), and the values were 1000 kg/m³ for food waste; 300 kg/m³ for garden waste; 400 kg/m³ for paper; 1100 kg/m³ for plastic and rubber; 300 kg.m⁻³ for textiles; 450 mg/m³ for wood; 600 kg/m³ for metal; 2900 kg/m³ for glass and ceramics; and 1800 Mg/m³ for ash, rock, and soil. Petrovic et al., (2022) also measured the particle density of municipal solid waste using an air pycnometer and reported a value of 1820 kg/m³, with a large standard deviation (SD) of ± 190 kg.m⁻³ owing to the heterogeneous nature of the sample.

Wang (2014) noted that high-particle-density biomass offers better flowability but low internal porosity, which could limit gas-solid interactions during fluidization. Particle density is a critical parameter in fluidization studies, particularly for determining the minimum fluidization velocity, controlling the stability of the fluidized bed, and influencing the tendency of particles to segregate or defluidize (Abanades et al., 2019; Rao et al., 2011). When there are substantial variations in particle densities of bulk material to be fluidized, the less dense particles are first fluidized while the denser ones remain unfluidized. In binary or multi-component systems, significant differences in particle density (or size) lead to segregation, where denser (jetsam) particles settle at the bottom, and lighter (flotsam) particles rise to the top (Li et al., 2024). Rao et al., (2011) concluded that segregation poses a significant challenge when predicting the solids-mixing state of a fluidized bed, thereby limiting the ability to fully exploit potential benefits such as uniform thermal conditions and improved product quality that depend on effective mixing control.

2.6.4. Bulk density

Bulk density, which is defined as the mass of material per unit volume, including the void space, is a critical parameter influencing the logistics, storage, and processing efficiency of biomass (Tasnim & Chen, 2025). It determines transport costs, required storage volume,

and equipment sizing for handling systems, where higher densities generally improve operational efficiency (ASABE, 2021). For biological materials, the bulk density is affected by particle size, particle shape, moisture content, and species/type of biomass. In fluidization, bulk density is a critical parameter that directly influences the void spaces (porosity) between particles, thereby regulating inter-particle movement and air penetration through the bed (Kalman & Portnikov, 2021). The bulk density determines how closely packed the particles are, which impacts the force required to move them apart and the efficiency of the gas-solid contact.

Numerous studies have examined the bulk density of different biological materials and how it correlates with other material properties. For example, research shows that the bulk density of polydisperse material with various sizes usually increases with an increase in the proportion of the particle size (Saw et al., 2013). Since small sizes fill the space between the bigger ones (Saw et al., 2013). Additionally, void spaces within a bulk product increase when particles do not pack together efficiently, a phenomenon primarily driven by shape irregularity, polydispersity (varied size distribution), and random orientation (Jaeggi et al., 2025). When particles are not uniform or spherical, they cannot arrange themselves to minimize the gaps between them, leading to a higher void fraction (or porosity). Hence, as particle size increases, void spaces increase and bulk density decreases, which can alter fluidization behavior, resulting in channeling or segregation, especially in multi-component particle fluidization. Furthermore, the moisture content of a feedstock has been reported to affect the bulk density. Generally, an increase in moisture content results in a decrease in bulk density. An increase in moisture increases the particle weight, but the increment rate is lower compared with the resulting volumetric expansion of the bulk, as explained by (Oginni et al., 2016). For instance, Littlefield et al., (2011) reported that the bulk density of pecan shells reduced from 460.3 to

396.7 kg/m³ when the moisture content increased from 4.4% to 24.7% wet basis. The author attributed this to the addition of moisture, which increased the bulk volume of pecan shells at a faster rate than their mass. Other research also concluded that the moisture content in the biomass significantly affects its bulk density (Olatunde et al., 2017 & Lu et al., 2023).

2.6.5. Moisture content

In addition to the physical properties of biomass, including density, particle size, shape, porosity, and particle size distribution, moisture also plays a deterministic role in preprocessing biomass materials. Biomass, including pine residue and organic fraction municipal solid waste (OFMSW), naturally contains a significant amount of moisture, often ranging from 40% to 80% or more by weight, depending on the source and weather conditions (Shija, 2026). Moisture content (MC) is one of the major causes of the high variability in the properties of biomass feedstock (Olatunde et al., 2017). This is because moisture influences mechanical properties (flowability, compressibility, cohesion, and adhesion of particles) during storage and transportation, which are responsible for the formation of inter-particle bonds with water molecules. In addition, the moisture content of biomass alters its thermochemical conversion efficiency, as it often results in incomplete combustion (Kumar et al., 2014), lowers the reactor temperature, and consequently reduces the product quality, the net energy output, and increases tar formation. Literature reported that an optimal range (10-20%) can sometimes enhance hydrogen production (Kumar et al., 2014). On the other hand, high levels (>30%) often may result in lower CO concentrations, higher tar, and reduced conversion efficiency. Kumar et al., (2014) reported a reduction in the gasification efficiency from 65 to 37%, and power deployment from 8 to 4.1kW when the moisture content in the biomass increased from 15 to 45%. Furthermore, Huangfu et al., (2014) investigated the influence of fuel moisture content on the thermal and emission performance of a natural-draft

semi-gasified (TLUD) biomass cookstove. Using wood pellets with moisture contents ranging from 5.9% to 22.1%, the authors evaluated thermal efficiency, burning rate, cooking power, charcoal production, and emission factors of CO and particulate matter (PM_{2.5}). The results showed that increasing moisture content significantly reduced burning rate, cooking power, and both CO and PM_{2.5} emission factors, and increased boiling time. Interestingly, thermal efficiency increased with moisture content up to 18.2%, although the magnitude depended strongly on the calculation method (charcoal omitted vs. charcoal corrected). Charcoal yield on a dry basis remained relatively constant (~26–27%), indicating that moisture did not alter the dry fuel-to-char conversion process. Contrary to findings reported for rocket-type stoves, the study demonstrated that higher moisture levels in semi-gasified stoves can reduce emissions due to slower combustion and longer gas residence time in the secondary combustion zone. The authors emphasized that fuel moisture content should be carefully controlled or specified in stove testing protocols, as it significantly affects performance evaluation and emission estimation.

Currently, most modern, high-efficiency combustion systems and fluidized bed systems are designed to operate within a certain range of parameters to ensure that performance meets emissions and efficiency specifications, and a range of acceptable moisture content for the fuel is usually specified. This requires careful design of these operating systems to be able to perform at their desired capacity. This has attracted the attention of many researchers to investigate the effect of moisture content on fluidization processes. For example, Brammer & Bridgwater, (2002) investigated the influence of feedstock moisture on biomass gasification performance, which has been extensively examined in combined heat and power (CHP) systems. In a fluidized bed gasifier engine configuration, increasing moisture content from 45% to 100% (dry basis) was shown to

reduce overall efficiency from 70% to 60%, while simultaneously increasing the cost of electricity from 10.5 to 12.0 ¢/kWh. The decline in efficiency was primarily attributed to the additional energy required for moisture evaporation, which lowered cold gas efficiency and reduced engine output. The study further demonstrated that feedstock drying can substantially improve system performance; however, the economic benefit depends strongly on the drying method. Waste heat integration was found to be the most favorable strategy, as it enhances efficiency without significantly increasing operating costs. These findings highlight the critical role of moisture management in optimizing both the technical and economic performance of biomass gasifier-based CHP systems.

Olatunde et al., (2017) investigated the effect of various moisture contents (8 to 27%) on the fluidization behavior of loblolly pine grind with different diameters and reported that increasing moisture content resulted in higher minimum fluidization velocity due to enhanced inter-particle cohesive forces caused by liquid bridge formation. Additionally, as moisture increased, fluidization quality deteriorated, with greater tendencies of channeling, agglomeration, and reduced bed expansion. Pressure drop characteristics were also affected, indicating less stable bed hydrodynamics at elevated moisture levels. The study demonstrated that high-moisture biomass exhibit more cohesive behavior, resembling Geldart C-type particles, thereby complicating fluidized bed operation.

In summary, the physical characteristics of biomass, including extreme particle shapes, broad size distribution, non-uniform densities, and substantial moisture variability of biomass feedstocks, make it technically challenging to determine which material properties should be prioritized when designing fluidization systems. Experimental determination of key parameters under specific operating conditions can be difficult, often requiring complex setups and specialized expertise. As a result, researchers commonly rely on existing

equations and correlations developed for other feedstocks to estimate these parameters, though such models may need adjustment because they were derived under different conditions. The next section reviews several of these equations used to estimate fluidization parameters and outlines the fundamental assumptions underlying their development.

2.7. Empirical and modeling approaches for determining minimum fluidization velocity of multicomponent systems

In this section, the mathematical modeling studies related to the prediction of minimum fluidization velocity and computational fluid dynamics models that have previously been used to predict the state of the bed during fluidization are reviewed and presented. Experimental determination of minimum fluidization velocity (U_{mf}) and bed conditions in particulate mixture systems is disadvantageous due to high costs, time-consuming procedures, and challenges in handling complex, non-uniform particles that cause segregation, inconsistent data, and potential particle entrainment. Furthermore, experimental results may not easily be scaled up to industrial applications due to errors that can arise from mistakes such as improper probe placement, which may result in inaccurate data acquisition. Over the past decades, researchers have developed various techniques to predict the minimum fluidization velocity and bed hydrodynamic behavior in such systems (Agu et al., 2019; Debnath et al., 2021a; Luo et al., 2022; Mahmoudi et al., 2021; Xu et al., 2021). These approaches range from simplified equations of motion to advanced three-dimensional, unsteady models based on fundamental mass, momentum, and energy balance relationships. Broadly, these techniques can be classified into three main categories: (1) pressure-based approaches, (2) empirical model approaches, and (3) computational fluid dynamics (CFD) modeling approaches. These techniques are mostly derived from experimental data using the properties of the fluidizing gas and particle characteristics (e.g., densities of the particle and

gas, particle sphericity, porosity, and others), which are only valid for specific conditions and bed material systems. For example, Correlations derived from single-component or homogeneous biomass sources often fail to predict the behavior of multi-component systems due to the complex, non-linear interactions between biomass physical properties (Bai & Si, 2020a; Cáceres-martínez et al., 2023; Paudel & Feng, 2013; Shao et al., 2013). Hence, a form of modification has to be done to suit the desired system (Alghamdi, Peng, Almutairi, Alibrahim, Al-alweet, et al., 2021).

2.7.1. Pressure drop approach

The pressure drops (ΔP) derived from a force balance within the bed of material relative to the height of the bed and the cross-sectional area (A) is the most used method to determine the minimum fluidization velocity (Alghamdi et al., 2021; Cáceres-martínez et al., 2023; Korkerd et al., 2020; Let et al., 2022). Conceptually, when an airflow is passed through a bed of particulate material, the pressure drops inside the bed increase linearly with increased airflow velocity until the weight of material in the bed counterbalances the updraft created by the airflow. At this point, the bed is said to be in a fluidized state (Let et al., 2023). This approach was developed by Ergun, and the resulting correlation is known as the Ergun equation (Eqn. 2.2). However, the applicability of this equation is restricted by several underlying assumptions, including a homogeneous bed composed of spherical or near-spherical particles, random packing, constant bed porosity, and validity within a specific range of particle Reynolds numbers (Ho et al., 2018). The Ergun equation integrates both laminar (viscous) and turbulent (inertial) contributions, accounting for the pressure drop arising from energy losses as the fluid flows through the packed bed.

$$\frac{\Delta P}{L} = 150 \frac{(1-\varepsilon)^2}{\varepsilon^3} \frac{\mu_g U_{mf}}{\phi d_p^2} + 1.75 \frac{(1-\varepsilon)}{\varepsilon^3} \frac{\rho_g U_{mf}^2}{d_p} \quad (2.2)$$

The pressure drop across the bed can also be expressed in terms of the bed void fraction, particle and gas densities, and the weight of solids per unit cross-sectional area. It is also known as the pressure drop across the entire bed when it has fluidized, expressed in Eqn 2.3.

$$\frac{\Delta P}{H} = \frac{W}{AH} = (1 - \varepsilon)(\rho_p - \rho_g)g \quad (2.3)$$

This expression relates the pressure gradient to the effective weight of the particles (accounting for buoyancy) distributed over the bed volume.

Where,

ΔP : pressure drop in the bed (Pa)

H: bed height (m)

ε : bed voidage

μ_g : gas viscosity (Pa. s)

U_{mf} : minimum fluidization velocity (m.s⁻¹)

d_p : particle diameter (m)

g : acceleration due to gravity (m.s⁻²)

ρ_p : particle density (kg.m⁻³)

ρ_g : gas density (kg.m⁻³)

A : cross-sectional area of the bed

w : weight of the bed material

The bed voidage represents the ratio of the volume of the bulk volume calculated using the

following formula $\varepsilon = 1 - \frac{\rho_b}{\rho_p}$

Where ρ_b is the bulk density (kg.m⁻³)

Accurate prediction of the minimum fluidization velocity (U_{mf}) using the pressure drop method requires precise determination of the particle properties, including particle diameter,

bed porosity, and particle sphericity, which are difficult to determine in real systems containing non-uniform, wide size distribution and heterogeneous, and a of materials like pine residues and organic fraction of municipal solid waste (OFMSW). Hence, the Ergun equation is not usually appropriate for these materials unless some modifications are made. For example, the effective particle diameter is often used to represent the particle when the pressure drop method is used for the determination of the U_{mf} in a bed of biomass material (Ho et al., 2018). The effective particle diameter is a representative particle size used to describe non-spherical or irregular particles as if they were equivalent spherical particles for modeling in the Ergun equation.

2.7.2. Empirical model approaches

Several correlations have been developed to predict the bed of non-spherical, heterogeneous, and multi-component materials (Jena et al., 2008b; Vasconcelos et al., 2023). Shao et al., (2013) predicted the minimum fluidization velocity of ternary mixtures of four types of particles, including solid waste, silica, and sand with different shapes, sizes, and densities, using the correlation proposed by (Jena et al., 2008b; Vasconcelos1 et al., 2023). The correlation used was given by eqn 2.4 through 13.

$$U_{mf} = a \left[\frac{d_{pe}^2 (\rho_{pe} - \rho_g) g}{\mu_g} \left(\frac{\rho_{pe}}{\rho_g} \right)^b \right]^c \quad (2.4)$$

where a, b, and c are constants to be determined based on the characteristics of the particles studied, ρ_{pe} is the effective particle density including irregular particles, d_{pe} is the effective particle diameter of the mixture, ρ_g is the density of the fluidized gas, and μ_g is the gas viscosity. The effective density and particle diameter of the mixture were calculated using equations 2.7 and 2.8.

$$\rho_{pe} = x_1 \rho_{pe1} + x_2 \rho_{p2} \quad (2.5)$$

$$d_{pe} = d_{pe2} \left[\left(\frac{\rho_{p2}}{\rho_{pe1}} \right) \left(\frac{d_{pe1}}{d_{p2}} \right) \right]^{x_1/x_2} \quad (2.6)$$

x_1 is the mass fraction of irregular particles in the mixture, and x_2 is the mass fraction of bed material in the mixture, with $x_1 < x_2$, ρ_{pe1} , and d_{pe1} representing the effective particle density and effective particle diameter of the irregular particles, which can be calculated using eqn. 2.7 and

$$\rho_{pe1} = \sum \alpha_i \rho_{pi} \quad (2.7)$$

Where α_i , ρ_{pi} , and d_{pi} represent the volume fraction, particle density, and effective diameter of the individual type of irregular particle within the mixture. By applying the multivariate regression analysis to the experimental data values, the final correlation for the minimum fluidization velocity of the ternary mixtures was developed as eqn 2.8.

$$U_{mf} = 1.28 \times 10^{-3} \left[\frac{d_{pe}^2 (\rho_{pe} - \rho_g) g}{\mu_g} \left(\frac{\rho_{pe}}{\rho_g} \right)^{1.2} \right]^{0.356} \quad (2.8)$$

2.7.3. CFD modeling approach

Experimental investigation is limited to understanding the complex phenomena that take place in a fluidized bed, such as particle-particle interaction or particle interaction with the fluid medium or the wall (Yang et al., 2022). The harsh environment of high-temperature and high-pressure fluidized bed reactors, specifically during pyrolysis or gasification, creates significant limitations for direct, real-time observation of internal hydrodynamics (Sivri, 2021). These conditions often lead to a lack of understanding regarding the complex, multi-scale, and multi-physics processes occurring within the bed. Therefore, numerical simulation methods using computational fluid dynamics (CFD) are usually implemented to mimic the conditions of the bed material. Computational fluid dynamics (CFD) is an essential tool for investigating the fluidization of biomass particles (single- or multicomponent mixtures) because the positions

and velocities of the particles must be tracked throughout the flow (Lu et al., 2020). CFD methods have been successfully applied to multi-component fluidization, a complex process involving multiple solid types, gas, or liquid phases driven by advancements in computational power and high-performance computing (HPC). High-performance computing, including GPU (graphics processing unit) acceleration, has enabled detailed 3D simulations of large-scale industrial fluidized beds (Golshan et al., 2020). However, the most significant drawback of the CFD model is that its sophistication means computational time for 3D modelling is significantly longer and requires special training before it can be effectively deployed.

Xiong et al., (2024), reviewed the most used CFD approaches for biomass–sand mixture systems, particularly in fluidized beds. In these systems, sand, biomass, and gas can be modeled using different multiphase frameworks. These include the Euler–Euler two-fluid model (TFM), where all phases are treated as interpenetrating continua; the Euler–Euler–Lagrange approach, in which the gas and sand are modeled as continuous phases while biomass is treated as discrete particles; and the Euler–Lagrange–Lagrange approach, where the gas phase is considered continuous and both sand and biomass are treated as discrete entities. In these approaches, it is usually assumed that the flow is isothermal, the gas phase is incompressible, and particles are spherical and monetized. The solid and gas phases are modeled by applying the mass and momentum conservation equations for each phase.

In CFD multiphase gas–solid systems, TFM, the solid phase is commonly described using the kinetic theory of granular flow (KTGF) to account for particle collision and granular temperature, while the gas phase is described using the Navier-Stokes equation for continuum fluid. The equations used to model each phase are given as follows:

Gas phase continuity equation

$$\frac{\partial(\alpha_g \rho_g)}{\partial t} + \nabla \cdot (\alpha_g \rho_g \vec{u}_g) = 0 \quad (2.9)$$

α_g : gas volume fraction

ρ_g : gas density

$\vec{u}_g$: gas velocity

Gas phase momentum equation

$$\frac{\partial(\alpha_g \rho_g \vec{u}_g)}{\partial t} + \nabla \cdot (\alpha_g \rho_g \vec{u}_g \vec{u}_g) = -\alpha_g \nabla p + \nabla \cdot \boldsymbol{\tau}_g + \alpha_g \rho_g \vec{g} + \vec{M}_{gs} \quad (2.10)$$

p : pressure (shared by phases)

$\boldsymbol{\tau}_g$: viscous stress tensor

$\vec{M}_{gs}$: interphase momentum exchange (drag force)

Gas phase stress tensor equation

$$\boldsymbol{\tau}_g = \alpha_g \mu_g [\nabla \vec{u}_g + (\nabla \vec{u}_g)^T] + \alpha_g \left(\lambda_g - \frac{2}{3} \mu_g \right) (\nabla \cdot \vec{u}_g) \mathbf{I} \quad (2.11)$$

Solid phase equations based on KTGF

Granular temperature

$$\Theta = \frac{1}{3} \langle c'^2 \rangle \quad (2.12)$$

Solid phase continuity equation

$$\frac{\partial(\alpha_s \rho_s)}{\partial t} + \nabla \cdot (\alpha_s \rho_s \vec{u}_s) = 0 \quad (2.13)$$

Solid phase momentum

$$\frac{\partial(\alpha_s \rho_s \vec{u}_s)}{\partial t} + \nabla \cdot (\alpha_s \rho_s \vec{u}_s \vec{u}_s) = -\alpha_s \nabla p - \nabla p_s + \nabla \cdot \boldsymbol{\tau}_s + \alpha_s \rho_s \vec{g} + \vec{M}_{sg} \quad (2.14)$$

Solid stress tensor

$$\boldsymbol{\tau}_s = \alpha_s \mu_s [\nabla \vec{u}_s + (\nabla \vec{u}_s)^T] + \alpha_s \left(\lambda_s - \frac{2}{3} \mu_s \right) (\nabla \cdot \vec{u}_s) \mathbf{I} \quad (2.15)$$

Where,

μ_s : solid shear viscosity

λ_s : solid bulk viscosity

τ : stress tensor

In gas–solid systems, particles in motion are subjected to several forces, including acceleration forces, gravity, interparticle (solid) stresses, and internal stresses within the solid phase. The acceleration-related forces consist primarily of drag, lift, and virtual mass forces (Zhang, 2019). The interparticle stress (often termed solid stress, solid pressure, or particle phase stress) and the internal stress within the solid phase in a fluidized bed are primarily due to the collisions and friction that occur during particle movement within the fluid (Banik et al., 2025; Shuyan et al., 2009). For multiphase systems, the drag force can be characterized by two-phase structures, namely a particle-dominated dense phase and a gas-dominated dilute phase, where each phase consists of two types of particles with different diameters and/or density (Quan Zhoua, 2015) as shown in Fig 2.8.

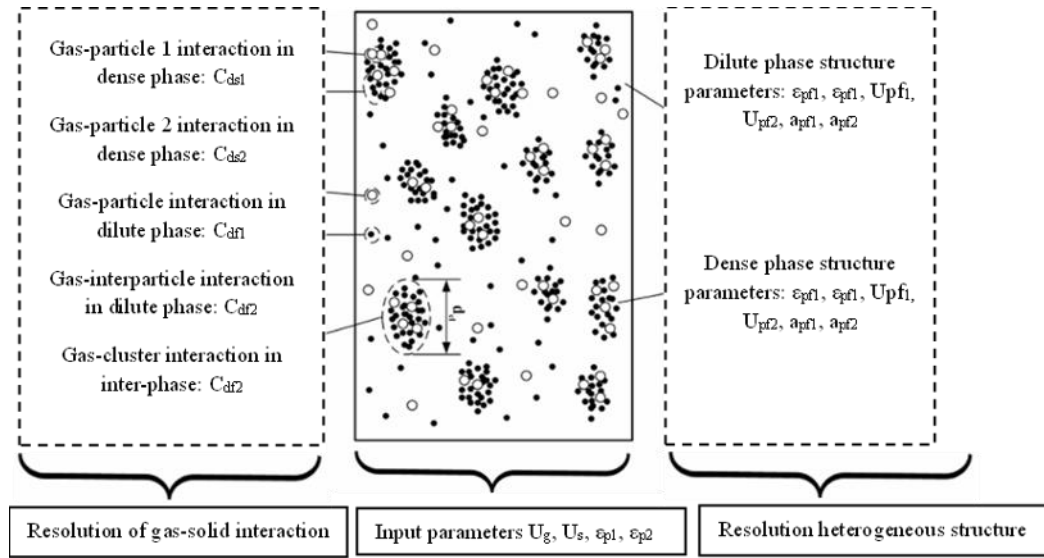


Figure 2.8: Multi-scale resolution of gas-solid interaction in the binary gas-solid flow

Various drag models have been reported in the literature, most of which are empirical or semi-empirical correlations derived from experimental data. Commonly used models include the Syamlal O'Brien model (Gera et al., 1998), the Gidaspow model (Gidaspow, 1993), the Wen-Yu model, and the Zhang and Reese model (Gera et al., 1998). Lu et al., (2020) proposed a hybrid drag simulation of sand and biomass mixtures, coupled with the Syamlal-O'Brien drag model, for the coarse-grained by discrete element method (CG-DEM) and compared with the Gidaspow drag model. The finding revealed that the simulations with hybrid drag captured better the mixing of biomass and sands, whereas the Gidaspow drag model overpredicted the drag force on biomass particles. Anicic et al., (2020) simulated the mixing and segregation degree of binary solid phases of glass and polystyrene particles in a dense fluidized bed. The impact of reactor geometry, radial distribution function, and solid pressure was evaluated using different models, such as the Energy Minimization Multi-Scale (EMMS) coupled with the Ma-Ahmadi solid pressure and radial distribution models, Syamlal O'Brien drag model, and Lun et al model. And found that the EMMS drag model associated

with the Ma-Ahmadi solid pressure and radial distribution models predicted a more reasonable axial distribution of solid phases than the Syamlal O'Brien drag model. Similarly, a study by Quan Zhoua,(2015) proposed a multifluid model (MFM) combined with the EMMS drag model for binary gas-solid systems. The effects of different drag force models, kinetic theories, and particle-particle drag force models were systematically evaluated. It was shown that MFM with the proposed EMMS drag model and the kinetic theory correctly predicted the mixing and segregation pattern in the fluidized bed.

Sun et al., (2022) performed a CFD study of biomass co-firing in a 300 MW tangentially fired pulverized coal boiler to assess the effects of biomass blending ratio and feeding conditions on combustion behavior using an Euler–Lagrange framework with $k-\epsilon$ turbulence modeling. They evaluated co-firing ratios of 0%, 15%, and 30%. The results showed that increasing biomass content reduced peak furnace temperatures, improved temperature uniformity, decreased char concentration, and significantly lowered NO_x emissions (by 20% and 28% at 15% and 30% blending, respectively). An optimal co-firing ratio of approximately 20% was recommended to balance emission reduction and operational constraints. Similarly, Banik et al., (2025) numerically investigated the hydrodynamics of biomass–coal blending in a dual fluidized bed gasification (DFBG) system using a 2-D Eulerian–Eulerian two-fluid model (TFM) implemented in MFiX with Kinetic Theory of Granular Flow (KTGF). Gas–solid interactions were modeled using the Gidaspow drag model, while solid–solid interactions employed the Syamlal drag formulation. The study analyzed six biomass–coal blending ratios and reported that increasing biomass fraction reduced static pressure and bed pressure drop, increased axial voidage, and altered suspension density due to lower particle density and enhanced drag effects. Radial profiles exhibited inverted U-shaped voidage and velocity distributions,

indicating stronger core fluidization and particle clustering near walls. The study provides insight into the hydrodynamic behavior of ternary particle mixtures in DFBG systems.

Despite the various drag models reported in the literature, careful selection of an appropriate drag model remains essential for systems containing multi-component particles with different sizes and densities, such as blends of pine residues, municipal solid waste, and waste coal.

Previous studies have shown that the Eulerian–Eulerian model based on the KTGF is suitable for analyzing particle motion in fluidized beds. However, its application may be limited because it typically assumes a single representative particle size to describe the bed material, which does not accurately reflect the wide particle size distribution characteristic of biomass materials. Therefore, further investigation is required to evaluate the potential of combining the Eulerian–Eulerian approach with the Dense Discrete Phase Model (DDPM) in ANSYS Fluent to better capture the hydrodynamic behavior of multi-component particle systems. Some recent studies on CFD for biomass and coal blends fluidization simulation, and thermochemical conversion routes are presented in Table 2.1

Table 2.1: Recent studies on CFD simulation of biomass and coal systems

Material used and properties	Blend ratios/operating conditions	Type of model	Key finding	Source
Sand: $\rho=2350\text{kg.m}^{-3}$, $d_p=300\text{ }\mu\text{m}$ Coal: $\rho=1250\text{ kg.m}^{-3}$, $d_p=100\text{ }\mu\text{m}$ Torrefied Biomass: $\rho=680\text{ kg.m}^{-3}$, $d_p=700\text{ }\mu\text{m}$ Fluidizing gas: Air	0:5, 1:4, 2:3, 3:2, 4:1, 5:0 (Biomass: Coal)	2-D Euler–Euler (TFM) with KTGF in MFIX Gas–solid drag: Gidaspow Solid–solid drag: Syamlal model, Laminar flow assumption	- Increasing biomass fraction reduces static pressure (~20%) and pressure drop in both gasifier and riser - Coal exhibits the highest solid velocity (small size, moderate density); sand shows, lowest velocity (high density) - Biomass increases bubble formation and promotes axial expansion but reduces radial solid velocities	(Banik et al., 2025)

			at higher blending ratios	
Cellulose biomass: ρ : 1500 kg.m ⁻³ dp = 250–900 μ m Sand: ρ =2560 kg.m ⁻³ dp: 440 μ m fluidizing gas: Air Biomass fine: ρ =1242 kg.m ⁻³ dp: 0.0003m fluidizing gas: air	Cellulose: Sand ratios = 0.1:0.9, 0.25:0.75, 0.5:0.5 Superficial velocity = 1–3 Umf	Eulerian–Eulerian multi-fluid model KTGF Drag models: Gidaspow model Solid–solid drag: Syamlal–O’Brien model Implemented in ANSYS Fluent (2D and 3D domain)	- Increasing superficial gas velocity enhances mixing and reduces Particle Segregation Number - Higher biomass (cellulose) fraction increases segregation, and a larger biomass particle diameter promotes mixing - 3D simulations show slightly lower PSN and smoother segregation behavior compared to 2D - Segregation strongly depends on density difference, particle size ratio, and gas velocity	(Hameed et al., 2019)
Biomass fine: ρ =1242 kg.m ⁻³ dp: 0.0003m fluidizing gas: air	Inlet gas velocities = 0.05, 0.10, 0.15, 0.19, 0.55 m/s	Eulerian–Eulerian TFM and KTGF, 2D domain Syamlal–O’Brien drag model Second-order discretization Transient CFD (ANSYS Fluent)	- Good agreement between CFD and experimental results for pressure drop, bed expansion, and fluidization behavior	(Debnath et al., 2021b)

			- Pressure drop is maximum at the bottom of the bed and decreases along column height; it becomes nearly constant at minimum fluidization	
Loblolly pine wood: ρ : 1453kg.m ⁻³ Moisture: 8.45% Fluidizing gas: air	Air velocities = 0.1–0.6 m/s (experimental) Wider simulated range: 0.08–1.2 m/s Transient simulation (10 s) 3D cylindrical domain Void fraction $\approx$ 0.7	Eulerian–Lagrangian (E–L) approach DEM + Dense Discrete Phase Model (DDPM) in ANSYS Fluent Drag models: Gidaspow, Wen & Yu, Syamlal–O’Brien, Non-spherical (Haider & Levenspiel) k– ϵ turbulence model Body-force correlation implemented via UDF	All standard drag models underpredicted pressure drop for biomass grinds Non-spherical drag model best predicted minimum fluidization velocity ($U_{mf} \approx$ 0.2 m/s) with <5% mean relative deviation (MRD) - Incorporating biomass void-fraction-based body force improved prediction for the non-spherical drag model but had minimal impact on others - DEM+DDPM with the non-spherical drag law was more suitable for non-uniform, irregular	(G. A. Olatunde & Fasina, 2019)

			biomass particles	
Southern pine biomass: $\rho =$ Sand: $d_p: 280 \mu m$, $\rho = 2650 kg.m^{-3}$ Lignin coal, municipal waste plastics	Blend composition: PET (40%), HDPE (18%), LDPE (18%), PVC (5.9%), PP (2%), PS (12%), others	Eulerian–Eulerian (TFM), KTGF for solid phase Drag models: Syamlal–O’Brien	Overall RMSE: 0.10–1.10% Higher H_2 yield due to strong water–gas shift reaction Freeboard height critical for maximizing H_2 2D model was more reliable than 3D with a maximum of 2.16% deviation	(Bhattarai et al., 2025)
Coal (lignin) Waste plastics (PE, PP, mixed plastic)	Biomass ratio: 0–0.5 Plastic ratio: 0–1 Temperature: 750–902 °C	Machine learning (ML) approach: Random Forest (RF), SVM, Multi-Layer Perceptron (MLP) Artificial Neural Network (ANN): FFBP, CFBP, EFBP, Artificial Neural Network (ANN): FFBP	- ML models can serve as fast pre-assessment tools for optimizing tri-feedstock gasification systems ANN and MLP significantly outperformed SVM and RF	(Yan et al., 2025)

2.8. Summary

In this chapter, the importance of pine residues and municipal solid waste (MSW) alternatives for fossil fuels for energy generation was discussed. The rationale for the choice of blending pine residues, MSW, and waste coal was also explained. Thermochemical conversion methods, including pyrolysis, gasification, and hydrothermal liquefaction, have been reviewed and were found to be suitable conversion methods for these types of feedstocks. The fluidized bed, a segment in the gasifier unit, is the reactor where these biomasses are converted through the fluidization method. Fluidization is a process used in many industries for mixing, drying, or combustion. It occurs when the feedstock is subjected to an upward flow of fluid, which could be a gas or a liquid, depending on the industry. The advantages of using a fluidized bed for gasification were reviewed. Before biomass can be used as a feedstock in a fluidized bed system, the size must be reduced to a range that can be easily fluidized. The properties of the feedstocks, including size and size distribution, shape, non-uniform densities, and moisture content, which are usually difficult to measure, limit the design and operation of the fluidized bed. Therefore, industries mostly rely on empirical correlations to predict the behavior of a fluidized bed. Most of the proposed correlations are limited to specific types of particles with specific properties, which are different from pine residues, MSW, and waste coal. In this review, pressure-drop, empirical, and computational fluid dynamics approaches were identified as the three types of approaches to predict fluidization behavior of pine residues, MSW, and waste coal blends. For fluidized bed CFD simulation, the Eulerian-Eulerian approach is popular and used widely because of its lower computational time. However, with the inability to track individual particle the results obtained

from E-E limit its application; hence, the Dense Discrete Phase Model using the Eulerian–Lagrangian framework is becoming more accepted.

2.9. References

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Chapter 3. Investigating moisture and blend ratio effects on rheological properties of waste coal, pine residues, and organic fraction municipal solid waste: statistical and machine learning methods

3.1. Abstract

Blending waste coal (WC), pine residue (PR), and the organic fraction of the municipal solid waste (OFMSW) for thermochemical energy production offers a sustainable way to utilize diverse waste streams while ensuring a consistent feedstock supply chain. However, the heterogeneous nature and inherent moisture of the feedstock pose challenges for efficient handling processes. Statistical and machine learning approaches are powerful tools for accurately predicting the properties of such blends, thereby reducing the time and cost associated with extensive experimental work. However, these methods have not been widely applied to biomass and waste-derived feedstocks. Therefore, this study employs statistical and machine learning techniques to investigate the effects of moisture content and blend composition on the physical and flow behavior of these materials. Ten blends of different ratios of WC, PR, and OFMSW were designed, and moisture levels were adjusted to 10, 20, 30, and 40% by adding water. Bulk, particle, and tap densities, flow index (FI), cohesion, angles of internal and wall friction, and adhesion properties were measured. The Pearson correlation matrix and the SHAP (Shapley Additive explanations) were used to identify relationships and key influential parameters on these properties. Various models, including the RF (random forest), XGBoost (eXtreme Gradient Boosting), and the support vector regression (SVR), were also trained and tested, and their performance was measured using MAE, RMSE, and R^2 coefficient. The SHAP

analysis revealed that moisture and OFMSW content are the dominant controlling predictors influencing flow behavior of the blends, leading to reduced flowability. WC exhibited a stronger influence on the bulk and tap density. FI showed a strong negative correlation with cohesion (–0.85) and adhesion (–0.54), confirming that increased interparticle bonding adversely affects flowability. Similarly, a positive correlation between cohesion (0.68), AIF (0.63), AWF (0.9), and adhesion (0.7) was observed, indicating that these properties are interrelated and collectively contribute to resistance to flow. The models trained successfully predicted the physical and flow properties with R^2 ranging between 83 and 96%. These findings provide valuable guidance for the design and sizing of handling equipment for heterogeneous and non-uniform materials such as pine residues and municipal solid waste.

3.2. Introduction

Waste is a global challenge due to its significant contribution to environmental pollution. For instance, wood residues generated from forest harvesting are often abandoned in the forest, increasing the risk of forest fires (Manisha et al., 2024). Similarly, waste coal, also known as legacy coal, generated from coal plant processing, often leaches into the groundwater, damaging the ecosystem through soil corrosion, water pollution, and acid mine drainage formation (Acharya & Kharel, 2020). On the other hand, municipal solid waste (MSW), particularly organic components like food and yard waste, while decomposing in the landfill, can release 20 times more anthropogenic methane into the atmosphere than fossil fuels (Singh et al., 2018). Methane is known for its significant global warming potential (GWP), which is about 28–36 times higher than the GWP of fossil fuels (Bo-feng et al., 2014). All these waste streams pose a significant threat to the environment, which needs to be addressed.

Current approaches to waste management involve transforming these wastes into value-added products, such as syngas for energy generation in power plants (Maitlo et al., 2022), biochar for soil amendment (Amalina et al., 2022), and bio-oil as a transportation fuel and chemical. Thermochemical conversion processes such as pyrolysis, gasification, and hydrothermal liquefaction (Dikici et al., 2024) are employed to obtain these value-added products from these feedstocks. The integration of waste coal (WC), the organic fraction of municipal solid waste (OFMSW), and pine residues (PR) into thermochemical conversion processes offers a promising strategy for both waste management and sustainable energy production. Utilizing OFMSW provides a low- or even negative-cost feedstock because municipalities often incur tipping fees for its disposal, thereby reducing the economic and environmental impacts

associated with landfilling. Furthermore, diverting OFMSW from landfills prevents its anaerobic decomposition, which generates methane, a greenhouse gas with a global warming potential approximately 28–34 times greater than that of carbon dioxide over 100 years. This methane avoidance alone represents a significant climate benefit, regardless of any displacement of fossil fuels. In addition, the co-utilization of biomass and coal has been widely reported to reduce net carbon dioxide (CO₂) emissions, as well as other pollutants such as sulfur dioxide (SO₂) and mercury that are commonly associated with coal combustion. Because biomass absorbs atmospheric CO₂ during growth, it is generally considered carbon-neutral over its life cycle. Consequently, blending biomass with coal provides a practical and cost-effective approach to lowering the overall greenhouse gas emissions and environmental footprint of conventional coal-based energy systems while simultaneously promoting the beneficial use of waste-derived feedstocks. (Wu et al., 2025). Biomass and coal mix also provides a consistent low-cost feedstock supply to ensure the continuous operation of integrated biorefineries, thereby supporting the circular economy (Chen et al., 2018). However, the success of this process depends on efficient feedstock handling, which necessitates thorough characterization of the feedstock to effectively design storage and feeding systems.

Challenges that have been encountered when a mixture of two or more biomass feedstocks includes unsteady flow, arching, flow blockages, segregation, and the development of preferential flow patterns in equipment such as hoppers and feeders (Cheng et al., 2022 & Lu et al., 2023). These issues can lead to material losses, safety risks, and increased operational costs in downstream processing units, including combustors, gasifiers, and pyrolyzers (Lu et al., 2023). Such problems are largely attributed to the variability in feedstock characteristics, particularly

bulk density, particle shape and size, and moisture content (Jamileh et al., 2019). For example, many biomass particles are elongated and needle-like in shape with random orientations, which makes them susceptible to interlocking during flow (Johanson, 2012). In comparison, the organic fraction of municipal solid waste (OFMSW) is characterized by its fluffiness, high compositional heterogeneity, and significant moisture content, both of which increase the complexity of its handling (Liu et al., 2025). Waste coal, by contrast, typically consists of small particles that tend to agglomerate and form clumps under wet conditions, thereby making handling more challenging due to poor flowability.

Good flow behavior means that the bulk solid moves easily and does not consolidate or compact when it can flow out of a silo or hopper under gravity alone without any flow-promoting device. The flowability of bulk material is usually evaluated by the magnitude of load applied to initiate the flow (Schulze, 2021). The flowability of biomass and coal blends is influenced by a range of intrinsic and extrinsic factors, including particle size and shape, physicochemical composition, and moisture level (Cheng et al., 2022). In general, the amount of moisture present in a granular bed has a direct influence on how particles interact with one another. Moisture can either decrease or slightly increase the relative movement of particles of granular blends (Lu et al., 2018; Przywara, Przywara, Chutkowski, et al., 2023; Little et al., 2011 Moya et al., 2024; Juarez-enriquez et al., 2017 & Wang et al., 2014). This is because moisture forms a liquid bridge, also known as a capillary bridge, between the particles. Liquid bridges and the resulting capillary forces play a crucial role in wet particle behavior by enhancing adhesion, cohesion, agglomeration, and fluidization. These forces increase particle attraction through surface tension and viscous effects, thereby limiting particle mobility (Wang et al., 2024). Other studies revealed

that the same way moisture may hinder particle flow due to its binding properties, it may also slightly improve flowability depending on the capillary bridge volume, due to its lubricating property (Xiao et al., 2020). Numerous studies on the flowability of biomass and biomass-coal blends at varying moisture contents e.g., Louati et al., (2015); Chen et al., (2018); Allen et al., (2022); Lu et al., (2018); Guo et al., (2014); Przywara et al., (2023) and Lu et al., (2023) consistently conclude that moisture alters particle mobility. Many authors have reported that biomass particle volume may expand (swelling effect) upon addition of moisture, thereby reducing its bulk and particle density and improving its compressibility due to its porous nature (Bernhart & Fasina, 2009; Aviara et al., 2007; Arzola-villegas, Lakes, and Plaza, 2019).

The success of the design of processing equipment for biomass and coal blends mainly depends on accurate prediction of their physical and flow attributes; hence, tailored approaches are necessary to ensure reliable predictions. Dependence on experimental measurements alone can be costly, time-consuming, and susceptible to experimental errors. Coupling statistical analysis with machine learning (ML) provides an efficient strategy for the accurate prediction of biomass properties. Statistical techniques facilitate understanding of the relationships between feedstock properties, whereas machine learning models enable accurate prediction of their physical and flow characteristics. Statistical metrics such as the Pearson correlation coefficient (r) are commonly used to quantify the strength and direction of a linear relationship between two variables, with values ranging from -1 to 1 (Behkamal et al., 2025). A value of -1 indicates a perfect negative correlation, while 1 represents a perfect positive correlation, and 0 signifies no linear relationship. While such statistical measures are useful for identifying simple linear associations, machine learning (ML) models extend this capability by capturing complex and

multidimensional patterns that may not be easily discerned through conventional experimental or statistical approaches (Nakato et al., 2025). Moreover, ML techniques are particularly effective in modeling non-linear relationships, making them highly adaptable to diverse biomass types and variable feedstock properties.

For instance, ML algorithms can predict critical material properties such as density, flow index, and compressibility index using input variables including moisture content, particle size, and biomass blending ratios. By learning from these input features, ML models can identify optimal feedstock combinations and operating conditions, such as appropriate moisture levels, to enhance flowability and handling performance. Various ML approaches, including SHapley Additive exPlanations (SHAP), Random Forest (RF), and eXtreme Gradient Boosting (XGBoost), have been applied to evaluate the influence of input parameters (e.g., chemical composition, temperature, and pressure) on thermochemical processes such as gasification, with outputs including syngas composition, tar yield, and heating value values (Kafle et al., 2025; Liu *et al.*, 2025 & Nakato *et al.*, 2025). Because gasification efficiency strongly depends on biomass characteristics such as density, particle size distribution, moisture content, and blend ratio in co-firing systems, numerous studies have focused on predicting process performance. However, limited attention has been given to identifying the optimal feedstock conditions required to maximize yield. Therefore, this study leverages key variables such as moisture content and blending ratio within advanced ML algorithms to provide rapid, non-destructive, and accurate predictions of bulk and particle density, flow index, angle of internal and wall friction, cohesion, and adhesion for blends of pine residues, organic fraction of municipal solid waste (OFMSW), and waste coal parameters that influence biomass handling and conversion.

3.3. Material and method

3.3.1. Sample preparation

The materials used for this study consisted of pine residues (PR) collected from a sawmill (West Fraser, Inc., Opelika, Ala.) in the city of Auburn, Alabama, waste coal (WC) received from a private property in Auburn, and an organic fraction of municipal solid waste (OFMSW) provided by BRUCELL-08142023, a waste management company in Alabama. The forest residues and the waste coal were ground using a hammer mill (model 358, New Holland Grinder, New Holland, Pa.) fitted with a 1/8-inch (3.175 mm) screen, while the granulator (SG-4390, 38241 Willoughby Parkway, Willoughby, OH44094) equipped with a 3/16" screen was used to grind the organic fraction of municipal solid waste. The individual samples were sieved using a Vibro screen separator (Kason, M-7555, 67-71 East Willow Street, Millburn, NJ 07041), equipped with 1.91 and 1.29-mm screen sizes and a pan (Figure 1). The samples retained on a 1.91 mm screen were used for further experimentation.



Figure 3.1. Pictures of sample preparation equipment: a) hammer mill, b) plastic granulator, c) Vibro screen separator

3.3.2. Proximate and ultimate analysis of the samples

The samples (waste coal, OFMSW, and pine residues) were analysed for moisture content (Mettler Toledo MJ33), volatile matter (ASTM E872/D3175), ash content (ASTM E1755/D3174), fixed carbon, heating values (Bomb calorimeter, IKA C200, Model: C200S1), and CHNS (ASTM D5373 – 16) and the results are presented in Tables 3.2 and 3.3. The fixed carbon and the total oxygen were calculated using eqn 3.1 and 3.2. All the results are reported on the wet basis moisture content.

$$F.C = 100 - VM\% - Ash\% \quad (3.1)$$

$$O\% = 100 - C\% - N\% - S\% - H\% - Ash\% \quad (3.2)$$

Table 3.1: Proximate analysis of waste coal (WC), pine residues (PR), and the organic fraction of municipal solid waste (OFMSW), dry basis.

Sample	Moisture content (%)	Volatile matter (%)	Ash content (%)	Fixed carbon (%)	HHV (MJ/kg)
Waste coal	2.5 ±0.1	22.6 ±0.2	33.5 ±0.2	44.4±0.5	22.5 ±0.0
Pine Residues	7.1 ±0.2	90.6 ±3.7	1.7 ±0.0	18.3 ±5.4	19.8 ±0.1
OFMSW	6.1 ±0.0	59.4 ±0.2	33.5 ±0.3	6.7 ±0.5	16.1 ±0.0

Table 3.2: Ultimate analysis of waste coal (WC), Pine residues (PR), and the organic fraction of municipal solid waste (OFMSW)

Sample	C (%)	H (%)	N (%)	S (%)	O (%)
Waste coal	57.3 ±1.1	3.6 ±0.1	1.02 ±0.01	0.3 ±0.1	4.8 ±1.1
Pine Residues	53.4 ±0.4	6.9 ±0.1	0.08 ±0.0	0.01 ±0.0	38.4 ±0.4
OFMSW	42.3 ±0.1	5.8 ±0.1	1.2 ±0.01	0.4 ±0.02	16.8 ±0.1

3.3.3. Physical properties measurement

3.3.3.1. Particle size distribution

The particle size distribution of the individual sample was measured using a Camsizer (Retsch Technology, Haan, Germany) - a dynamic imaging analysis system equipped with two high-speed LED cameras that measure particle size and shape. The cameras measure simultaneously the large and smaller particles using different magnifications. The software of the equipment analyses each particle to determine its size (particle length, width, area, and Feret diameter) and shape (sphericity, aspect ratio, and roundness). For this test, approximately 50 g of dry sample was fed into the machine through a funnel and conveyed into the measurement field via a vibratory feed chute. The particle size distribution on a volume basis was recorded and analyzed by the software provided by the equipment manufacturer.

3.3.4. Preparation of the blends and moisture adjustments

Ten sample blends containing various ratios of PR, WC, and OFMSW were formed according to the recipe shown in Table 3.3. The moisture content of each blend was adjusted to 10%, 20%, 30%, and 40% by adding a corresponding mass of water calculated according to eqn 3.3. Each conditioned blend was placed in sealed plastic bags and allowed to equilibrate in the refrigerator at 4 °C for at least 3 days. The moisture content achieved for each blend after equilibration is shown in Table 3.4.

$$x_{coal} * mass_{coal\ waste} + x_{pine\ residues} * mass_{pine\ residues} + x_{OFMSW} * mass_{OFMSW} + mass_{water\_needed} = (mass_{total} + mass_{water\_needed}) * target\ moisture\ content$$

(3.3)

Where x is the initial moisture content of the sample.

Table 3.3: Blend nomenclature (mass ratio)

Blend #	% WC	% PR	% MSW
B1	100	0	0
B2	50	50	0
B3	50	0	50
B4	0	100	0
B5	0	50	50
B6	0	0	100
B7	33	33	34
B8	66.6	16.7	16.7
B9	16.7	66.6	16.7
B10	16.7	16.7	66.6

**Waste coal (WC), pine residues (PR), organic fraction of municipal solid waste (OFMSW)*

Table 3.4: Actual moisture content of blends (wet basis)

Target	B1	B2	B3	B4	B5	B6	B7	B8	B9	B10
10%	9.8	11.6	11.6	9.8	10.8	9.9	11.5	9.0	10.4	11.1
	±0.0	±0.1	±0.1	±0.8	±0.1	±0.1	±0.1	±0.1	±0.8	±0.1
20%	20.0	20.2	22.4	20.9	20.5	20.9	21.9	19.3	21.8	20.1
	±0.4	±0.2	±0.5	±0.1	±0.0	±0.1	±0.6	±0.1	±1.1	±0.5
30%	25.7	30.7	29.7	29.9	30.9	30.2	30.3	29.4	29.6	28.9
	±0.1	±0.8	±0.4	±0.5	±0.5	±1.1	±0.3	±0.2	±0.8	±0.3

40%	nd	39.5	40.3	39.8	39.9	37.4	39.6	40.2	30.8	37.9
		±0.1	±0.3	±0.7	±0.3	±0.9	±0.0	±0.2	±0.0	±0.2

**no data (nd), for waste coal above 25% due to its high sensitivity to moisture*

This section outlines some reasons why the moisture content of waste coal could not be adjusted to higher level.

Fig 3.2 illustrates the effect of moisture content on the physical appearance of the WC sample at various levels of moisture content. At low moisture content (2.3%), the particles appear loose. As moisture increases to 6.5%, slight agglomeration is observed; at high moisture content (22.2%), pronounced clustering and the formation of large agglomerates were evident, reflecting strong interparticle bonding. These observations demonstrate the strong influence of moisture on fine WC particles. Because of these discrepancies, some properties of WC could not be measured at elevated moisture levels.

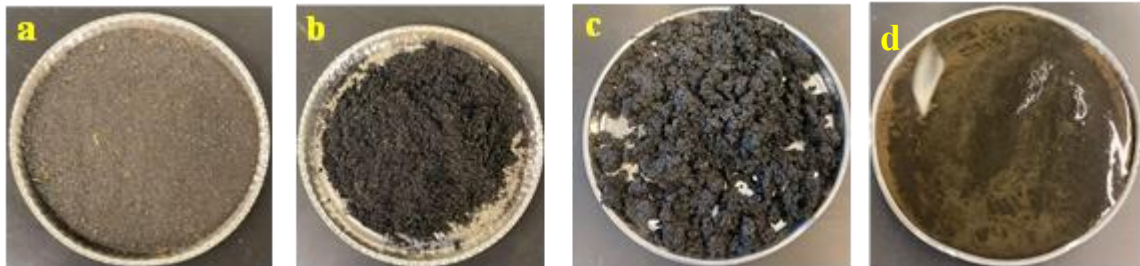


Figure 3.2: WC sample appearance with different moisture content: a) 2.3MC%, b) 6.5%MC, c) 22.2%MC, d) 35%MC

3.3.4.1. Bulk density measurement

The bulk density of the samples (individual and blend) was determined by the ASABE standard (S269.5) using a Burrows Co., Evanston, Ill (ASABE, 2021). The blend was poured into a

measuring container of a known volume (1137 ml) from a funnel at a height of 610 mm above the edge of the container. The hopper outlet lid, which was initially closed, was removed to allow the sample to settle into the container. The sample was leveled to ensure that particles that have more than half of their volume above the top edge of the container are removed. Bulk density was obtained from the sample mass ratio to the container's volume (Eqn.3.4).

$$\rho_b = m_s/V_c \quad (3.4)$$

Where ρ_b , m_s , and V_c are respectively the container's bulk density, sample mass, and volume.

3.3.4.2. Particle density measurement

Particle density was measured using the helium gas pycnometer (Accupyc 1330, Micromeritics Instrument Corp., Norcross, GA) according to the ASTM standard B923. A known mass of a sample was placed in the pycnometer container and inserted into the cell of the machine. Helium gas under pressure was allowed to flow into the cell containing the sample. The average volume and the standard deviation were displayed on the screen of the instrument after the completion of the measurement. The particle density (ρ_p) was calculated as the ratio of the measured mass of sample (m_s) to the skeletal volume (V) provided by the apparatus software (Eq. 3.4).

$$\rho_p = m_s/V \quad (3.4)$$

3.3.4.3. Tap density measurement

A tap density equipment (model TD-12, Pharma-Alliance Group, Inc., Valencia, Cal.) was used to measure the tap density of the samples. A 250 mL graduated cylinder was filled with the sample. The cylinder-filled sample was lifted about 14 mm and dropped 500 times at a rate of

300 taps per minute. Afterward, it was tapped an additional 750 times. The volumes were measured after the initial 500 taps and again after the subsequent 750 taps. The final volume was used to calculate the tap density when the difference between the first and the second volume was less than 2%; otherwise, the test was continued. Tap density (ρ_t) was calculated as the ratio of sample mass (m_s) in the cylinder to the volume (V_t) of the sample at the end of tapping (Eqn. 3.5).

$$\rho_t = m_s / V_t \quad (3.5)$$

3.3.5. Flow properties measurement

3.3.5.1. Flow function measurement

A Brookfield Powder Flow Tester (PFT, Model 230VAC, Brookfield Engineering Laboratories, Middleboro, MA) was used to characterize powder flow behavior. The tester operates based on Jenike's principle to determine the flow function properties of powder, according to the standard ASTM method D6128 (Ganesan et al., 2008). The device consists of an annular shear cell with a top knifed lid. The cell trough has a total volume of 263 cm³ and a 15.24 cm diameter. The lid was used to apply consolidation stress to the sample. Once a desired consolidation stress level was reached, a shear force was applied to the cell. A torque force generated through the powder to the lid is recorded, which calculates the Mohr circle and the unconfined failure strength at the consolidation stress level. Flow function curves were generated by the software of the tester, and the software also calculates the following flow properties for each sample: angle of internal friction, angle of wall friction, cohesive strength, flow index,

unconfined failure strength, and major consolidating stress. The flow index for each sample was used to classify the flowability of the sample (Fig. 3.3).

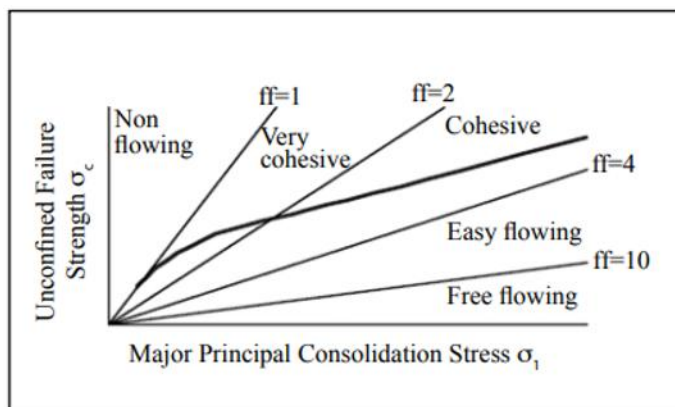


Figure 3.3: Flow function graph

3.3.5.1.1. Wall friction test

The angle of wall friction (AWF) represents the angle at which a wall surface must be inclined to cause powder to slip. The angle of wall friction was measured by replacing the Vane Lid with the Wall Friction Lid made of stainless steel - a commonly used material for the design of storage and transportation equipment such as silos, chute bunkers, and hoppers for biological material. The test was performed using the same principle for the flow function curve. The tester software was used to estimate the adhesion and the angle of wall friction for each sample

3.3.6. Statistical analysis

All experiments were carried out in triplicate. Statistical tool (SAS software, version 9.4), to perform the statistical analysis. The Analysis of variance (ANOVA) was performed to evaluate the significance of variables on the response at a 95% confidence interval. Results are presented in the next sections using the means and standard deviations obtained from the triplicate runs

(repeated sample, not repeated measurement of the same sample). Standard deviations were used to measure the uncertainty or variability in the measurements. To understand the correlation between feedstocks and moisture content on physical and flow properties, the Pearson Correlation Coefficient between variables was calculated and presented in a matrix for easy understanding. It is a widely used statistical tool, and its details have been discussed in a previous publication (Kafle, et al., 2025).

3.3.7. Machine learning analysis

SHAP analysis, also known as Shapley Additive exPlanations, based on Shapley value theory from cooperative game theory, is used to determine how much an input variable contributes to a model's prediction relative to the average prediction (Abdelfattah *et al.*, 2025; Kafle et al., 2025). It quantifies the magnitude of each feature (input variable) by assigning a SHAP value, which represents that feature's contribution to pushing the prediction higher or lower. Features with large positive or large negative SHAP values have a strong effect on adding or reducing the output variable. The SHAP Beeswarm plot, for example, uses dots to represent an individual sample. The plot typically uses two main colors: red and blue, to indicate the strength of feature values. Red dots correspond to higher feature values, while blue dots represent lower feature values. The position of the dots along the horizontal axis shows the direction and magnitude of their influence on the prediction, with points farther from zero having a stronger impact.

After identifying the most influential factors, multiple most common machine learning models, such as linear-based models such as Lasso and Ridge, kernel-based SVR (support vector regressor), instance-based KNN (K-nearest neighbors), and tree-based RF (random forest) and

XGBoost (extreme gradient boosting), were developed. The models were developed using 80% of the dataset and trained on the remaining 20%. The model was evaluated using mean absolute error (MAE), coefficient of determination (R^2), and root mean square error (RMSE) as performance indicators for each target property notably flow index (FI), angle of internal friction (AIF), cohesion, angle of wall friction (AWF) adhesion, bulk, particle and tap densities, Carr's compressibility index (CCI), and Hausner ratio.

3.4. Results and discussion

3.4.1. Physical properties

3.4.1.1. Bulk density

Fig. 3.4 shows that for some of the blends, bulk density significantly increased with increasing moisture content ($p < 0.05$) (B3, B5, B6, B7, and B10). Blends such as B3, B5, B6, B9, and B10 (blends with a higher ratio of OFMSW) maintained a relatively consistent increase in their bulk density as the moisture was increased. Moisture in these cases may have added weight (the density of water being higher than the density of dried biomass) to the bed and caused the bulk density to increase, due to structural rearrangement and particle contact. This result is also consistent with the work of Fu et al., (2025).

B1 exhibited the highest bulk density, especially under dry conditions (control, 2.3%MC), which could be due to its smaller particle size ($d_{50} = 0.27\text{mm}$). This blend also experienced a significant drop in its bulk density as the moisture was raised to about 9.89%, then gradually increased when the moisture was raised to 25.74%. A similar trend was also noticed in B2, B4, and B8, although the drop in bulk density was observed at a higher moisture content for B2. These blends contained higher proportions of either coal waste or PR. A similar result was reported by (Allen et

al., 2022), who observed a decrease in the bulk density of corn stover at moisture levels between 0 and 15%. The presence of moisture (at a certain level) can disrupt the bulk structure by forming a liquid layer on the surface of the particle, leading to reduced particle packing (increased void) and a decrease in bulk density, as explained by Cheng et al., (2022). Furthermore, increasing the moisture content can enhance particle cohesion and promote agglomeration by strengthening capillary forces (attraction between a material surface and a liquid) between particles, especially for mineral materials like coal with fine size. This causes the particles to adhere to one another strongly, thereby improving packing efficiency and increasing bulk density.

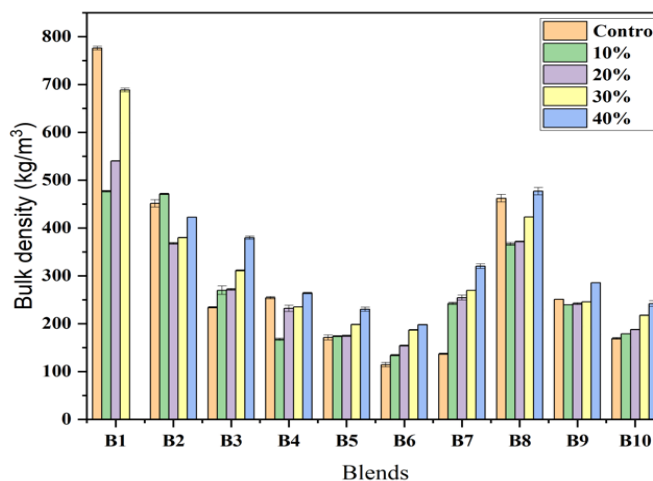


Figure 3.4: Bulk density of the blends at various moisture content (%wb)

3.4.1.2. Particle density

As represented in Fig.3.5, the blend particle density decreased significantly with increasing moisture content ($p < 0.05$). This trend aligns with previous findings by (Littlefield et al., 2011, Chinwan & Castell, 2019 & Thoreson et al., 2014), and is primarily because the particles' expansion in size is higher than the increase in particle mass due to moisture absorption. For instance, the mean particle size of PR varied with moisture content as follows: 1.63 mm at 9.82%

MC, 1.89 mm at 20.88% MC, 1.85 mm at 29.93% MC, and 1.95 mm at 39.79% MC. The added water likely infiltrated the void spaces within the particles (porosity = 0.83), causing them to swell and increase in size compared to their original dimensions.

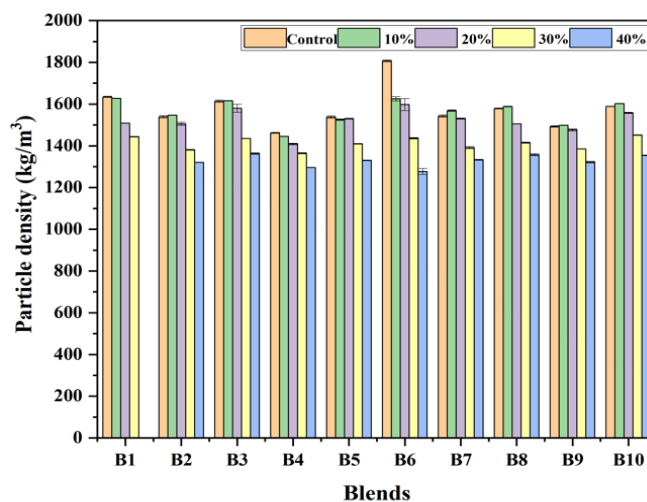


Figure 3.5: Particle density of the blends at various moisture content (%wb)

3.4.1.3. Tap density

The tap density of the blends increased significantly with the addition of moisture ($p < 0.05$), as shown in Fig. 3.6. Similar observations were reported by Chinwan & Castell, (2019). This phenomenon can be attributed to the natural tendency of particles to rearrange and settle into closer packing under tapping or vibration, thereby reducing internal voids and improving packing efficiency. When combined with applied pressure during tapping, moisture further enhances compaction and particle agglomeration in biologically derived materials, which are inherently soft (Braga, 2018 & Fu et al., 2025). An overall increase between 9.85 to 68.2% was observed in the blend's tap density when the moisture content moved from 10% to 40%.

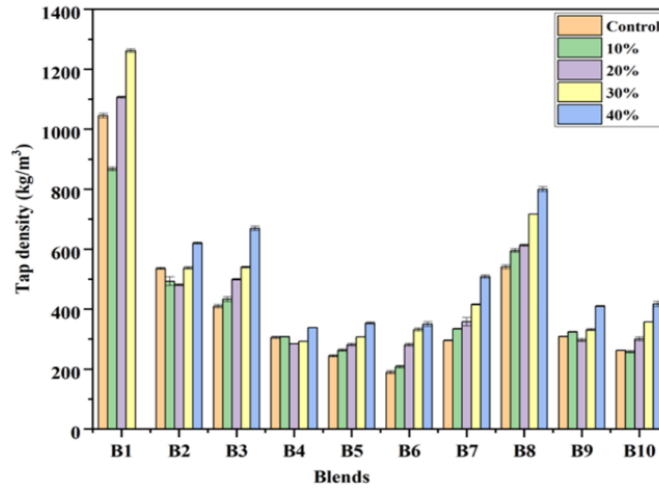


Figure 3.6: Tap density of the blends at various moisture content (%wb)

3.4.2. Flow properties

3.4.2.1. Flow index

The flow index (FI) values were obtained from the inverse slope of the linear fit of the flow function graph (plot of major consolidation stress vs unconfined yield strength). In general, the flow index (Fig. 3.7) varied between $1.1 < FI < 4.5$, categorising the blends (except B1 with FI of 7.7) as very cohesive and cohesive (Garg et al., 2018). The blends exhibited a sharp drop in flow index when moisture content was increased from 10% to 20% (MC), indicating reduced flowability. However, a slight increase in the flow index was observed when the blend moisture content was above 20%, suggesting a temporary improvement in flowability for B1, B2, B3, B4, B5, and B9, respectively. This finding is corroborated by Cheng et al., (2022), who reported that the flow function of corn stover decreased and then slightly increased, reaching a plateau when the moisture was raised to 50%. Notably, blends B6, B8, and B10 demonstrated a continuous decline in flow index across the entire moisture range. This finding suggests that moisture can either alter or favor particle flowability. Moisture creates a film-like layer, also called liquid

bridges, between solid particles' surfaces and water molecules, binding them together. This connecting force is due to the surface tension and wetting properties of water. The formation of a liquid bridge can create attractive (adhesive) or repulsive (due to increased liquid volume) forces between particles (Kralchevsky & Nagayama, 2001; Megias-Alguacil & Gauckler, 2010; L. Yang et al., 2021). One of the direct consequences of liquid bridge formation is particle agglomeration and particle clustering (in cases where the adhesive force is stronger) (Yang et al., 2021), preventing particles from flowing. Based on the results from this study, at a moisture content of around 20%, the adhesive force between the water molecule and the sample particle is stronger, causing water to behave more like a binder. However, as the moisture increases to 30%, the strength of this adhesive force slightly reduces due to the increase in capillary volume, leading to a slight improvement in flowability. According to Pierrat & Caram (1997) & Lu et al., (2023), at the fibre saturation point (FSP), the liquid bridge between water molecules and solid particles weakens, which can lead to enhanced flowability. For most biological materials, including pine residue, the FSP is typically around 30% (Lu et al., 2023). This may explain the slight improvement in flowability observed in the blends.

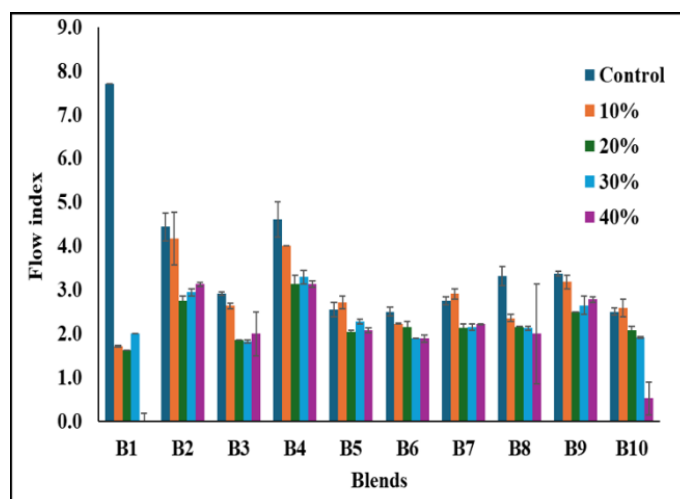


Figure 3.7: Effect of moisture content (%wb) on the flow index

3.4.2.2. Angle of internal friction

Figure 3.8 illustrates the variation in the angle of internal friction (AIF) for the blends at different moisture levels. Overall, AIF increased significantly with increasing moisture content across all blends ($p < 0.05$). This trend can be attributed to the enhancement of interparticle forces such as van der Waals and moisture-induced capillary forces, which increase interparticle friction and resistance to shear. At approximately 30% moisture content, a slight reduction in AIF was observed for blends B1, B2, and B3. Among them, B1 was particularly sensitive to moisture, showing a pronounced increase in AIF as moisture content rose from low to high levels. In contrast, the remaining blends exhibited relatively stable AIF values across the tested moisture range.

Blends with lower and more stable AIF values can be considered to have better flow performance, as a lower angle of internal friction indicates reduced internal shear resistance and improved handling characteristics. According to Lu et al., (2022), the angle of internal friction for

biomass materials typically ranges between 27° and 50°. The AIF values obtained in this study fall within this reported range.

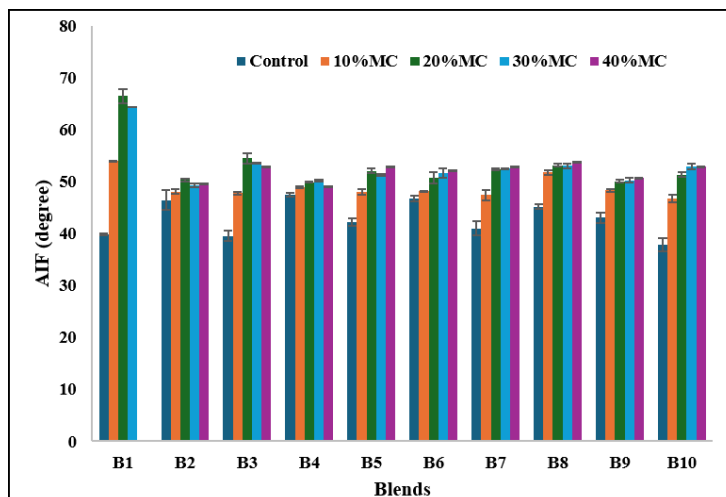


Figure 3.8: Effect of moisture content (%wb) on the angle of internal friction (AIF)

3.4.2.3. Cohesion

Cohesion represents the ability of a bulk material to resist shear stress; therefore, higher cohesion corresponds to greater shear resistance and poorer flowability. Fig.3.9 illustrates the influence of moisture content on the cohesion strength of the blends. The results show that cohesion increased significantly with increasing moisture content across all blends, reflecting enhanced interparticle attraction. This increase is primarily attributed to moisture-induced capillary forces and hydrogen bonding between water molecules and particle surfaces. At approximately 30% moisture content, a slight reduction in cohesion was observed for blends B1, B2, B3, B4, and B7, whereas blend B8 continued to show a consistent increase across all moisture levels. When moisture content was further increased to 40%, blends B4, B5, and B7 exhibited a rise in cohesion, while the remaining blends showed a decline. These observations further highlight the dual role of water in granular systems. At moisture levels below 20% and

above 30%, water tends to act as a binding agent, strengthening interparticle attraction and increasing cohesion. In contrast, within the intermediate moisture range of 20–30%, water exhibits a lubricating effect by reducing capillary bridge strength and interparticle friction, thereby decreasing cohesion. This phenomenon is consistent with the work done by findings reported by Chen et al., (2018)

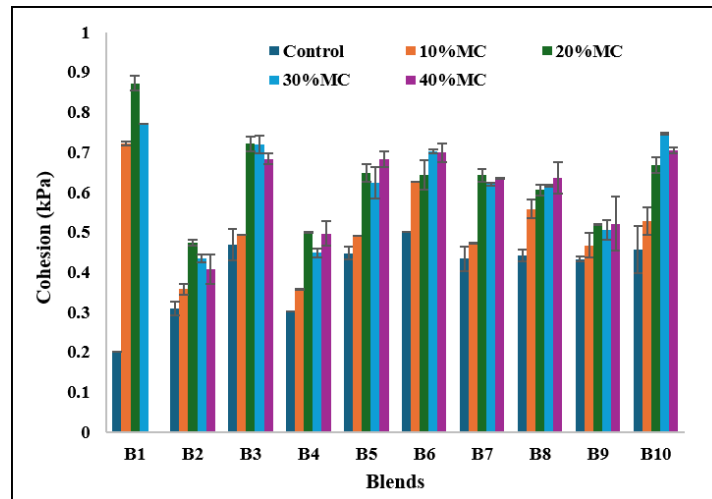


Figure 3.9: Effect of moisture content (%wb) on cohesion

3.4.2.4. Angle of wall friction

As depicted in Fig. 3.10, the AWF increased as the moisture content of the blends increased ($p < 0.05$). This revealed the general understanding that particles with high moisture content tend to stick to the wall of the material on which they are in contact, requiring a larger angle to initiate flow (Allen et al., 2022). This phenomenon is consistent with the findings of this study; most blends experienced a consistent significant increase in their AWF throughout the moisture levels ($p < 0.05$), except for blends B3, B7, B9, and B10, where the AWF slightly decreased when the moisture was raised to 40%. This result means that the friction force caused by the capillary bridge at the sample and the wall interface becomes higher as moisture is added.

For B3, B7, B9, and B10, respectively, the friction force decreases when the moisture reaches 40%, indicating the capillary force is replaced by the effect of lubrication. This result is consistent with the study reported by Brocca et al., (2025), who observed that the AWF of fine limestone increased from 22.4° to 26.4° when the moisture was raised from 0% to 14% and then dropped sharply to 22.1° when the moisture was further raised to 16% on the stainless steel wall surface. Allen et al., (2022) reported that as moisture increases, more liquid bridges form between corn stover particles, enhancing adhesion to the stainless-steel surface and elevating AWF. Once moisture reached 50% or higher, AWF plateaued, suggesting the liquid bridges had filled the available interparticle spaces. Cheng et al., (2022) suggested that an AWF greater than 30 signals a high likelihood of wall binding during discharge. Accordingly, in this study, the blends are most prone to adhere at 30% moisture, the level at which most blends exhibited AWF ≥ 30 .

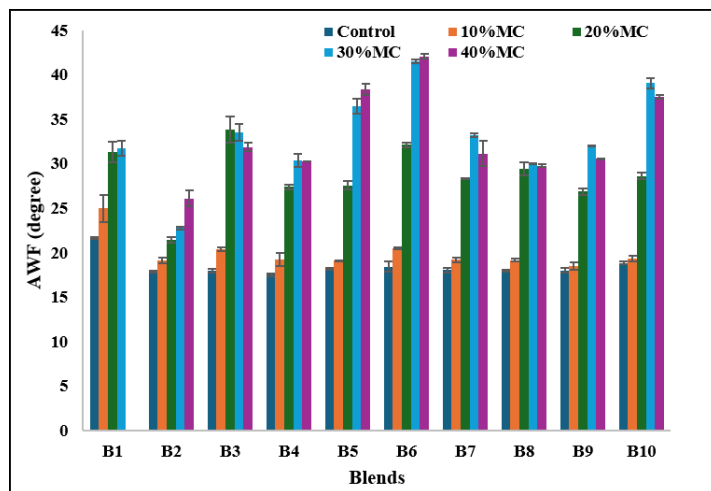


Figure 3.10: Effect of moisture content (%wb) on the angle of wall friction (AWF)

3.4.2.5. Adhesion

The adhesion behavior of the blends on a stainless-steel surface was evaluated at different moisture contents, as presented in Fig. 3.11. The results indicate that adhesion generally

increased with increasing moisture content. This trend can be attributed to enhanced particle wall attraction caused by the presence of water, which promotes the formation of liquid bridges at the interface. However, blends B3, B4, B7, B9, and B10 exhibited a reduction in adhesion strength at 40% moisture content. This observation aligns with the findings in Fig. 3.10, where the angle of wall friction for these blends decreased when the moisture content exceeded 30%. These results confirm that beyond 30% moisture, the lubricating effect of water becomes dominant. Similar behavior was reported by Cheng *et al.*, (2022), who attributed the reduction in adhesion at higher moisture levels to the saturation of interparticle voids by liquid bridges, which decreases adhesion forces.

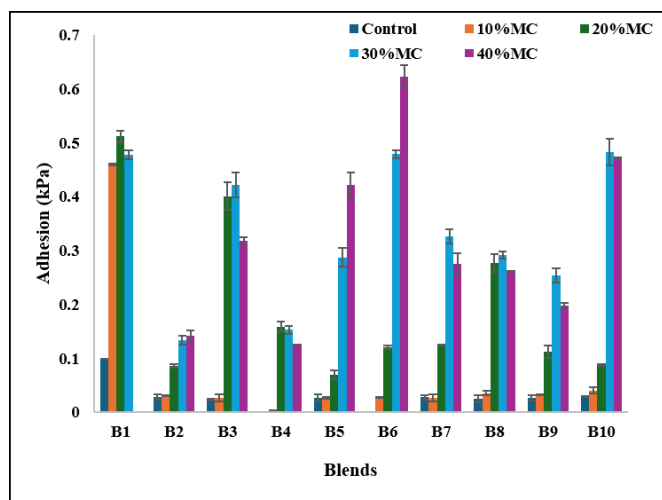


Figure 3.11: Effect of moisture content (%wb) on adhesion

3.4.3. Statistical prediction of the physical and low probability of the blends

The physical and flow properties of the blends were modeled as functions of blend composition using generalized linear mixture modeling, and the resulting predictive equations are presented in Table 3.5. The results indicated that both the individual factors and their interaction

effects significantly influenced the properties of the blends. This finding demonstrates that the properties of the blends cannot be adequately explained by the characteristics of individual components alone but rather arise from complex interactions among feedstocks with differing physical attributes, including particle size distribution, particle shape, porosity, and moisture retention capacity. These highlight the importance of considering interaction effects when designing blended feedstocks for thermochemical conversion systems, as neglecting such interactions may lead to inaccurate predictions of handling and processing performance

Table 3.5: Statistical prediction of the physical and low probability of the blends

Blend properties	Equation	R ²
Bulk density (kg/m³)	$Blends_{bulk} = 4.81x_{WC} + 2.39x_{PR} + 1.12x_{OFMSW} + 3.03x_{moisture} - 0.24x_{WC} * x_{OFMSW} -$ $0.002x_{WC} * x_{PR} + 0.02x_{PR} * x_{OFMSW} + 0.0013x_{WC} * x_{moisture} - 0.023x_{PR} * x_{moisture} +$ $0.01x_{WC} * x_{PR} * x_{OFMSW}$	0.97
Particle density (kg/m³)	$Blends_{particle} = 16.8x_{WC} + 15.31x_{PR} + 17.53x_{OFMSW} - 10.09x_{moisture} - 0.051x_{WC}$ $* x_{OFMSW} + 0.013x_{PR} * x_{OFMSW} + 0.0037x_{WC} * x_{PR} - 0.052x_{WC} * x_{OFMSW}$ $+ 0.016x_{WC} * x_{moisture} + 0.040x_{PR} * x_{moisture}$	0.99
Tap density (kg/m³)	$Blends_{tap} = 8.43x_{WC} + 2.84x_{PR} + 2.15x_{OFMSW} + 4.87x_{moisture} - 0.051x_{WC} * x_{OFMSW}$ $+ 0.04x_{PR} * x_{OFMSW} - 0.072x_{WC} * x_{PR} - 0.53x_{WC} * x_{OFMSW}$ $+ 0.04x_{WC} * x_{moisture} - 0.027x_{PR} * x_{moisture}$	0.96
Flow index	$Blends_{FI} = 0.019x_{WC} + 0.039x_{PR} + 0.025x_{OFMSW} - 0.0257x_{moisture} -$ $0.051x_{WC} * x_{OFMSW} - 0.24 * 10^{-3}x_{PR} * x_{OFMSW} + 0.02 * 10^{-2}x_{WC} * x_{PR} + 0.6 * 10^{-3}x_{WC} *$ $x_{OFMSW} + 0.26 * 10^{-3}x_{WC} * x_{moisture} + 0.28 * 10^{-4}x_{PR} * x_{moisture}$	0.97

AIF (°)	$Blends_{AIF} = 0.56x_{WC} + 0.49x_{PR} + 0.47x_{OFMSW} + 0.19x_{moisture} - 0.051x_{WC}x_{OFMSW} +$ $0.75 * 10^{-3}x_{PR} * x_{OFMSW} + 0.026 * 10^{-2}x_{WC} * x_{PR} - 0.75 * 10^{-2}x_{WC} * x_{OFMSW} + 0.53 *$ $10^{-3}x_{WC} * x_{moisture} - 0.17 * 10^{-3}x_{PR} * x_{moisture}$	0.97
Cohesion (kPa)	$Blends_{cohesion}$ $= 0.0075x_{WC} + 0.003x_{PR} + 0.0057x_{OFMSW} + 0.0045x_{moisture}$ $- 0.051x_{WC}x_{OFMSW} + 0.75 * 10^{-3}x_{PR} * x_{OFMSW} - 0.78 * 10^{-4}x_{WC} * x_{PR}$ $- 0.18 * 10^{-3}x_{WC} * x_{OFMSW} - 0.42 * 10^{-4}x_{WC} * x_{moisture}$	0.98
AWF (°)	$Blends_{AWF} = 0.30x_{WC} + 0.17x_{PR} + 0.16x_{OFMSW} + 0.75x_{moisture} - 0.0032x_{WC}x_{OFMSW}$ $- 0.17 * 10^{-4}x_{PR} * x_{OFMSW} - 0.003x_{WC} * x_{PR} - 0.75 * 10^{-2}x_{WC} * x_{OFMSW}$ $+ 0.65 * 10^{-3}x_{WC} * x_{moisture} - 0.39 * 10^{-2}x_{PR} * x_{moisture}$	0.98
Adhesion (kPa)	$Blends_{AWF} = 0.45 * 10^{-2}x_{WC} + 0.2 * 10^{-3}x_{PR} - 0.18 * 10^{-3}x_{OFMSW} + 0.019x_{moisture}$ $- 0.17 * 10^{-4}x_{WC}x_{OFMSW} - 0.8 * 10^{-4}x_{WC} * x_{PR} + 0.19$ $* 10^{-3}x_{WC} * x_{moisture} - 0.16 * 10^{-4}x_{PR} * x_{moisture}$	0.92

3.4.4. Correlation matrix of physical and flow properties of the blends

The correlation matrix of physical and flow properties relative to blend composition is shown in Fig. 3.12. The correlation analysis indicated that moisture content was the variable more strongly associated with the flow behavior of the blends, exhibiting the highest correlations with several flow-related properties. Specifically, moisture content was negatively correlated with the flow index (FI) ($r = -0.46$). In contrast, moisture content showed positive correlations with the angle of internal friction (AIF), cohesion, angle of wall friction (AWF), and adhesion, with correlation coefficients of $r = 0.56, 0.46, 0.78$, and 0.63 , respectively. These results suggest that increasing moisture content promotes interparticle and particle-wall interactions, thereby reducing flowability. Conversely, OFMSW content exhibited the strongest correlations with several packing and physical properties of the blends, showing positive correlations with the Hausner ratio ($r = 0.46$) and compressibility index ($r = 0.50$), and negative correlations with tapped density ($r = -0.48$) and bulk density ($r = -0.64$). These findings indicate that OFMSW plays a significant role in determining the packing characteristics of the blends, and blends with higher proportions of OFMSW with high moisture are more prone to discharge instability and flow obstruction. Waste coal significantly correlated with bulk density and tap density which is typical for high density and carbonaceous materials. Additionally, correlation coefficient of $r = -0.85$ was observed between cohesion and flow index. High cohesion promotes agglomeration, which adversely particle handling and processing. As cohesion and adhesion increase, wall shear resistance increases correspondingly, which has direct implications for hopper and silo design.

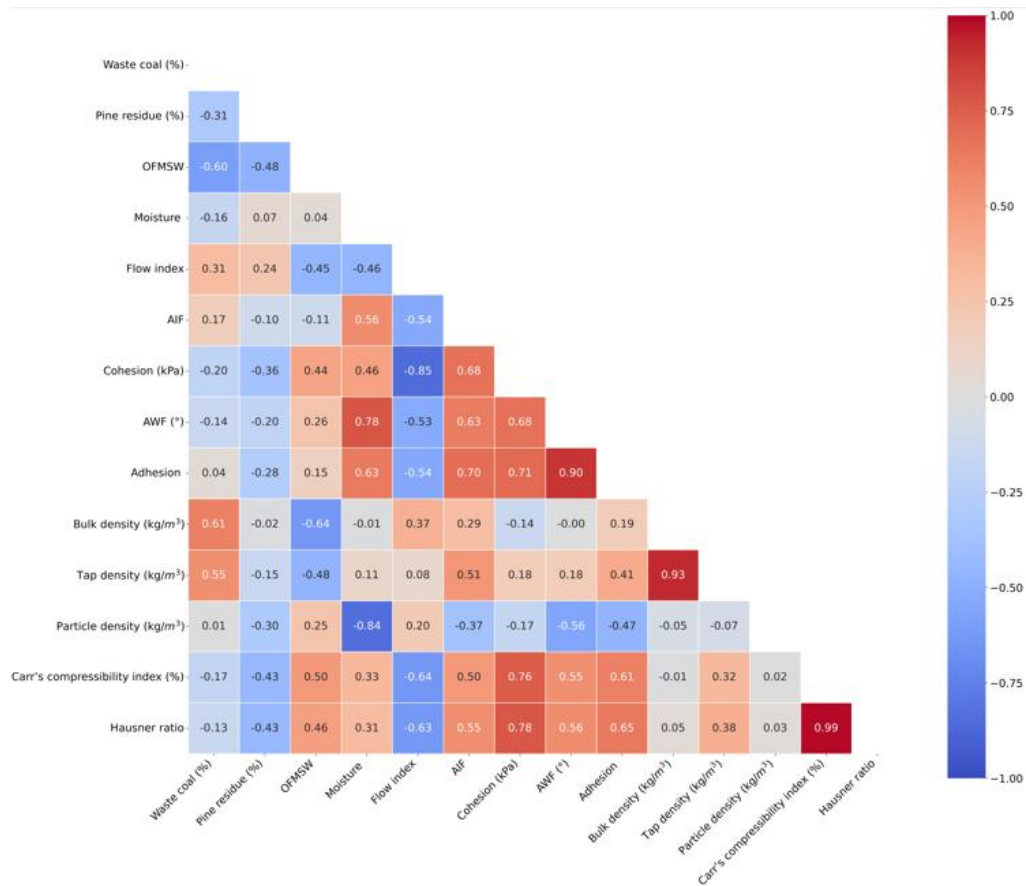


Figure 3.12: Pearson correlation of physical and flow properties: each box has a value between -1 and +1, showing the effect of one variable on the other. Perfect correlation is given a value of +1, and perfect negative correlation is given a value of -1; 0 indicates no correlation between the variables.

3.4.5. Model performance of machine learning

Figure 3.14 presents the comparison between actual and predicted values for all measured properties across the different models. Among the algorithms tested, XGBoost, Random Forest (RF), and Support Vector Regression (SVR) demonstrated superior predictive capability for the physical and flow characteristics of the blends. XGBoost exhibited the strongest overall performance, achieving R^2 values above 90% for six out of the ten evaluated properties. This was followed by RF, which accurately predicted two properties, while SVR showed strong predictive capability only for one flow property.

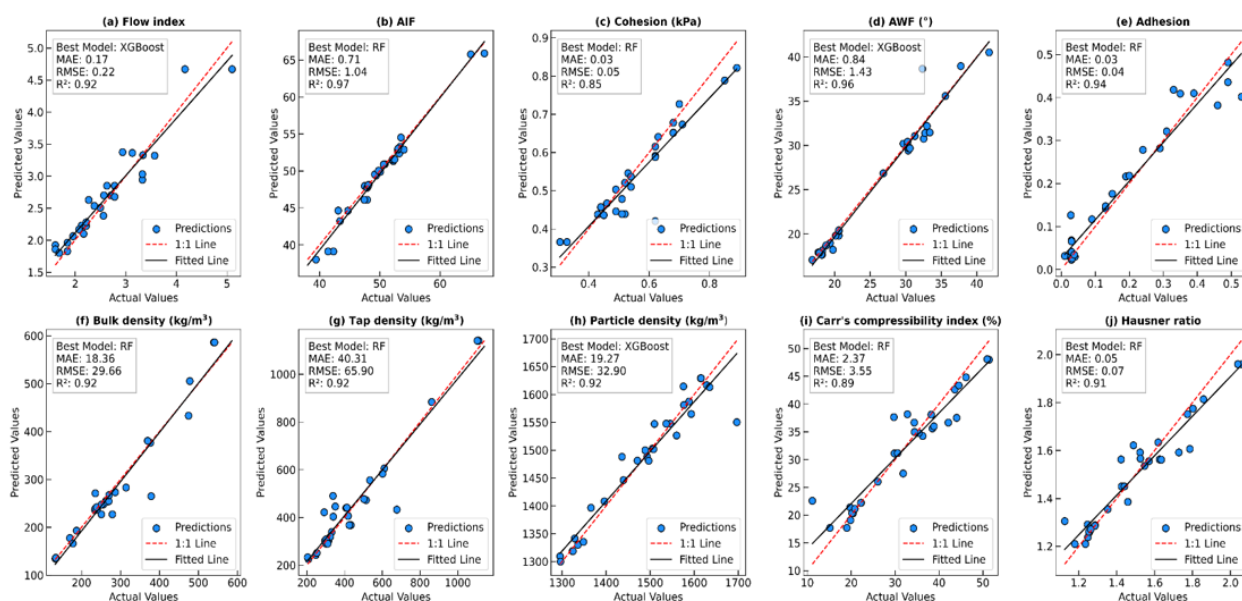


Figure 3.13: Comparison of the predicted and actual values for the best-performing machine learning models in the dataset: each subset reveals the name of the best model using MAE, RMSE, and R² as performance metrics

3.4.6. SHAP analysis of the key factors influencing rheological properties of the blends

The SHAP summary plots of the model's output are presented in Fig. 3.14. Each model comprises a red bar chart (left) showing the mean SHAP value and a Beeswarm plot (right) showing the direction and magnitude of the feature effect (low or high overall feature impact). Moisture is clearly the dominant factor affecting the flow index (Fig. 3.14a), with the highest mean sharp value (0.505) followed by PR, WC, and OFMSW. A dense cluster with low feature values (blue dots) has a positive effect on the model output (more blue dots on the right-hand side of the plot), and a large cluster with high feature values (red dots) has a negative impact on the model output (more red dots on the left-hand side of the plot). This means that low moisture improves the flow index, while high moisture reduces it. Moisture promotes capillary forces between particles, leading to stronger inter-particle bonding and modifying particle mobility (Dopfer et al., 2013). The analysis reveals that a high value of PR (SHAP value = 0.230 and red dot to the right), a high value of waste coal (SHAP value = 0.169, red dots to the right),

and a low value of OFMSW (SHAP value = 0.146, blue dot to the right) and low moisture will result in improved flow index and overall flowability.

From Fig. 3.14b, we can see that the AIF was also influenced strongly by moisture (highest mean SHAP value = 3.463, followed by WC (mean SHAP value = 1.243°), OFMSW (mean SHAP value = 0.514°), and PR (mean SHAP value = 0.425°). The low moisture (blue dots) extended towards the left, suggesting that low moisture content has a stronger reducing effect on the AIF than high moisture content on increasing the AIF. Low AIF is required for better flowability. Additionally, Fig. 3.14b shows that a higher waste coal content (red dots extending to the far right of Fig. 3.14b greatly increases the AIF. Moreover, OFMSW and PR (red dots) presented a small but positive overall impact on the AIF. A similar trend was observed for cohesion and AWF, as shown in Fig. 3.14c and 3.14d, where moisture content and OFMSW exhibited the strongest influence on these parameters (both parameters showed the highest mean SHAP values for both properties), while PR and WC had the least influence (lowest mean SHAP values for both properties). Moisture may also increase the soft nature of OFMSW, resulting in enhancement of mechanical interlocking and self-compaction under its own weight, further contributing to increased cohesion, particle adhesion, and wall friction. This finding confirms the strong positive correlation that was found between cohesion and the AWF in Fig 3.12.

Fig. 3.13e further reveals that moisture content exerts the greatest influence on adhesion (SHAP mean value = 0.119 kPa), followed by PR (SHAP mean value = 0.049 kPa), OFMSW (SHAP mean value = 0.035 kPa) and WC (SHAP mean value = 0.020 kPa). This suggests that the presence of moisture modifies the surface characteristics of the granular material, enhancing interfacial attraction and increasing the tendency of particles to adhere to surfaces in contact with.

For bulk density (Fig. 3.14f), waste coal exhibited the greatest influence, contributing significantly to higher bulk density values, as reflected by its high mean SHAP value =56.041 kg/m³, followed by OFMSW (mean SHAP value =39.957 kg/m³), Moisture (mean SHAP value =30.933 kg/m³), and OFMSW (mean SHAP value =22.294 kg/m³). Inorganic materials such as coal are inherently dense due to their geological formation process. Coal is produced through the long-term compaction of organic matter under elevated pressure and temperature conditions over geological time scales, resulting in a structurally compact and dense material (Zhang et al., 2025). OFMSW is found to be the second most influential factor; however, it contributes strongly to reduced bulk density. This is obvious since OFMSW is a fluffy and lightweight biomass composed mostly of food waste, paper, and cardboard waste (Liu et al., 2025). High moisture content also resulted in an overall additive impact on the bulk density. This could suggest that the moisture effect on bulk density may depend on the sample characteristics, such as its ability to absorb and retain moisture. Fig.3.14g shows that increasing coal highly predicted tap density (SHAP value 108.447 kg/m³), which is confirmed by the strong positive correlation ($r=0.55$) between coal and tap density. OFMSW showed the least influence on tap density, showing a SHAP value of 1.164 kg/m³. Fig. 3.14h revealed that moisture has the strongest influence on the particle density, with a SHAP mean value of 85.451 kg/m³. Adding moisture to the blend highly decreased particle density (high feature value: red dots towards the left of Fig. 3.14h). This was followed by OFMSW (SHAP value of 27.684 kg/m³). This strong influence on the particle density could be due to the heterogeneous nature of OFMSW, which may absorb moisture differently.

Carr's Compressibility Index (CCI) and Hausner Ratio (HR) plots (Fig. 3.14i and 3.14j) confirm that OFMSW and moisture content are primary determinants of blend flow behavior. For CCI, OFMSW exhibited the highest mean absolute SHAP value (4.650), indicating that

increasing OFMSW proportion significantly increases compressibility. Moisture also demonstrated a strong positive contribution, suggesting enhanced inter-particle cohesion due to capillary bridge formation. In contrast, coal showed comparatively minor influence on compressibility, and HR exhibited a SHAP value of 1.645 and 0.031, respectively. A similar trend was observed for the Hausner Ratio (Fig. 14j), where OFMSW (mean SHAP value =0.089), PR (mean SHAP value =0.085), and moisture (mean SHAP value = 0.064) contributed to increasing HR values, indicating reduced flowability. The clustering of high feature values (red dots) on the positive SHAP axis confirms that increasing these variables tends to increase compressibility and HR, which worsen flow characteristics.

In conclusion, from a fluidization perspective, these findings have direct hydrodynamic implications. Increased compressibility and cohesion elevate the minimum fluidization velocity (U_{mf}) due to stronger inter-particle forces that must be overcome by the gas phase. Moisture-driven cohesion and OFMSW-induced structural heterogeneity likely promote channeling, agglomeration, and non-uniform bed expansion, thereby reducing fluidization quality. In contrast, the contribution of waste coal and pine residues suggests a comparatively stable and less cohesive behavior within the blend. These findings suggest that both compositional heterogeneity and moisture-induced cohesive forces govern the densification and packing behavior of the blended materials, thereby controlling bulk handling performance.

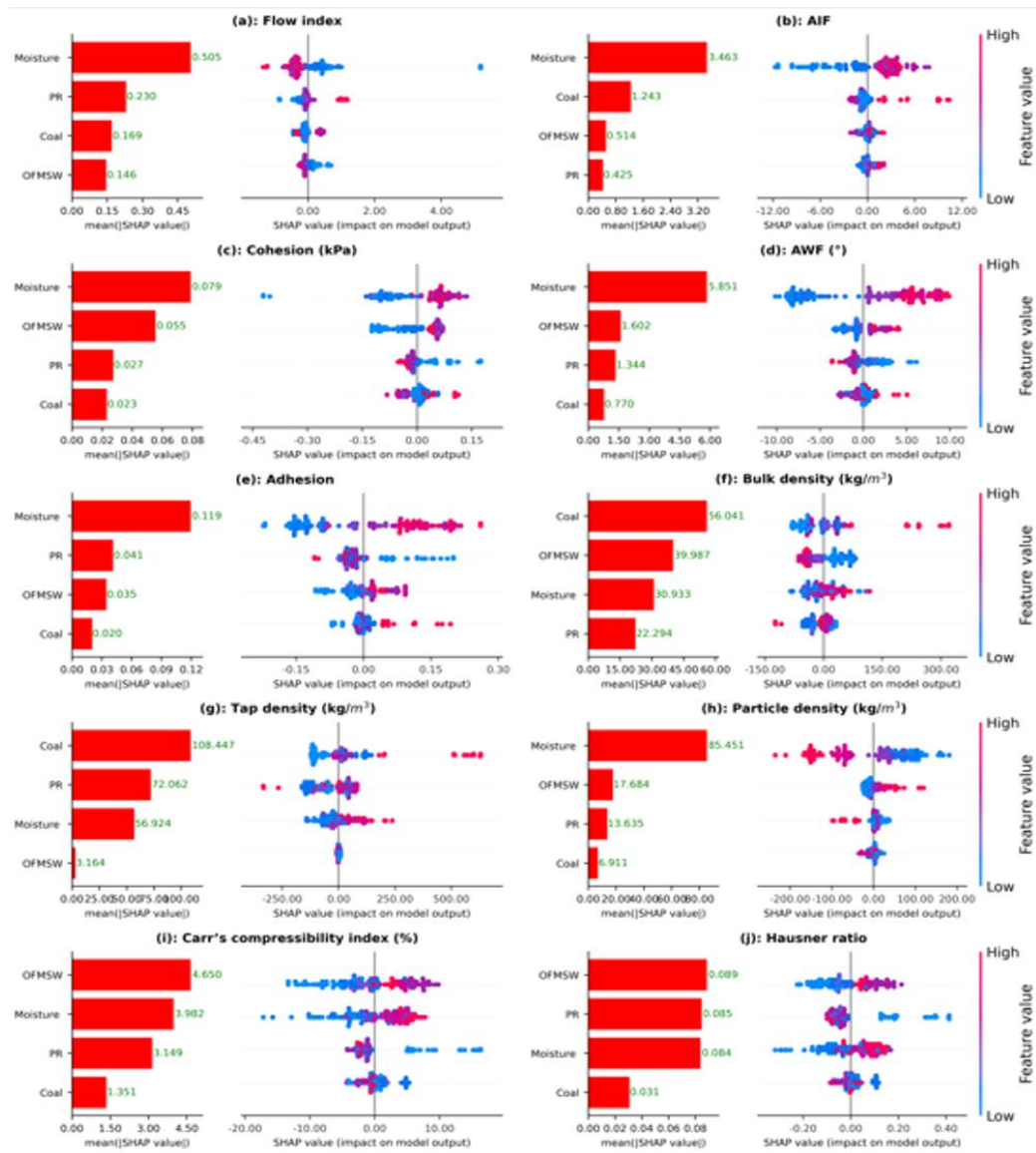


Figure 3.14: SHAP analysis summary of the physical and flow properties of pine residues, organic fraction of municipal solid waste, and waste coal. The plot shows the variables ranked by their absolute SHAP value, indicating their relative impact on the outcome. The dots to the right represent increasing impact on the outcome, whereas the ones to the left indicate reduced impact on the outcome.

3.4.7. Conclusion

This study investigated the influence of moisture content on the physical and flow characteristics of pine residues (PR), the organic fraction of municipal solid waste (OFMSW), and their blends with waste coal. The findings indicate that moisture addition can either increase the overall mass of the material, leading to higher bulk density, or promote particle swelling, which increases volume and consequently reduces particle density. For PR and waste coal, a nonlinear relationship was observed between bulk density and moisture content. At low moisture levels, volume expansion occurred more rapidly than mass gain, suggesting a pronounced swelling effect. When the moisture content exceeded 20%, the increase in mass became more significant, contributing more noticeably to bulk density. In contrast, OFMSW and blends with high OFMSW proportions exhibited a steady increase in bulk density as moisture content increased.

Flowability of the blends declined markedly within the 10–20% moisture range but showed slight improvement beyond 20% moisture. This trend reflects the dual role of water in powder systems: at lower moisture contents, water forms liquid bridges that enhance interparticle cohesion and reduce flowability; at higher moisture levels, increased capillary volume enables a lubricating effect, improving particle movement. The flow index (FI) ranged from 1.1 to 4.5, categorizing the blends as very cohesive to cohesive.

Both the intrinsic properties of the individual materials and their interactions governed the overall physical and flow behavior of the blends. Since each component exhibits distinct flow characteristics, their combined effects must be considered when evaluating blend performance. The Pearson correlation matrix revealed strong positive relationships among cohesion, flow index, Carr's Compressibility Index (CCI), and Hausner Ratio, while the angle of wall friction showed strong correlation with adhesion. As cohesion and adhesion increased,

wall shear resistance also rose, underscoring important considerations for hopper and silo design.

SHAP analysis identified moisture content and high OFMSW proportions as key contributors to reduced flowability. Conversely, blends with higher waste coal content demonstrated improved bulk density and lower compressibility, facilitating better handling characteristics.

Among the machine learning models evaluated, XGBoost, Random Forest (RF), and Support Vector Regression (SVR) exhibited strong predictive performance for the physical and flow properties. XGBoost achieved the highest overall accuracy, with R^2 values exceeding 90% for six of the ten properties assessed. RF accurately predicted two properties, while SVR showed strong performance for one property.

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Chapter 4. Thermal Behavior of Blended Biomass Feedstocks

4.1. Abstract

Feedstock drying is one of the earliest and most critical preprocessing steps in thermochemical conversion processes. Effective drying improves material handling, storage, and transportation, while also enhancing the quality and consistency of downstream products. However, due to its high energy requirements, optimizing the drying stage is essential to improve overall process efficiency. This study investigated the drying behavior of biomass feedstocks, including waste coal (WC), pine residues (PR), and the organic fraction of municipal solid waste (OFMSW), blends, across a range of moisture contents. Ten blend formulations with varying proportions of WC, PR, and OFMSW were prepared, and their moisture contents were adjusted to 10, 20, 30, and 40% (wet basis). Thermogravimetric analysis (TGA) and Fourier-transform infrared spectroscopy (FTIR) were employed to characterize the behavior of the materials in the presence of moisture, while drying energy per unit mass of water removed was determined using differential scanning calorimetry (DSC). The results showed that PR and OFMSW exhibited a higher affinity for water due to the presence of oxygenated and hydroxyl functional groups, whereas WC, characterized by more aromatic and carbonaceous structures, demonstrated lower water affinity. For individual feedstocks, drying energy decreased nonlinearly with increasing moisture content, with PR and OFMSW consistently requiring higher energy per unit moisture removed compared to WC. In contrast, the blends exhibited a slight increase in drying energy with increasing moisture content, indicating a trend opposite that observed for individual materials. Despite this, the overall drying energy of the blends remained lower than that of their individual components, suggesting a synergistic, non-additive effect. Statistical analysis further revealed that drying energy is predominantly influenced by the structural characteristics of the blend components.

and their interactions, rather than moisture content alone. Overall, these findings demonstrate that blending biomass with materials of differing chemical and structural properties is an effective strategy for reducing drying energy requirements. This approach offers a promising pathway for process intensification in biomass preprocessing and supports the development of more energy-efficient thermochemical conversion systems

4.2. Introduction

Biomass encompasses a wide range of organic materials originating from biological sources, including wood, dedicated energy crops, and agricultural and forestry residues. These resources represent some of the most abundant and widely utilized renewable energy feedstocks. However, the moisture content of biomass is a critical factor influencing both feedstock logistics and conversion efficiency. Moisture significantly affects fuel quality, storage stability, handling characteristics, transportation costs, and overall conversion performance. High moisture levels increase the mass of material that must be transported and stored without contributing to its energy value, thereby reducing the effective energy density of the feedstock and increasing associated operational costs (Oyedeji & Fasina, 2017). Many low-value biomass resources, particularly forest residues and the organic fraction of municipal solid waste (OFMSW), typically contain moisture contents ranging from 30 to 60% on a wet basis (Brys, 2016). At these moisture levels, a substantial portion of the biomass mass consists of water rather than combustible material, leading to lower net heating values and less efficient utilization. Excessive moisture can also create challenges during long-term storage by promoting biological degradation and material deterioration. In thermochemical conversion processes such as pyrolysis and gasification, feedstock moisture content is generally reduced to approximately 10–15% to ensure stable operation, improve energy efficiency, and maximize product yields (Raj et al., 2023; Brys, 2016). Furthermore, water present in biomass can negatively affect the quality of biooil by lowering its calorific value, increasing ignition difficulties, and reducing storage stability. Consequently, biomass drying is often a necessary pretreatment step to minimize the adverse effects of moisture and enhance the efficiency and performance of subsequent conversion processes.

Drying refers to the thermal removal of liquid water from a material (Kozlov et al., 2021). The drying technology can be classified into conventional and non-conventional drying methods. Conventional drying includes sun-drying, hot air drying, and spray drying, and non-conventional methods are Infrared (IR), microwave drying, and Electrohydrodynamic are used in many industries for drying of food products (Kian-Pour, 2020). The key factors influencing drying include the temperature and pressure of the drying medium, as well as the slip velocity when air is used as the medium. The energy required to evaporate moisture can be delivered through various mechanisms, including convection, conduction, radiation, and microwave heating (Aljabri et al., 2023). In the convection type drying, the moisture evaporation happens by applying heat from the surrounding atmosphere or by covering the material with a drying agent (e.g., flue gas, superheated steam, or inert gas like N_2). It is the most popular method used for wood chips drying (Vigants et al., 2015). Dryers such as Belt, tunnel, rotation, pneumatic, spray, and fluidized bed use convection heat transfer to dry the material. In the conductive type, moisture evaporation happens through the material's contact with a hot surface. For the radiation-type dryers, heat is supplied via a radiation process using infrared radiation, which penetrates deeper into the inner layer of the material (El-mesery et al., 2021; Kaveh et al., 2020). Microwave drying is done through electromagnetic radiation that can spread through the material by both electric and magnetic field.

Moisture in biomass is generally classified into two forms: free moisture and bound moisture. Free moisture is located on particle surfaces and within accessible pore spaces, whereas bound moisture is retained within the internal structure of the biomass through stronger interactions with the solid matrix (Brys, 2016). Because these two forms of water differ in their degree of association with the biomass, they exhibit distinct drying behaviors and energy requirements during moisture removal (Kozlov et al., 2021). Thermal analysis, including

differential thermal analysis (DTA), differential scanning calorimetry (DSC), and thermogravimetric analysis (TG), is a convenient, reproducible, and useful method to quantitatively characterize the properties of polymers, pharmaceutical products, as well as biomass materials, including their dehydration process. TGA and DSC measure sample mass loss and heat flow, and the heats required or released during biomass pyrolysis and combustion can be calculated by integrating the heat flow with respect to time or temperature. Recently, the heat requirement or release for some biomass dryings have been reported. For example, Brys, (2016) investigated the drying behavior of spruce, beech, willow, and alder biomass with initial moisture contents ranging from 42.2 to 52.4% (wb) and reported that the heat required for water evaporation increased with moisture content, varying from 467 ± 27 to $865 \pm 41 \text{ kJ kg}^{-1}$. The authors observed that drying at 80°C reduced the moisture content to 4.8–13.8% (wb) after 4 h and established a strong correlation between moisture content and drying energy ($R^2 = 0.9653$). Dong & Zhu, (2012) investigated the first stage of biomass pyrolysis (moisture evaporation) for rice husk and cotton stalk with initial moisture contents of 6.31 and 6.95 wt.%, respectively, using TG/DSC experiments, and found that moisture removal occurred primarily between room temperature and 150°C , with a pronounced water-loss peak at $65\text{--}75^\circ\text{C}$. The heat required for dehydration was 251 kJ kg^{-1} for rice husk and 269 kJ kg^{-1} for cotton stalk. Furthermore, (Chen et al., 2012) applied TG-DSC to study drying characteristics and heat requirements of cotton stalk at four temperatures (60, 80, 100 and 120°C). They showed that the heat requirements of cotton stalk during drying ranged from 189 to 406 kJ/kg . In the present study, we have investigated the moisture evaporation characteristics of WC, PR, and OFMSW blends using differential scanning calorimetry (DSC) and FTIR spectroscopy and subsequently determined the energy

requirements associated with their drying and the potential improvements in energy efficiency that may be achieved by blending these feedstocks.

4.3. Material and method

4.3.1. Sample preparation

The material used in this work consists of waste WC (WC), PR (PR), and organic fraction of municipal solid waste (OFMSW). Waste WC was collected in an area around Auburn, AL. PR was obtained from a sawmill (West Fraser, Inc., Opelika, AL) in the city of Auburn, Alabama; OFMSW was provided by a waste management company in Auburn, Alabama. PR and WC were ground using a hammer mill (model 356, New Holland grinder, New Holland Pa) that was fitted with 1/8-inch (3.175mm). For this study, new samples were ground and sieved using the same method explained in Chapter 3. The sample retained on the 1.91 mm screen was used. To obtain a more uniform size for subsequent thermal analysis, the sample was further ground through a 1mm screen size using a Waley Mill (standard D Model N.3, Philadelphia, USA).

4.3.2. Proximate and ultimate analysis of the samples

The moisture content was measured using moisture analyser (Mettler Toledo MJ33), the volatile organic material was measured using the ASTM E872/D3175, higher heating values (HHV) was measured using a bomb calorimeter (IKA C200, C200SI, Wilmington, NC, USA) and elemental analysis (CHNS/O) was determined using the ASTM D5373-02 method using a Virio MICRO Cube Elementary (Ronkinkoma, NY, USA). The elemental analysis of the trace-level metal in the sample was carried out using inductively coupled plasma mass spectroscopy (ICP-MS) according to the EPA 200.6 standard. The results of the proximate, ultimate and the ICP analysis are presented in Tables 4.1 and 4.2. All measurements were

done in triplicate, and the average and standard deviation were reported. All moisture was reported in a wet-basis form.

Table 4.1: Physicochemical characterization of waste coal (WC), pine residues (PR) and organic fraction municipal solid waste (OFMSW)

	Waste WC	PR	OFMSW
Proximate analysis (Wt.%)			
Moisture	2.5 ±0.1	7.1 ± 0.2	4.9 ±0.0
Ash	33.5 ±0.2	0.4 ±0.1	22.5 ±0.5
Volatile matter (VM)	22.7 ±0.2	90.6 ±3.9	76.4 ±4.4
Fixed carbon	44.4 ±0.5	9.0 ±3.5	1.3 ±3.8
Elemental composition (wt.%)			
C	57.3 ±1.1	47.4 ±0.3	40.4 ±2.5
H	3.6 ±0.1	6.6 ±0.0	5.6 ±0.3
N	1.0 ±0.0	0.0 ±0.0	0.6 ±0.5
S	0.3 ±0.1	0.0 ±0.0	0.2 ±0.0
O	4.8 ±1.1	45.8 ±1.9	30.8 ±0.0
H/C	0.1 ±0.0	0.1 ±0.0	0.1 ±0.0
HHV (MJ/kg)	22.5 ±0.0	19.8 ±0.1	16.1 ±0.0

Table 4.2: Metal content analysis of waste coal (WC), pine residues (PR) and organic fraction municipal solid waste (OFMSW)

	Cr	Fe	Mn	Pb	Zn	Cd	Cu	Ni
WC	0.0 ±0.0	4.9 ±6.7	0.1 ±0.0	0.1±0.0	0.2 ±2.2	0.0 ±0.0	0.0 ±0.0	0.2 ±0.0
PR	0.1 ±0.2	15.2±1.7	0.5 ±0.0	0.9 ±1.3	1.0 ±0.0	0.0 ±0.0	0.0 ±0.0	1.1 ±0.0
OFMSW	0.0 ±0.0	0.8 ±0.7	0.0 ±0.3	0.1 ±0.5	0.1 ±0.0	0.0 ±0.0	0.0 ±0.2	0.0 ±0.0

Ten blends with different ratios of WC, PR, and OFMSW were formulated according to the recipe presented in chapter 3. The moisture content was adjusted to 10, 20, 30, and 40% wb by adding a corresponding amount of water. The blends were tightly sealed in plastic bags and stored in a 4°C refrigerator, and were allowed to stabilize for three days, and the final achieved moisture content was measured and reported in Table 4.3.

Table 4.3: Actual moisture content of the blend after moisture adjustment (%wb)

Target	B1	B2	B3	B4	B5	B6	B7	B8	B9	B10
Initial	2.5±0.1	4.8 ±0.0	4.3	7.1	6.6	6.1	5.2	3.4	6.2	5.7
Moisture			±0.3	±0.2	±0.2	±0.0	±0.3	±0.3	±0.9	±0.2
10%	9.7	10.8±0.5	13.9	10.1	10.1	9.6	9.9	10.3	11.9	11.2
	±0.0		±0.8	±0.1	±0.4	±0.1	±0.1	±0.3	±0.0	±0.1
20%	19.5	19.7	18.9	20.9	20.5	19.7	19.3	19.3	21.8	20.5
	±0.0	±0.4	±0.5	±0.1	±0.9	±0.5	±0.6	±0.1	±1.1	±0.5
30%	30.7	29.7	29.5	30.1	29.3	29.1	30.9	29.0	29.8	29.4
	±0.1	±0.8	±0.8	±0.1	±0.5	±0.2	±0.3	± 0.2	±0.1	±0.3
40%	nd	39.5	38.9	39.9	37.9	39.3	38.9	40.2	30.8	41.3
		±0.1	±0.3	±0.3	±0.9	±0.3	±0.0	±0.2	±0.0	±0.2

**The blends compositions are reported in Table 3.4 in chapter 3*

4.3.2.1. Thermal analysis

4.3.2.1.1. TGA measurement

Thermogravimetric analysis (TGA) is a widely used method to quantitatively determine the mass loss as a function of a gradual increase in temperature. For this work, a TGA Q5500,

device, manufactured by TA Instrument, was used to study the mass loss of the samples.

High-purity nitrogen (N₂) gas was used as the inert atmosphere. About 5 ± 0.1 mg of the samples were homogeneously placed into a platinum vessel of the device. Then heated up to 800°C at a constant rate of 10°C.min⁻¹ at a N₂ flow rate of 20 mL/min at the dry air media. The thermal scenario was determined using the thermogravimetric data (TG) curve and the first derivative data (DTG) curve using the formula shown in Eqn 4.1.

$$\frac{dW}{dt} = \frac{(T_{final} - T_{initial})}{(t_{final} - t_{inotial})} \quad (4.1)$$

Where T is the temperature (oC), t is time (min), W is the weight of the sample (g).

4.3.2.1.2. FT-IR spectroscopy

Fourier-transform infrared (FTIR) spectroscopy measurements were performed using a Thermo Scientific Waltham, MA, USA Nicolet 6700 FT-IR spectrophotometer equipped with an attenuated total reflection (ATR) accessory and controlled by OMNIC 7.3 software. Every FTIR scan began with a background scan, followed by measurement of the sample spectra, to achieve precise baseline correction. The instrument was regulated by PC running on the Windows 98 platform, allowing registration and processing of spectra and spectral data. The IR spectra were collected in the MIR (Mid Infra Region) range from 1500 cm⁻¹ to 4000 cm⁻¹ at a resolution of 4 cm⁻¹ (spectra range of interest), and the region of interest was related to water absorption range that is between 300-3700 cm⁻¹. For each sample, 32 spectra were registered and averaged. Baseline spectra were collected before each sampling event. The FTIR spectra were processed with Origin Lab software, OriginPro 2025 (10.2). The spectra were adjusted using the Asymmetric Least Squares Smoothing (ALS) method, as provided by the software.

4.3.2.1.3. DSC measurement

The DSC measures the difference in heat flow between the sample and reference pans, thereby quantifying the heat absorbed during the evaporation of water from the samples. The thermal properties of the samples and the heat absorbed during the drying process were determined using a TA Instruments Q2000 Differential Scanning Calorimeter (DSC Q2000 V24.11 Build 124) equipped with a normal-pressure DSC cell and a nitrogen cooling system. The measurements were conducted over a temperature range of 10–200 °C under a nitrogen atmosphere with a flow rate of 50 mL min⁻¹. Approximately 7–10 mg of each sample was placed in an aluminium pan, which was hermetically sealed with a lid before being introduced into the DSC sample cell. The heat of vaporization of the samples was evaluated at different moisture contents. The modulated DSC function of the instrument software was employed to determine the heat capacity of the samples based on Eqn 4.2. An empty aluminium pan was used as the reference. The latent heat of vaporization was calculated by integrating the area under the heat flow curve.

$$C_p = \frac{\text{Reversing heat flow}}{\text{heating rate}} \quad (4.2)$$

4.4. Result and discussion

4.4.1. Physicochemical characterisation

The results of the proximate analysis, ultimate (CHNS) analysis, higher heating value (HHV), and metal content of waste WC (WC), PR (PR), and the organic fraction of municipal solid waste (OFMSW) are presented in Table 4.1. PR exhibited a very low ash content (0.4 ± 0.1%) and a high volatile matter content (90.6 ± 3.9%), which is characteristic of woody biomass primarily composed of combustible organic constituents such as cellulose and

hemicellulose. In contrast, OFMSW (ash: $22.5 \pm 0.5\%$; volatile matter: $76.4 \pm 4.4\%$) and WC (ash: $33.5 \pm 0.2\%$; volatile matter: $22.7 \pm 0.2\%$) showed substantially higher ash contents, reflecting their greater mineral fractions.

Moreover, WC exhibited the highest carbon content ($57.3 \pm 1.1\%$) and the lowest oxygen content ($4.3 \pm 1.1\%$), whereas PR and OFMSW showed comparatively lower carbon contents. This trend is consistent with the higher HHV (22.5 ± 0.0 MJ/kg) measured for WC, indicating its greater energy density. The CHNS elemental analysis (Table 4.1) showed that PR and the OFMSW contain greater proportions of hydrogen (H) and oxygen (O) than WC. This indicates a higher concentration of oxygenated functional groups, including hydroxyl ($-\text{OH}$), carboxyl ($-\text{COOH}$), and ether ($\text{C}-\text{O}-\text{C}$) groups, which enhance the affinity of these materials for water. Consequently, PR and OFMSW are more likely to retain larger amounts of bound moisture and therefore require greater energy during the drying process. In contrast, WC, which contains lower O and H contents, is relatively more carbon-rich and hydrophobic, resulting in lower moisture adsorption and a comparatively faster drying behavior.

The result in Table 4.2 shows that traces of metal such as Cr, Fe, Mg, Pb, Zn, Cu, Cd, and Ni are present in the samples. Of all the metals, Fe was the most abundant in the samples. PR had the highest concentration of Fe (15.2 ± 1.7 mg/kg), followed by WC (4.9 ± 6.7 mg/kg), and OFMSW showed the lowest value (0.4 ± 0.7 mg/kg). This result was not expected, especially the fact that PR showed the lowest ash content. However, this value was within the range reported in the literature (Bachmaier et al., 2021; Pazalja et al., 2021; Sandra Meier, 2013).

The Fe content in PR usually comes from the soil uptake during plant growth or other contaminants accumulated during harvesting.

4.4.2. Thermogravimetric analysis (TGA)

Thermogravimetric analysis (TGA) is an important technique for studying drying behavior because it provides valuable insight into the different forms of moisture present in a material during heating, including surface moisture, free water, and bound water. These moisture types can be identified through distinct mass-loss regions observed during thermal analysis. TGA is commonly coupled with derivative thermogravimetric analysis (DTG), which enables identification of the temperatures at which the maximum rates of mass loss occur. This combined analysis helps determine the temperature ranges at which moisture is released, thereby providing useful information for optimizing drying conditions.

In this study, a TGA analysis was performed on the individual samples which are waste WC (WC), PR (PR), and the organic fraction of municipal solid waste (OFMSW), and their TG and their corresponding DTG curves are presented in Fig. 4.1. The curves reveal multiple thermal events, including an initial drying stage followed by devolatilization and decomposition stages. For PR and OFMSW, the curve explicitly shows four zones of thermal weight loss, unlike WC, where the DTG curve was almost flat up to about 350 °C. The behavior observed for PR and OFMSW is typical for cellulosic materials, whereas WC might be due to its mineral nature, and to the initial low moisture content (2.5%wb), suggesting that the surface moisture evaporation stage has not been detected.

The first thermal zone is within a temperature of less than 100 °C, where the moisture lessens as the temperature rises, marked by a small peak in the DTG curve (more revealing for PR Fig. 1b). This feature is characteristic of a drying period. During this stage, unbound moisture and light volatile compounds are released, which are associated with the breaking of weak hydroxyl bonds. Weight losses of approximately 2.9%, 8.5%, and 5.5% were observed for WC, PR, and OFMSW, respectively, which are consistent with the moisture obtained from

the proximate analysis (Table 4.1). The second zone was depicted around 100 to 250 °C. In this zone, the weight loss TG curve is almost flat for all the samples, indicating the start of the release of volatile compounds. This again characterizes the behavior of biomass material. Generally, at this temperature range, biomass changes into an amorphous solid (like glass), with no crystalline structure, marking the start of the depolymerization process. The third zone ranges from 250 to 360 °C, normal for PR and OFMSW (Fig. 4.1b and 4.1c), corresponding to the pyrolysis process of cellulose and hemicellulose, respectively, and represents the major decomposition stage. This stage is characterized by the decomposition of organic matter and the release of volatile organic compounds. Significant weight losses of approximately 60.9%, 90.9%, and 71.2% were recorded for WC, PR, and OFMSW, respectively. These values match the value of the volatile matter observed in the proximate analysis (Table 4.1). These decomposition events are also reflected by the prominent peaks observed in the DTG curves, particularly for PR and OFMSW. In contrast, WC exhibits a less pronounced DTG peak, likely due to its predominantly carbonaceous composition and the absence of major biomass constituents such as cellulose and hemicellulose. The fourth zone, corresponding to the final decomposition stage, occurs above 360 °C for all the samples. Indicating the formation of residual inorganic material and ash. The remaining mass fractions were approximately 36.11%, 0.9%, and 20.3% for WC, PR, and OFMSW, respectively, which correspond to their respective mineral and ash contents.

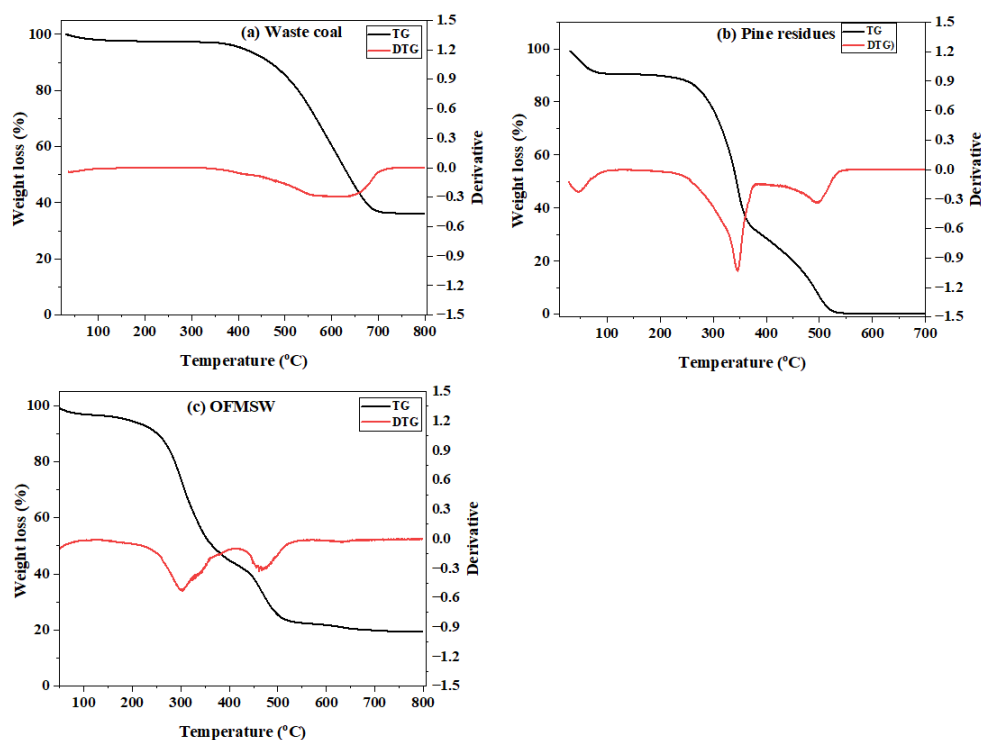


Figure 4.1: Thermogravimetric analysis of WC, PR, and OFMSW

4.4.3. Fourier transform infrared (FTIR) analysis

Fig. 4.2 shows the FTIR spectra for WC, PR, and OFMSW, revealing substantial differences in their functional group composition and their interaction with moisture. A broad absorption band (solely originated from the vibration of water) observed in the region of 3200–3600 cm^{-1} corresponds to O–H stretching vibrations, which are characteristic of hydroxyl groups present in cellulose, hemicellulose, lignin, and other oxygenated organic compounds in biomass materials. In both PR and OFMSW (Fig. 4.2b and 4.2c), the intensity and width of the O–H peak increased as the moisture content increased (Guo et al., 2016). The broadening of this band indicates enhanced hydrogen bonding interactions between water molecules and the hydroxyl functional groups of the biomass structure, as well as hydrogen bonding among water molecules themselves (Trache et al., 2016). This behavior suggests that water is not only physically adsorbed on the surface but is also strongly associated with the biomass matrix through bound and capillary moisture (Trache et al., 2016). The presence of these

hydrophilic functional groups results in high moisture absorption capacity and strong moisture retention for PR and OFMSW. Water molecules can penetrate the porous structure of these lignocellulosic materials and form hydrogen bonds with the hydroxyl groups of cellulose and hemicellulose, leading to the formation of bound water. Because bound water requires additional energy to break hydrogen bonds, these materials generally exhibit higher drying energy requirements compared to more hydrophobic materials. In contrast, the FTIR spectrum of WC in Fig. 4.2a shows a comparatively weaker O–H stretching band and is dominated by aromatic carbon structures and mineral components, indicating a relatively hydrophobic surface chemistry. The limited presence of hydrophilic functional groups reduces the WC's affinity for water, meaning that moisture is primarily present as surface water rather than chemically bound water. Consequently, it would typically exhibit lower moisture absorption and retention capacity, and the energy required for drying would be correspondingly lower.

Overall, the FTIR results suggest that OFMSW has the highest moisture affinity due to its heterogeneous organic composition rich in polar functional groups, followed by PR with its lignocellulosic structure, while WC exhibited the lowest moisture affinity due to its more hydrophobic carbonaceous composition. The increase in the intensity and broadness of the O–H stretching band with increasing moisture content confirms the strong interaction between water molecules and hydrophilic functional groups in biomass materials.

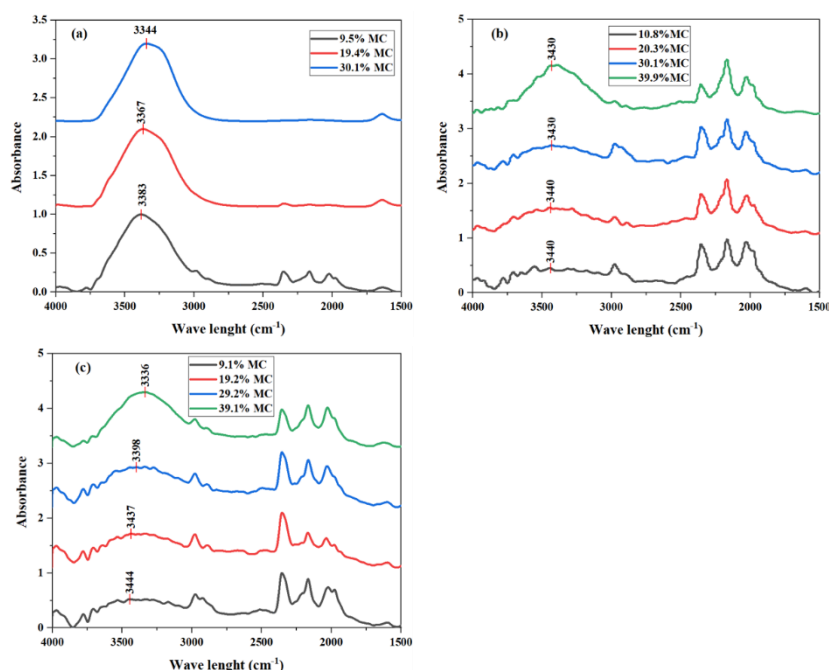


Figure 4.2: FTIR spectra of a) waste WC (waste coal), b) PR (pine residue) and c) OFMSW (organic fraction municipal solid waste)

Correlation of BET Surface Area, Surface Energy, and FTIR Functional Groups with Moisture Retention and Drying Behavior

Surface free energy is an important surface property that governs the interaction of a material with surrounding substances. It is closely associated with surface wettability, adhesion, and the affinity of a solid surface for liquids. Knowledge of a material's surface free energy provides valuable insight into its behavior when in contact with liquids, particularly water, and helps explain the intermolecular forces responsible for wetting and adhesion phenomena (Iglesias et al., 2023). Because surface free energy reflects the energetic state of surface atoms and their propensity to interact with other materials, it serves as a useful indicator of moisture affinity and adsorption behavior.

In this section, the surface free energy and specific surface area of waste WC (WC), PR (PR), and the organic fraction of municipal solid waste (OFMSW) were determined using inverse gas chromatography (IGC) to better understand their wetting characteristics, and

consequently their drying behavior. The BET surface areas of WC, PR, and OFMSW were 4.08, 0.33, and 1.11 m²/g, respectively. The larger surface area of WC could be attributed to its smaller size (0.27mm) compared to PR (1.63 mm) and OFMSW (3.53 mm). Some studies have reported the surface area of herbaceous biomass like corn stover to be in the range of 0.80 -1.25 m² /g (Leal et al., 2019). Analysis of the surface energy distributions obtained from incremental surface area versus surface energy plots revealed maximum peak energies between 42–45, 33–35, and 28–32 mJ/m² for WC, PR, and OFMSW, respectively. The surface energy measured for the various mineral reported in the literature varied from 49–336 mJ/m² (Arsalan et al., 2013) and for various biomass to be between 43.95–90.67 mJ/m² (Leal et al., 2019). These results were unexpected because FTIR analysis suggested that WC exhibited a more hydrophobic character than the biomass materials (Fig. 4.2a) which reflected lower affinity with water. This high BET surface area and surface energy obtained for WC may be attributed to its more developed porous carbonaceous structure and greater aromatic character. The FTIR results support this interpretation, as WC exhibited stronger aromatic C=C absorption bands around 1600 cm⁻¹ vibration (Fig. 4.2a). Consequently, the lower polarity of WC may reduce its tendency to strongly bind water compared with PR and OFMSW. Although WC possessed higher BET surface area and surface energy values, the FTIR spectra of PR and OFMSW indicated a greater abundance of oxygen-containing functional groups, including hydroxyl, carbonyl, and ether groups (Fig. 4.2b and 4.2c). These functional groups increase surface polarity and provide additional sites for hydrogen bonding with water, promoting stronger water–solid interactions and greater moisture retention. This suggests that water retention PR and OFMSW are influenced more by the presence of hydrophilic functional groups than by total surface area or surface energy which all have great influence in their drying ability and the total energy requirement for drying.

4.5. Drying energy requirement

Drying is an indispensable, and energy intensive pretreatment stage in biomass processing and conversion. The energy requirement for drying WC, PR and OFMSW was estimated by means of a DSC and the results are discussed in this section. The DSC curve, showing the heat flow through the samples for WC, PR, and OFMSW at the measured moisture levels, is presented in Fig. 4.3. An endothermic peak in the 80-120 °C temperature range is observed for all samples, indicating the evaporation of moisture, mostly unbound or surface water present in large pores and on the surface of the material, as indicated by the TGA result shown in Fig. 4.1. (Chen et al., 2017). The curve characterizes the heat required to break the intermolecular bonds to transition water to vapor. Because of the chemical and mineral composition of the samples, the endothermic peak temperatures were slightly different as the moisture level increased. The endothermic peaks broadened as the moisture content increased for all the samples. The peak temperature slightly moved to a higher temperature as the moisture content increased. An average increase of at least 4 °C was observed on the peak temperature when moisture moved from level of moisture to a higher level for all samples. This shift is likely due to several factors, including the heterogeneous nature of the samples: PR used in this study content materials such as bark, leaves, and roots, and OFMSW contained paperboard, food waste etc which may behave differently when heated. Also the type of water (including free, and bound water) present at a particular moisture content, which may each evaporate at different temperatures within the structure as explained by Sambale et al., (2019). These combined effects may have influenced moisture evaporation of moisture, resulting in a slightly higher evaporation temperature at high moisture content in the samples.

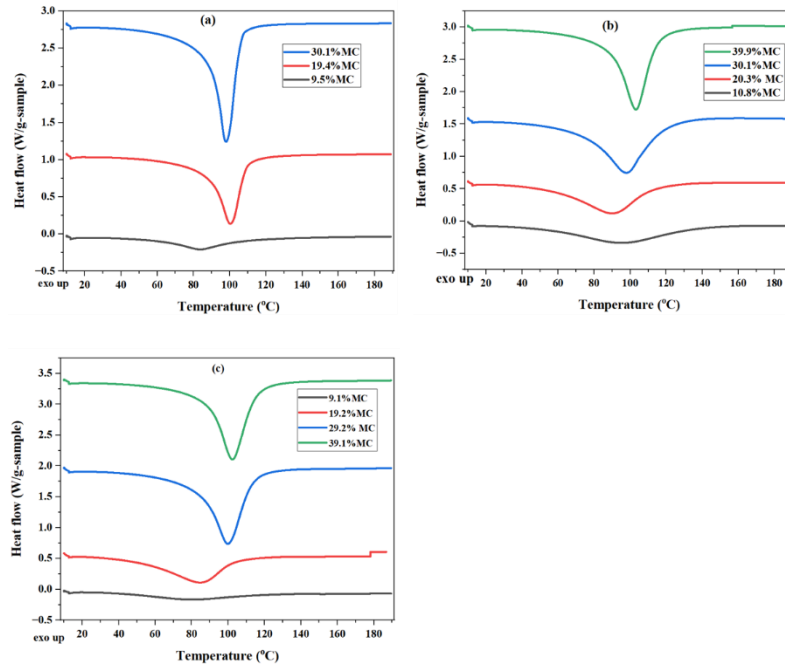


Figure 4.3: Differentials scanning calorimetry of a) waste WC (waste coal), b) PR (pine residue) and c) OFMSW (organic fraction municipal solid waste)

Enthalpy associated with the moisture removal for each sample was obtained by integrating the DSC endothermic heat flow curves (Fig. 4.3), and the result is shown in Fig. 4.4. The value increased with increasing moisture content, showing a strong linear relationship in the temperature range between 80–120 °C with a correlation coefficient varying from $R^2 = 0.96$, 0.98 and 0.99 for WC, PR and OFMSW respectively. This behavior indicates that moisture evaporation is the dominant thermal process in the analysed temperature range, while deviations reflect material-specific water binding and heat transfer effects (Sambale et al., 2019). Also, at an increasing moisture level, more free water molecules become available at the surface of the wet sample, which requires more heat absorbed by the DSC to achieve evaporation. The higher slopes (representing the incremental heat requirement) observed for PR and OFMSW compared with waste WC reflect stronger water binding within the cellulosic and organic matrices (Etale et al., 2023).

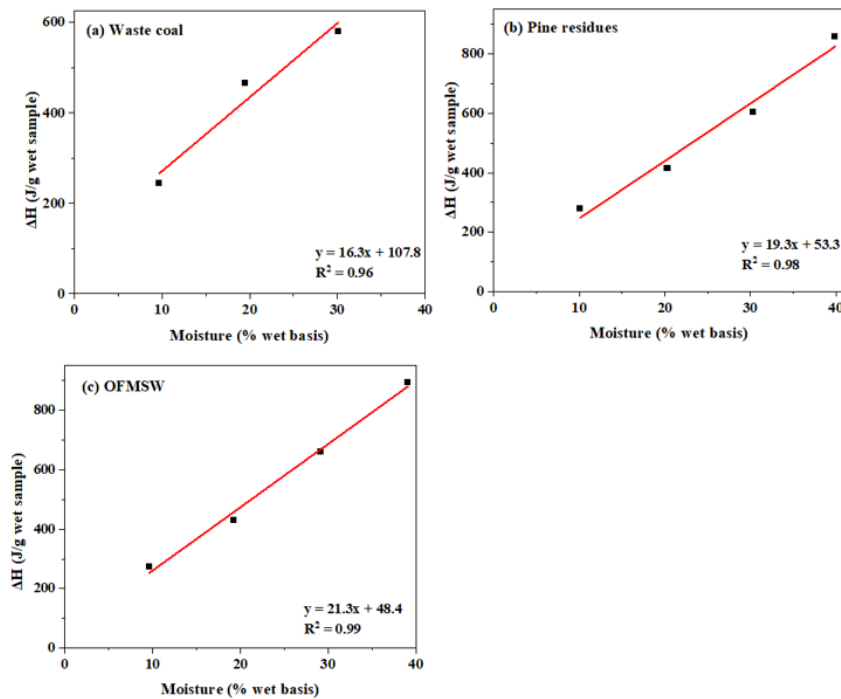


Figure 4.4: Heat of vaporization of per gram of sample for WC, PR and OFOFMSW at various moisture content (wb)

After normalizing the DSC curve by the moisture fraction, the apparent enthalpy of vaporization per unit of water removed was calculated, and the values are shown in Table 4.4. For WC, PR and OFMSW at low moisture content, the values were slightly higher than the latent heat of vaporization of pure water, reflecting that water at this moisture level is in the form of bond water, which requires additional energy to break water sample interactions. Moreover, above 10%M, the enthalpy of vaporization per unit water removed was closer to the latent heat of vaporization of pure water (~ 2260 kJ/kg). Since free water needs less energy to remove than the bound water, the energy per water added decreases. No significant difference ($p > 0.05$) was found for the heat of vaporization across the moisture range after 10%M.

Table 4.4: Latent heat of vaporization of WC, PR, and OFMSW at different moisture levels (wb)

Latent heat of vaporization (kJ/kg water removed)			
Moisture (%)	WC	PR	OFMSW
10	2316.6a ±11.5	2761.7a ±74.3	2737.4a ±94.3
20	2133.7b ±32.6	2041.6b ±15.8	2075.1b ±12.4
30	1793.9b ±37.2	2009.3b ±86.6	2162.1b ±72.2
40	Nd	2145.6b ±64.6	2152.2b ±10.5

**Letter groups display differences between mean using the Tukey pairwise comparison test followed by the standard deviation of tree replicate. Values with the same letter are not statistically different at $\alpha=0.05$. The true values of the moisture content are presented in Table 4.3*

The drying energy requirement for the samples and their respective blends at various moisture contents was calculated according to Eqn. 4.3, and the results are presented in Table 4.5. The enthalpy of vaporization ΔH was obtained from the integration of the DSC heat flow curve for the blends.

$$E = m_s \frac{\Delta H}{m_{\text{water removed}}} \quad (4.3)$$

Where m_s is the wet sample mass, ΔH is the heat absorbed during the drying process, $m_{\text{water\_removed}}$ is the mass of water removed. The mass of water removed was obtained from the difference between the mass of sample before and after the DSC measurement.

Table 4.5 presents the drying energy per unit mass of water removed for the blended samples. The results show that drying energy of the blends was the highest at 10%M, then decreased from 10% to 20% then increased from 20% to 30% and decreased further as the moisture moved to 40% for almost all blends. Interestingly, blended samples consistently required less drying energy than the individual materials across all moisture levels. For example, comparing the drying energy for the individual samples (B1: WC, B4:PR and B6: OFMSW), their drying

energy was consistently higher than the rest of the blends. For example, the drying energy for PR and OFMSW at 10%M was 3940.45 kJ/kg, and 3310.66 kJ/kg and when blended both samples at 50% ratio the overall drying energy was 2570.10 kJ/kg, resulting in about 22.37% reduction in the drying energy. This is an indication that blending may have altered the way water is held and distributed within the mixture matrix. When materials with different physical and compositional properties such as WC, PR and OFMSW are combined, they form a more complex and heterogeneous system that no longer behaves as independent components. These differences in physical properties may also cause bias during sampling, as only a smaller amount (~10mg) of sample is able to fit into the DSC pan. In such a system, moisture may redistribute unevenly among the components. For instance, water may preferentially migrate toward more hydrophilic regions or become trapped at particle interfaces, reducing its accessibility for evaporation. For instance, the hydrophobic nature of waste WC may limit overall water uptake in certain regions, while the fibrous structure of PR and OFMSW may introduce void spaces that alter packing behavior and moisture distribution. These combined effects can lead to the formation of a new structural matrix with distinct drying behaviors, hence affecting the overall drying energy. Overall, these results demonstrate that the blends behave as a new system with modified drying behavior, where blending enhances drying efficiency relative to individual materials.

Table 4.5: Experimental drying energy of the blends

Drying energy requirement (kJ/kg water removed)				
Blends	10%	20%	30%	40%
B1	3343.4 ^{ab} ±16.4	2397.2 ^{ab} ±33.1	2232.3 ^{ab} ±34.3	Nd
B2	2415.4 ^{abc} ±19.1	2079.27 ^{abc} ±52.03	2112.26 ^{ab} ±6.33	2096.8 ^b ±17.03

B3	2385.32 ^{bc} ±82.5	2826.48 ^{abc} ±50.81	2176.03 ^{ab} ±15.82	2120.1 ^b ±19.06
B4	3940.5 ^a ±67.8	2404.36 ^{ab} ±15.7	2606.3 ^{ab} ±11.3	2420.7 ^{ab} ±78.8
B5	2570.1 ^{abc} ±14.1	2360.5 ^a ±16.4	2105.12 ^b ±33.3	2060.35 ^c ±19.7
B6	3310.7 ^{ab} ±15.1	2520.1 ^a ±25.95	2702.2 ^a ±19.3	2509.1 ^a ±37.1
B7	2718.25 ^c ±31.7	2505.13 ^c ±98.03	2349.2 ^{ab} ±40.69.	2084.2 ^b ±18.52
B8	2737.24 ^{bc} ±41.5	2007.36 ^{abc} ±55.38	2099.14 ^{ab} ±14.83	2094.7 ^b ±16.90
B9	2222.64 ^c ±87.3	2313.52 ^{abc} ±50.99	2003.60 ^{ab} ±22.55	2099.20 ^b 20.83
B10	2422.03 ^c ±42.3	2268.2 ^{ab} ±54.83	2040.4 ^{ab} ±19.06	2119.1 ^b ±10.37

**Letter groups display differences between means using the Tukey pairwise comparison test followed by the standard deviation of tree replicate. Values with the same letter are not statistically different at $\alpha=0.05$. The true values of moisture content are presented in Table 4.3*

4.5.1. Response Surface Analysis of Drying Energy

Fig. 4.5 presents the response surface showing the variation of specific drying energy as a function of moisture content and blend composition. The results demonstrate that drying energy was strongly influenced by the interaction between blend composition and moisture content, with a clear nonlinear response observed across the surface. The presence of curved contours and distinct regions of high (red region) and low (green region) drying energy indicates that the drying behavior of the blends was not additive but rather governed by synergistic interactions among the blend components.

The response surface revealed that the highest drying energy values were generally observed at lower moisture contents, while lower drying energy regions occurred at higher moisture contents for several blends. At low moisture contents, most of the remaining moisture exists as bound water, which is more strongly associated with the biomass structure through hydrogen bonding, capillary interactions, and internal pore confinement. Consequently,

additional energy is required to overcome these interactions and remove the remaining moisture. In contrast, at higher moisture contents, a larger fraction of the moisture exists as free or loosely bound water, which evaporates more readily and therefore requires less energy per unit mass of water removed.

The regression analysis further confirmed that blend composition and component interactions were the primary factors influencing drying energy, with all mixture interaction terms showing high statistical significance ($p < 0.05$). This indicates the presence of strong non-additive synergistic behavior within the blends. In contrast, the linear effect of moisture content was not statistically significant ($p > 0.05$), suggesting that moisture alone did not directly govern the drying energy. However, the quadratic moisture term was significant ($p < 0.05$), indicating that moisture exerted a nonlinear influence on the drying behavior of the blends. These findings demonstrate that drying energy in the system was predominantly controlled by compositional and structural interactions, while moisture contributed to a secondary nonlinear factor.

Additionally, correlation analysis revealed no significant correlation between drying energy and moisture content, nor between moisture content and the individual blend components. However, strong negative correlations were observed among the component fractions themselves. This further suggests that moisture did not directly control the drying behavior of the system; rather, the interaction between moisture and blend composition, together with the interactions among the blend components, governed the drying response. These results support earlier observations that blending alters the structural and moisture distribution characteristics of biomass systems, resulting in non-additive and synergistic drying behavior

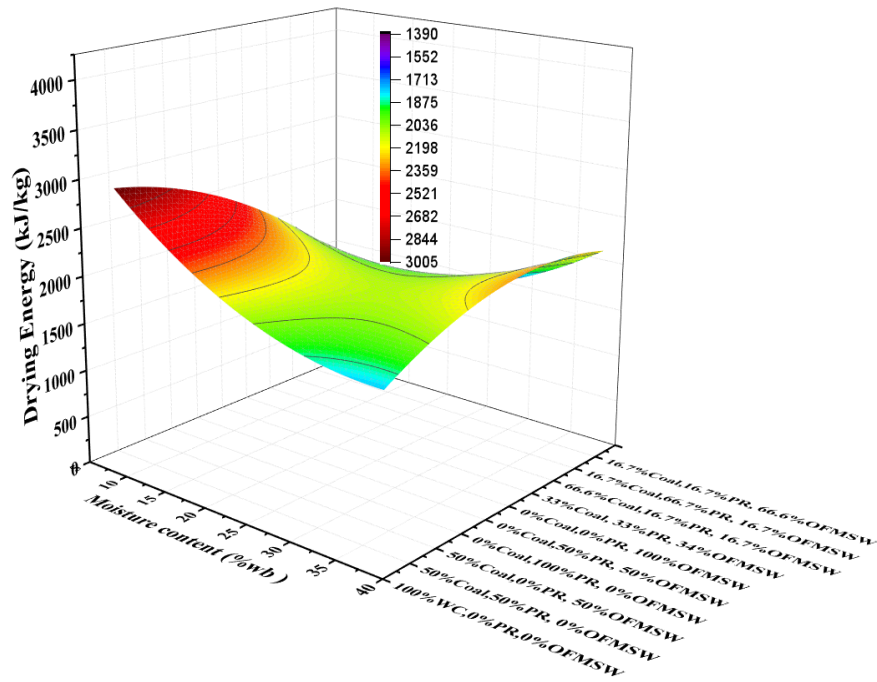


Figure 4.5: Response surface plot of the drying energy per kg of water removed of the blends

4.5.2. Approximate predictive models for the drying energy requirement of the blends

Table 4.7 presents the estimated predictive models for the individual samples WC, PR, and OFMSW. It can be observed that the drying energy requirement for PR and OFMSW exhibits a non-linear relationship with moisture content, showing a typical drying process trend. The negative slope indicates that as drying advances, the energy needed for drying increases. This finding is consistent with the study Moya et al., (2013) who reported that as the wood dries, it may shrink or experience structural changes affecting the moisture migration and efficiency of heat transfer. The drying energy of the blend was estimated using a mass-fraction-weighted polynomial model derived from the individual drying energy model of PR and OFMSW. This approach provides a simplified prediction of blend behavior based on linear additivity, although it does not account for possible physicochemical interactions between components during drying.

Table 4.6: Predictive models for the drying energy requirement per unit mass of water of WC, PR, and OFMSW

Sample	Drying model kJ/kg water removed	R ²
WC	$E = -62.34MC + 3931.9$	0.99
PR	$E = 3.39MC^2 - 215.92MC + 5855.9$	0.96
OFMSW	$E = 3.08MC^2 - 303.84MC + 5863.3$	0.94

The drying energy for WC, PR, and OFMSW could be expressed as follows

$$E_{WC}(MC) = -a_1MC + k_1 \quad (4.4)$$

$$E_{PR}(MC) = b_1MC^2 - b_2MC + k_2 \quad (4.5)$$

$$E_{OFMSW}(MC) = c_1MC^2 - c_2MC + k_3 \quad (4.6)$$

Where MC is the moisture content (%wb), and E is the drying energy required per kg of moisture removed in the sample, the coefficients k come from the fitted data. Assuming the total mass fraction of the blends is $x_1 + x_2 = 1$ for binary blends and $x_1 + x_2 + x_3 = 1$ for ternary blends where x_1 , x_2 , and x_3 are mass fractions of WC, PR, and OFMSW, depending on the blend composition

For binary blends, the model equation becomes

$$E_{Blends} = x_1(a_1MC + k_1) + (1 - x_1)(b_1MC^2 - b_2MC + k_2) \quad (4.5)$$

For the ternary blends, the model equation becomes

$$E_{Blends} = (1 - (x_2 + x_3))(a_1MC + k_{WC}) + (1 - (x_1 + x_3))(b_1MC^2 - b_2MC + k_2) + (1 - (x_1 + x_2))(c_1MC^2 - c_2MC + k_3) \quad (4.6)$$

These equations were used to estimate the drying energy per unit mass of water removed for the blended samples, and the predicted values as well as the MRD are presented in Table 4.7 and 4.8. The model consistently overpredicted the blend drying energy requirement, with a

slightly lower mean deviation at higher moisture contents (30–40%). This discrepancy arises because the model is based on the assumption that the drying behavior of the blend is simply the additive sum of the individual blend components. However, in reality, drying behavior is influenced by interactions between moisture and each component ratio, as well as interactions among the blend component themselves based on statistical analysis (see section 4.5.1). These interactions may significantly affect heat and mass transfer processes during drying. Since such effects are not incorporated into the model, deviations between predicted and experimental results become high.

Table 4.7: Calculated drying energy requirement (kJ/kg water removed) for the blended samples

Blends	10%	20%	30%	40%
B1	3308.5 ±16.4	2323.8 ±33.1	1900.5 ±34.3	Nd
B2	3672.3 ±10.8	2295.5 ±82.9	1968.9.1 ±5.9	Nd
B3	3085.5 ±11.8	2360.5 ±17.2	2125.7 ±31.1	Nd
B4	4035.7 ±67.8	2295.5 ±15.7	2037.3 ±11.3	2257.7 ±78.8
B5	3584.5 ±14.1	2360.5 ±16.4	2194.9 ±33.3	2216.4 ±19.7
B6	3310.7 ±15.1	2397.1 ±80.8	2351.3 ±19.3	2237.3 ±37.1
B7	3369.9 ±30.4	2330.8 ±30.1	2098.9 ±16.2	Nd
B8	3115.9 ±38.5	2326.6 ±41.40	1998.5 ±21.2	Nd
B9	3654.9 ±10.1	2298.3 ±5.99	2066.9 ±21.1	Nd
B10	3340.6 ±15.4	2363.2 ±27.3	2223.5 ±7.7	Nd

* Values are the means of tree replicate, and the numbers after are the standard deviation. The true values of the moisture content for each blend are presented in Table 4.3

Table 4.8: %Mean relative deviation of experimental and predicted draying energy

Blends	10%	20%	30%	40%
B1	-15.67	-15.58	-8.54	Nd
B2	-52.03	-34.16	-6.33	Nd
B3	-61.57	-0.93	15.81	Nd
B4	-2.41	-20.70	-19.23	9.66
B5	-58.92	-25.24	-17.58	-13.54
B6	-24.84	-25.95	-7.24	-19.0
B7	-40.86	-14.47	0.40	Nd
B8	-60.52	-20.00	-4.83	Nd
B9	-76.84	-24.47	-18.95	Nd
B10	-64.29	-29.73	-19.06	Nd

4.6. Conclusion

This study investigated the influence of moisture content on the drying behavior of waste coal (WC), pine residues (PR), and the organic fraction of municipal solid waste (OFMSW), both as individual feedstocks and in blended systems. The results revealed that these materials differ significantly in their moisture absorption and retention characteristics due to variations in their structural composition and functional groups. PR and OFMSW exhibited a strong affinity for water, attributed to the abundance of hydroxyl ($-OH$) groups, whereas WC, being predominantly carbonaceous, showed comparatively lower water affinity, as confirmed by FTIR analysis. Among the individual materials, PR and OFMSW demonstrated higher and non-linear drying energy trends across the tested moisture range. This behavior is attributed to their enhanced moisture retention capacity and the presence of hydrophilic functional groups, which promote the retention of bound water and increase the energy required for drying. Meanwhile, at higher moisture, at the fiber saturation point, water becomes mostly surface water and takes less energy to dry. In contrast, WC exhibited relatively lower drying energy across all moisture levels. Notably, for all individual materials, the drying energy decreased with increasing moisture content, indicating a transition from bound water to more easily removable free water as the moisture level in the sample increased. In blended systems, however, an opposite trend was observed: drying energy increased with increasing moisture content. Despite this increase, the overall drying energy of the blends remained consistently lower than that of the individual components. Statistical analysis further indicated that drying energy in the blends is predominantly governed by the structural characteristics of the feedstocks and their interactions, rather than moisture content alone. Specifically, no significant correlation was observed between drying energy and the linear moisture term, whereas strong correlations were identified with non-linear moisture

effects and component interactions. Overall, these findings demonstrate that drying blended feedstocks is more energy-efficient than drying individual components separately, highlighting the potential for optimizing feedstock preparation strategies in thermochemical conversion processes.

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Chapter 5. Moisture effect on the fluidization behavior of waste coal, pine residues, and organic fraction municipal solid waste blends

5.1. Abstract

Efficient fluidization of waste-derived biomass is essential for improving the design and performance of fluidized bed systems; meanwhile, the variability in their physical characteristics and sensitivity to moisture make their fluidization behavior difficult to predict. The objective of this study was to investigate the effect of moisture content on the fluidization behavior and minimum fluidization velocity (U_{mf}) of waste coal (WC), pine residues (PR), the organic fraction of municipal solid waste (OFMSW), and their blends. The samples were ground and screened using a 1/8-inch screen, followed by sieving through a 1.91 mm mesh. The moisture content of the samples was adjusted to four levels ranging from 10 to 40 wt.% on a wet basis. The particle size distribution, bulk density, particle density, coefficient of variation (COV), sphericity, and porosity of the individual materials and their blends were determined at the specified moisture contents. The U_{mf} velocities were obtained from a plot of pressure drop across the bed as a function of superficial gas velocity through the bed. The results showed that bulk density increased with increasing moisture content, whereas particle density and porosity decreased as moisture content increased. In addition, the coefficient of variation for PR decreased from 0.34 ± 4.6 at 9.8% moisture content to 0.32 ± 5.3 at 39.8% moisture content, while that of OFMSW decreased from 0.23 ± 1.7 at 9.9% moisture content to 0.14 ± 8.3 at 37.9% moisture content. In general, the U_{mf} velocity increased with increasing moisture content. The U_{mf} of PR increased from 0.67 m/s at 9.9% moisture content to 1.10 m/s at 39.8% moisture content. Similarly, the U_{mf} of OFMSW increased from 0.58 m/s at 9.8% moisture content to 0.83 m/s at 37.9% moisture content, while that of WC increased

from 0.23 m/s at 9.8% moisture content to 0.83 m/s at 20.0% moisture content. A synergistic effect was observed in the blended samples, where the addition of WC to either OFMSW or PR slightly reduced the overall U_{mf} of the blends. Furthermore, the developed correlation predicted the experimental fluidization velocity with a mean relative deviation of less than 10% at lower moisture contents.

5.2. Introduction

Fluidized bed technology is extensively used in processes such as chemical and petrochemical operations, WC combustion and gasification, fluid catalytic cracking, pharmaceutical production, and more (Chinonso et al., 2024; Nicolucci et al., 2026; Wang et al., 2026). Fluidization is when a gas or liquid is passed upward through a bed of solid particles at a sufficient velocity, causing the solid particles to suspend and move freely and therefore behave like a fluid (Menéndez et al., 2019). In this state, the bed expands and exhibits fluid-like characteristics, often resembling a boiling liquid or a vigorously mixed suspension (Ahmed et al., 2024) because there is a balance between the gravitational force acting on the particles and the drag force exerted by the fluid flowing through the bed. In biomass conversion processes, especially processes such as pyrolysis and gasification, a fluidized bed constitutes an important and most preferred unit operation, due to its ability to promote efficient mixing and enhanced mass and heat transfer, enabling uniform temperature distribution and reaction rate within the bed, which in return improves the conversion yield (Wu et al., 2017, Wynn & Ibekwe, n.d., Soanuch et al., 2020).

Biomass such as PR, and organic fraction municipal solid waste (OFMSW) can be converted by fluidized bed gasification or pyrolysis systems (Menéndez et al., 2019; Nakato et al., 2025; Vasconcelos¹ et al., 2023), into products such as syngas (e.g., for power generation), (Mondal & Rafizul, 2024), bio-oil (e.g., as transportation fuel), or biochar (e.g., for soil remediation) (Przywara et al., 2023). However, the properties of feedstocks (e.g., particle size, shape, density, and surface roughness) play a critical role in their fluidization behavior and also strongly influence particle–fluid interactions. PR and OFMSW typically exhibit irregular shapes, are cohesive, and have broad size distributions, low densities, and high moisture contents that make achieving stable fluidization particularly challenging (Jia et al.,

2017). Their heterogeneous nature often renders their fluidization unachievable or requires high gas velocities to fluidize. In most cases, smaller particles are more susceptible to entrainment, while large size and irregular shapes can promote agglomeration and hinder uniform fluidization, thereby increasing the overall complexity of the fluidization process (Wu et al., 2017; Genehr et al., 2020; Let et al., 2023; Si & Guo, 2008; Soanuch et al., 2020). Moreover, PR and OFMSW have high moisture ranging from 30 -60% (Olatunde et al., 2017), depending on the harvesting season. Moisture significantly influences the fluidization behavior of biomass by introducing liquid properties, enhancing interparticle liquid bridge forces (Jia et al., 2017; Bernhart & Fasina, 2009); all of these have a detrimental effect on the overall handling process. Beyond this, moisture further amplifies the inherent variability of biomass particles such as PR and OFMSW, which already exhibit wide particle size distribution, low bulk density, and high porosity (Olatunde et al., 2017). Increased moisture content reduces flowability by enhancing compressibility, cohesion, and adhesion through stronger interparticle bonding (Bernhart & Fasina, 2009; Chen et al., 2018; Cousin & Lekounougou, 2021). These effects contribute to operational challenges such as segregation, channeling, and even flow stoppage/plug during fluidization (Pan et al., 2020). Olatunde et al., (2017) and Grubecki, (2015) found that at high moisture contents, particles tend to agglomerate, leading to plug flow, defluidization, and overall poor fluidization quality. Particle formed cluster, which directly affect the heat and mass transfer between particles and the airflow during the drying process, affecting the final quality of products and the output (Geng et al., 2020). These authors also mentioned that moisture-induced particle cohesion increases flow resistance, requiring higher gas velocities to initiate fluidization. However, increasing the gas velocity can lead to particle entrainment and reduced gas–solid contact efficiency, negatively affecting

reaction kinetics in processes such as gasification. High moisture content lowers the energy density of the product gas and reduces overall system performance.

Fluidization gas velocity, particle composition, moisture content, and operating pressure are key factors influencing the flow dynamics of PR, OFMSW, and WC blends. Wu et al., (2017) reported the occurrence of agglomeration, channeling, slugging, and dead zones during the fluidization of rice husk and walnut shell at moisture contents above 10%. The authors assessed fluidization quality using a dimensionless parameter known as the fluidization index (FI), defined as the ratio of the pressure drop across the bed to the total weight of the bed. A bed was classified as fully fluidized when $FI > 0.95$, partially fluidized when $0.6 < FI < 0.95$, and poorly or not fluidized when $FI < 0.6$. Their findings showed that increasing moisture content led to a decline in FI . In the case of rice husk, when the moisture content reached 16.2%, the FI dropped below 0.35 regardless of increases in air velocity. This behavior was attributed to the formation of particle clusters at different scales within the bed, which promoted severe channeling and the development of dead zones, thereby reducing fluidization quality. Olatunde et al., (2017) observed an increase in the U_{mf} velocity of loblolly pine wood grind when moisture was raised from 8 to 27.02%, and found that the U_{mf} increased from 0.2 m/s at 8% MC to 0.32 m/s at 27.02 % MC. Similarly, Bai & Si, (2020b) also studied the effect of moisture content on the fluidization behavior of larch particles, and found that the U_{mf} increased with increasing moisture content, due to increased adhesion of particles, leading to increased resistance to flow, which resulted in a reduction in the fluidization quality. They reported that the FI decreased to 0.4% when the moisture content in the larch particle was 21.2%, indicating poor fluidization quality.

It is obvious that moisture content strongly affects the fluidization behavior of biomass feedstocks. In addition, blending these biomasses with WC particles adds another layer of

complexity to the fluidization quality, due to their distinct physical characteristics, including significant differences in density, size, shape, and moisture content; hence, it is worth investigating their fluidization behaviors in the presence of moisture. The focus of this study is to investigate how PR, OFMSW, and WC blends in the presence of moisture behave in fluidized beds. In this study, fluidization behaviors, including the minimum fluidization velocity and the bed pressure drop, were assessed for PR, OFMSW, and WC blends at various moisture levels

5.3. Material and method

5.3.1. Sample preparation

The materials used in this study included PR obtained from a sawmill (West Fraser, Inc., Opelika, AL), WC collected from a private property in Auburn, Alabama, and the organic fraction municipal solid waste (OFMSW) supplied by BRUCCELL-08142023, a waste management company in Alabama. The PR and waste WC were ground using a hammer mill (Model 358, New Holland Grinder, New Holland, PA) equipped with a 1/8-inch (3.175 mm) screen. The OFMSW was processed using a granulator (SG-4390, Willoughby, OH) fitted with a 3/16-inch screen. Following grinding, all samples were sieved using a vibro screen separator (Kason, M-7555, Millburn, NJ) with 1.91 mm and 1.29 mm screens, along with a collection pan (Fig. 5.1). Only the fraction retained on the 1.91 mm screen was selected for subsequent experiments, while the remaining material was discarded.



Figure 5.1: Pictures of sample preparation equipment: a) hammer mill, b) plastic granulator, c) Vibro screen separator

5.3.2. Physical properties measurement

5.3.2.1. Particle size distribution

The particle size distribution of the samples was determined using a Camsizer (Retsch Technology, Haan, Germany), a dynamic image analysis system equipped with two high-speed cameras that simultaneously capture both coarse and fine particles at different magnifications. The system analyzes individual particles to determine size parameters such as length, width, area, and Feret diameter, as well as shape descriptors including sphericity, aspect ratio, and roundness. For each measurement, approximately 50 g of dry sample was introduced through a funnel and transported into the measurement zone via a vibratory feed chute. The software provided by the manufacturer was used to generate and analyze the volume-based particle size distribution and sphericity data.

5.3.2.2. Moisture content adjustment

The sample that was retained on the 1.91 mm nominal screen size was used to prepare ten (10) blends that contain different ratios of PR, WC, and OFMSW according to the recipe shown in Table 5.1. The blends were formulated based on their total net zero carbon emissions. The moisture content of each blend was adjusted to 10%, 20%, 30%, and 40% by

adding a corresponding mass of water calculated according to Eqn. 5.2. Each conditioned blend was placed in sealed plastic bags and allowed to equilibrate in the refrigerator at 4 °C for at least 3 days. After equilibrium for three days, the moisture content was measured according to the ASTM 1756 standard using the Denver Instrument IR-200 instrument. This method consists of placing about 10 grams of the sample on an aluminium plate of the instrument and placing it in the instrument oven. The sample is heated at 105 °C until no moisture is detected by the instrument, and the result is calculated based on Eqn. 5.1 is displayed on the instrument screen. The measured moisture content of each blend after equilibration is shown in Table 5.2, on a wet basis (wb)

$$\text{Moisture (\%wb)} = \frac{W_i - W_f}{w_i} \quad (5.1)$$

Where W_i , and W_f are the initial (wet weight) and final weight (dry weight) of sample

$$x_{coal} * mass_{coal} + x_{pine\ residues} * mass_{pine} + x_{MSW} * mass_{MSW} + mass_{water\_needed} = (mass_{total} + mass_{water\_needed}) * target\ moisture\ content \quad (5.2)$$

Where x_{coal} , x_{pine} , x_{MSW} are the initial moisture content (in decimal) of the sample.

Table 5.1: Blend nomenclature (mass ratio)

Blend #	% WC	% PR	% OFMSW
B1	100	0	0
B2	50	50	0
B3	50	0	50
B4	0	100	0
B5	0	50	50
B6	0	0	100
B7	33	33	34

B8	66.6	16.7	16.7
B9	16.7	66.6	16.7
B10	16.7	16.7	66.6

* WC (waste coal), pine residues (PR), OFMSW (organic fraction of municipal solid waste)

Table 5.2: Actual moisture content of blends (wb)

Target	B1	B2	B3	B4	B5	B6	B7	B8	B9	B10
10%	9.8	11.6	11.6	9.8	10.8	9.9	11.5	9.0	10.4	11.1
	±0.0	±0.1	±0.1	±0.8	±0.1	±0.1	±0.1	±0.1	±0.8	±0.1
20%	20.0	20.2	22.4	20.9	20.5	20.9	21.9	19.3	21.8	20.1
	±0.4	±0.2	±0.5	±0.1	±0.0	±0.1	±0.6	±0.1	±1.1	±0.5
30%	25.7	30.7	29.7	29.9	30.9	30.2	30.3	29.4	29.6	28.9
	±0.1	±0.8	±0.4	±0.5	±0.5	±1.1	±0.3	±0.2	±0.8	±0.3
40%	nd	39.5	40.3	39.8	39.9	37.4	39.6	40.2	30.8	37.9
		±0.1	±0.3	±0.7	±0.3	±0.9	±0.0	±0.2	±0.0	±0.2

*no data (nd), for WC above 25% due to its high sensitivity to moisture

5.3.2.3. Bulk density measurement

The bulk density of the samples (individual and blend) was determined by the ASABE standard (S269.5) using a Burrows Co., Evanston, Ill (ASABE, 2021). The blend was poured into a measuring container of a known volume (1137 ml) from a funnel at a height of 610 mm above the edge of the container, and the hopper outlet lid, which was initially closed, was removed to allow the sample to flow into the container. The sample was levelled to ensure that particles that have more than half of their volume above the top edge of the container are

removed. Bulk density was obtained from the sample mass ratio to the container's volume (Eqn. 5.3).

$$\rho_b = \frac{W_s}{V_c} \quad (5.3)$$

Where ρ_b (kg.m⁻³), W_s (kg), and V_c (m³) are respectively the bulk density, sample weight, and volume of the container.

5.3.2.4. Particle density measurement

Particle density represents the actual density of the material, excluding all pores (open and closed) within a particle, and was measured using the helium gas pycnometer (Accupyc 1330, Micromeritics Instrument Corp., Norcross, GA) according to the ASTM standard B923. A known mass of a sample was placed in the pycnometer container and inserted into the cell of the machine. Helium gas under pressure was allowed to flow into the cell containing the sample. The average volume and the standard deviation were displayed on the screen of the instrument after the completion of the measurement. The particle density (ρ_p) was calculated as the ratio of the measured mass of the sample (m_s) to skeletal volume (V) provided by the apparatus software (Eq. 5.4).

$$\rho_p = \frac{W_s}{V_{particle}} \quad (5.4)$$

Where ρ_p (kg.m⁻³), m_s (kg), and V_p (m³) are respectively the particle density, sample weight, and volume of the particle excluding the void spaces.

5.3.2.5. Porosity

The porosity or bulk porosity (ε) of the sample was calculated from the bulk and particle density values as follows:

$$\varepsilon = 1 - \frac{\rho_b}{\rho_p} \quad (5.5)$$

Where ρ_b And ρ_p are the bulk density (kg.m^{-3}) and particle density (kg.m^{-3})

5.3.3. Fluidized bed system and fluidization experiment

Figure 5.2 presents a schematic of the fluidized bed system used to experimentally determine the minimum fluidization velocity and pressure drop of the sample blends. The column consisted of a transparent acrylic cylinder which allowed us to visualize the flow behavior of the sample in the system. The fluidized bed had an internal diameter of 10.16 cm and a height of 1 m. A uniformly perforated distributor with a pore size of 100 μm (Purolator, Model UNS 530403, Sacramento, CA) was installed at the base of the column to support the bed material and ensure even gas distribution. Air was supplied as the fluidizing medium using a blower (Black and Decker, Model LH5000, Antioch, CA). The airflow rate was controlled using a valve fabricated in the Biosystems Engineering workshop at Auburn University, positioned approximately 0.4 m from the blower. Air velocity was measured using a vane anemometer (FM Metal Vane Anemometer, Model 407113, Nashua, NH). The pressure drop across the bed was monitored using a U-Tube manometer connected at two points: 800 mm above and 200 mm below the distributor. For each experiment, approximately 200 g of sample (depending on blend composition) was introduced from the top of the column, resulting in an initial bed height of about 8 - 9 cm. The bed was leveled using a rod to ensure uniform packing. The blower was then activated, and the air velocity was increased in increments of 0.1 m/s. At each velocity, the system was allowed to stabilize for 60 seconds before recording the pressure drop and airflow rate. The minimum fluidization velocity was identified as the point where the pressure drop became relatively unchanged. This method has been used by many other authors for the determination of pressure drop and minimum fluidization velocity (U_{mf}) (Bai & Si, 2020b, 2020a; Vasconcelos¹ et al., 2023). To validate the experimental setup, the system was first tested using sand to determine its minimum fluidization velocity and

compared with literature data. All experiments were conducted in triplicate to ensure reproducibility and reduce variability in the results.

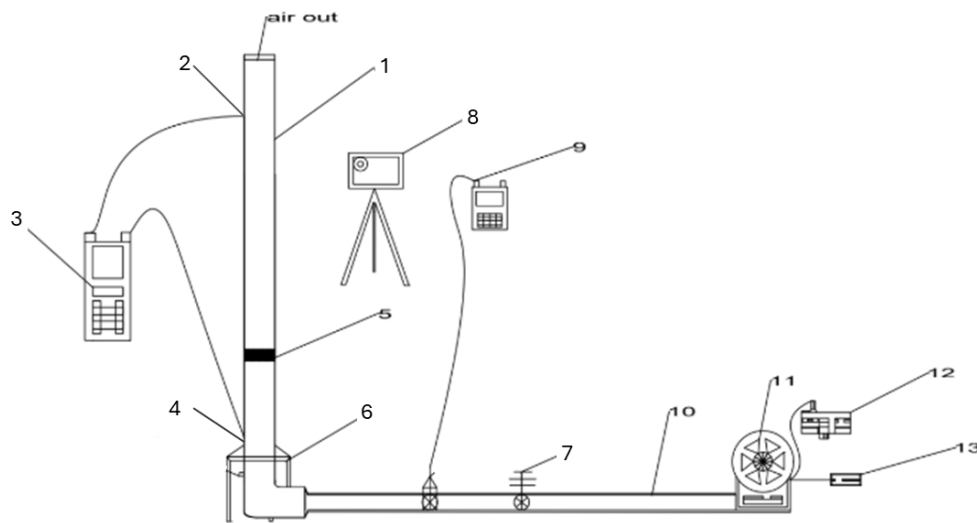


Figure 5.2: Schematic representation of the Fluidized bed used in this study: (1) Acrylic column, (2) pressure sensor point1, (3) U-tube manometer, (4) Pressure sensor point2, (5) distributor plate (6) column stand, (7) regulator valve, (8) camera, (9) air flow meter

5.3.4. Statistical analysis

All experiments were conducted in triplicate. The results were presented in the relevant sections as mean values and standard deviation. The effect of moisture content on the blend bulk density, particle density, porosity, pressure drop, and the minimum fluidization velocity was analyzed using a generalized linear model from SAS statistical software (SAS, 2011). In addition, a pairwise t-test using the least squares means procedure with Tukey multiple comparison test was computed for each effect and its interactions. All the tests were considered to be statistically significant when $p < 0.05$. The difference between predicted (minimum fluidization velocity based on some selected models) and observed (minimum fluidization velocity obtained from laboratory experiment) was evaluated by determining the mean relative deviation (MRD).

$$MRD (\%) = \frac{1}{n} \sum_{i=1}^n \frac{(P_i - E_i)}{E_i} \quad (5.6)$$

Where P_i and E_i are predicted and experimental values, and n is the number of experimental replicates.

5.4. Results and discussion

5.4.1. Effect of moisture content on the particle size distribution

Figs 5.2, 5.4, and 5.5 show the particle size distribution of WC, PR, and the OFMSW at various moisture levels. It can be observed that WC and PR particle size distributions exhibited right skewness, which is typical behavior for fine WC particles and biomass material (Fig. 5.3 and 5.5). For WC, fine particles less than 1 mm were predominant. Similar results were found by Song et al., (2019), although the shape looked different from the powder WC reported in the literature by Lu et al., (2015), exhibiting a more uniform shape as reported at a moisture content of 2.5%. The observed results may be attributed to the presence of root fibers in the WC sample, as it was collected from a pond. These fibers likely introduced some variability in the particle size distribution. OFMSW exhibited a more normal distribution, with particles concentrated around the mean. As the moisture was added to the PR and OFMSW, the peak of the distribution shifted. This observation indicates particle swelling due to water penetrating the pores of this material, resulting in a slight increase in particle size. For example, the size of PR increased from 1.63 to 1.88 mm when the moisture was raised from 7.4 to 40.3%. This effect was more pronounced for OFMSW; when moisture was raised above 10.2%MC, coarser particles were formed, as observed on the curve (larger shift toward the right side). These differences have significant implications for their fluidization behavior. For example, the formation of particle agglomeration as a response to moisture leads to reduced

bed homogeneity and increase particle cohesion, thus requiring higher air velocity to initiate flow (Wu et al., 2017).

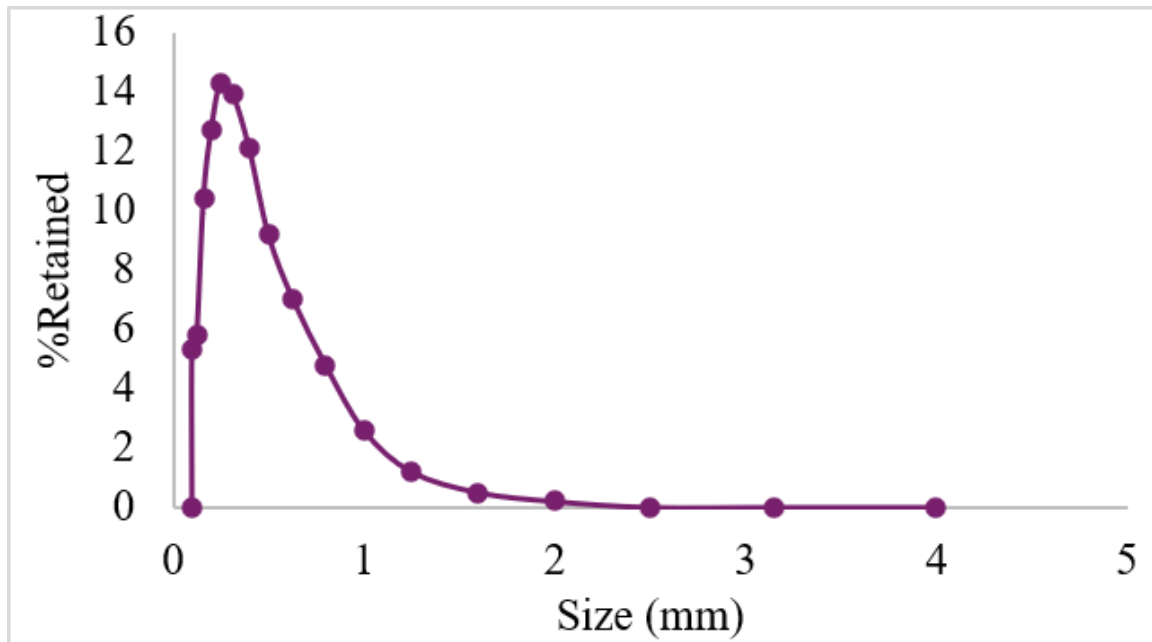


Figure 5.3: Particle size distribution of WC (2.3%M)

**Particle size distribution could not be measured at higher moisture content due to the sample becoming very cohesive, even at low moisture content*

Fig 5.4 illustrates the effect of moisture content on the physical appearance and cohesion of the WC sample. At low moisture content (2.3%), the particles appear loose and free flowing. The flow index at this moisture was found to be 7.68 indicating minimal interparticle interaction and low cohesion (0.15kPa). As moisture increases to 6.5%, slight agglomeration is observed due to the formation of liquid bridges between particles, resulting in increased cohesion (0.55kPa). At high moisture content (22.2%), pronounced clustering and the formation of large agglomerates were evident, reflecting strong interparticle bonding and significantly higher cohesion (0.87 kPa). These observations demonstrate the critical role of moisture in enhancing particle cohesion in fine WC particles, which adversely affects our ability to measure the particle size distribution at high moisture contents using Dynamic Image Analysis or sieve analysis.

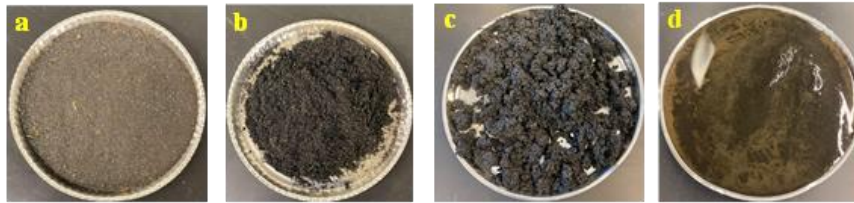


Figure 5.4: WC sample appearance with different moisture content: a) 2.3MC%, cohesion: 0.15kPa; B) 6.5%MC, cohesion:0.55kPa, c) 22.2%MC, cohesion: 0.87kPa, d) 35%MC

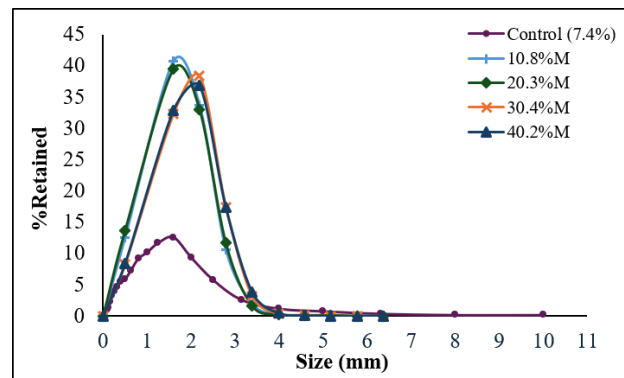


Figure 5.5: Effect of moisture content (MC, %wet basis) on the particle size distribution of PR: *Control in the legend indicates that the sample was used as received, and moisture was not adjusted.

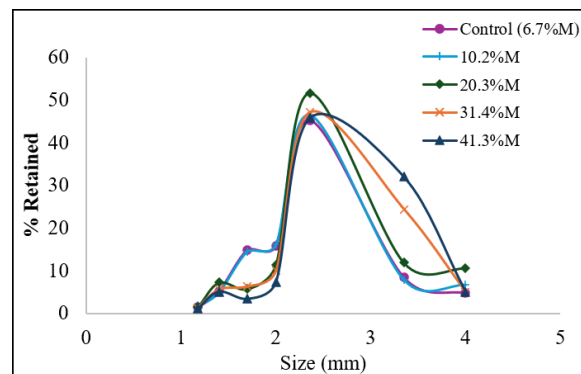


Figure 5.6: Effect of moisture content (MC, %wet basis) on the particle size distribution of OFMSW: *Control in the legend indicates that the sample was used as received, and moisture was not adjusted.

5.4.2. Effect of moisture content on the particle size of the blends

The particle size of the blends was expressed in terms of the surface volume diameter, also commonly referred to as the Sauter mean diameter. The value was calculated using the mass fraction weighted average of the individual samples using Eqn. 5.7, and the result is presented below. These values were used to determine the Geldart particle classification of the blends.

$$d_{32,blend} \approx \sum_i w_i d_{32i} \quad (5.7)$$

Table 5.3: Surface volume diameter (mm) of the blends at different moisture content

	Control	10	20	30	40
B1	0.24 ±0.00	nd	nd	nd	nd
B2	0.89 ±0.00	0.83 ±0.00	0.83 ±0.02	0.93 ±0.00	0.88 ± 0.00
B3	1.41 ±0.00	1.33 ±0.00	1.26 ±0.00	1.35 ±0.00	1.41 ±0.00
B4	1.53 ±0.00	1.42 ±0.00	1.41 ±0.03	1.62 ±0.00	1.53 ±0.00
B5	2.01 ±0.00	1.89 ±0.00	1.85 ±0.02	2.00 ±0.00	2.05 ±0.00
B6	2.58 ±0.00	2.36 ± 0.00	2.29 ± 0.02	2.46 ±0.02	2.58 ±0.00
B7	1.46 ±0.00	1.35 ±0.00	1.32 ±0.01	1.44 ±0.00	1.46 ±0.00
B8	0.85 ±0.00	0.79 ±0.00	0.77 ±0.01	0.84 ±0.00	0.85 ±0.00
B9	1.49 ±0.00	1.37 ±0.00	1.36 ± 0.02	1.53 ±0.00	1.49 ±0.00
B10	2.02 ±0.00	1.85 ±0.00	1.81 ±0.01	1.95 ±0.00	2.02 ±0.00

**The actual values of moisture content of the blends are presented in Table 5.2, *Control indicates that the sample was used as received, and moisture was not adjusted*

5.4.3. Geldart classification of particles

The particles were classified according to the Geldart classification scheme, considering both the density difference between the solid particles and the fluidizing medium

(air) and the representative particle size, as shown in Table 5.4. The particle size was expressed as the surface-volume mean diameter, commonly referred to as the Sauter mean diameter (d_{32}). Because the blend's particle size distribution could not be directly measured, the effective Sauter mean diameter of each blend was estimated from the mass-fraction-weighted average of the component d_{32} values. This estimated diameter, together with the measured blend particle density, was used to assign an approximate Geldart classification. The resulting classification should therefore be interpreted as nominal, since the true blend behavior may be affected by particle size distribution, irregular shape, and segregation effects. Particles fall in the Geldart, A, B, and D classifications, underscoring distinct or even opposite behaviour during fluidization. Blending different particle groups results in a different classification group. For example, blending B1 of group A with B4 of group D resulted in blends that have group B classification. This behavior renders the prediction of the bed behavior complex and uncertain.

Table 5.4: Geldart classification of the blends as affected by the moisture content and the blend ratios

Blends	10	20	30
B1	A	nd	nd
B2	B	B	B
B3	D	D	D
B4	D	D	D
B5	D	D	D
B6	D	D	D
B7	D	D	D
B8	B	B	B

B9	D	D	D
B10	D	D	D

5.4.4. Effect of moisture content on the porosity of the blends

Table 5.5 presents the porosity/void fraction of the sample blends at different moisture contents, computed from the bulk and the particle density of the blends. The porosity represents the percentage of void space within the bed of material. This value is critical for airflow and heat transfer during fluidization and combustion. It can be observed that all blends exhibited relatively high porosity (above 0.64 – 0.94) across the moisture range, except for B1, which was 0.52 at 10%wb moisture content. The blend's porosity was also significantly different across the moisture levels. The high porosity was found for PR and OFMSW, which reflects their porous and fibrous nature. Similar values have been reported in the literature for biomass grind (Cousin & Lekounougou, 2021; Hradil et al., 1992; Kalman & Portnikov, 2021). It was noticed that when blending biomass with WC, the porosity was slightly and consistently lower than that of the biomass alone. This shows that finer particles of WC filled the empty spaces between the biomass material, leading to a reduction in porosity of the blends. In the context of fluidization, a reduction in the porosity favors fluidization quality.

It was noticed that as moisture reached 40%, porosity slightly reduced; this is because excess moisture may have occupied the interparticle air spaces through capillary films, thereby reducing the overall void space within the particles. Grubecki, (2015) also found that the bed porosity of woodchips reduced by 31% as moisture increased from 8.1% to 64.5% wb. A similar trend was observed by Kalman & Portnikov, (2021), who explained that moisture introduces capillary forces between particles, promoting particle rearrangement and reducing interparticle void spaces. Additionally, water can occupy pore and interparticle void regions,

further decreasing the overall porosity. The high bed porosity in a packed biomass bed can promote channeling, where the airflow follows preferential pathways rather than being uniformly distributed through the narrow interparticle voids. This non-uniform gas flow may transport smaller and lighter particles, leading to the formation of larger voids as the bed structure rearranges. Consequently, segregation within the bed increases, and the pressure drop across the bed becomes higher

Table 5.5: Effect of moisture content on the porosity of the blends

	Control	10	20	30	40
B1	0.52e ±0.01	0.52f ±0.01	0.71f ±0.0	0.64h ±0.01	nd
B2	0.70d ±0.00	0.71e ±0.01	0.69f ±0.03	0.76f ±0.00	0.67f ±0.01
B3	0.85c ±0.01	0.85cd ±0.01	0.84d ±0.01	0.82e ±0.00	0.72e ±0.03
B4	0.83c ±0.00	0.82d ±0.00	0.83cd ±0.01	0.83c ±0.00	0.79c ±0.00
B5	0.89b ±0.00	0.89b ±0.06	0.89b ±0.00	0.86b ±0.02	0.83b ±0.00
B6	0.94a ±0.02	0.94a ±0.02	0.92a ±0.00	0.87a ±0.00	0.85a ±0.01
B7	0.85c ±0.01	0.85c ±0.00	0.84c ±0.01	0.81d ±0.00	0.75d ±0.00
B8	0.71d ±0.01	0.71e ±0.00	0.77e ±0.00	0.70g ±0.02	0.65g ±0.01
B9	0.83c ±0.00	0.83c ±0.06	0.84c ±0.04	0.82c ±0.00	0.78c ±0.00
B10	0.89b ±0.00	0.89b ±0.01	0.89b ±0.02	0.85b ±0.00	0.82b ±0.00

**Values followed by their standard deviations are means of triplicate runs. Means with different letter in a row are statistically significant ($p < 0.05$). Control is referred to sample that the moisture has not been adjusted. The actual values of the moisture are reported in Table 5.2.*

5.4.5. Effect of moisture content on the sphericity of the blends

The particle shape of materials is usually characterized by the sphericity values. The sphericity of the blend was estimated using the mass fraction weighted average of the

sphericity of individual samples, using Eqn. 5.8, and the results are reported in Table 5.5. It is worth mentioning that it was assumed that the sphericity of WC was constant across moisture ranges due to the same reasons explained in section 5.3. The values varied between 0.78 and 0.24, with B1 exhibiting the highest values, and B6 showing the lowest values across the moisture range. This shows that B1 is a near-spherical shape, whereas B6 has a flat shape. According to Rosenholm, (2023) sphericity of $\phi < 0.5$ designates extremely flat particles, $\phi > 0.5$ indicates flat particles, and $\phi > 0.8$ is nearly spherical particles. Based on this classification, the blends can be classified as flat particles. Islam & Nguyen, (2021) mentioned that fluidizing these types of particles results in unstable flow behavior and high minimum fluidization velocity and pressure drop compared to spherical particles. Flat particles tend to orient horizontally, causing interlocking, channeling, and higher and more erratic pressure drop due to high particle-particle interaction.

$$\varphi_{blend} = \sum_i x_i \varphi_i \quad (5.8)$$

Table 5.6: Effect of moisture content on the blend sphericity

	Control	10	20	30	40
B1	0.78 ±0.02	nd	nd	nd	nd
B2	0.64 ±0.02	0.68 ±0.02	0.67 ±0.00	0.64 ±0.02	0.66 ±0.01
B3	0.43 ±0.00	0.55 ±0.01	0.55 ±0.00	0.52 ±0.00	0.5 ±0.06
B4	0.51 ±0.01	0.58 ±0.00	0.57 ±0.00	0.53 ± 0.01	0.56 ±0.02
B5	0.43 ±0.01	0.44 ±0.09	0.45 ±0.01	0.42 ±0.12	0.40 ±0.01
B6	0.36 ±0.00	0.32 ±0.01	0.33 ±0.02	0.29 ±0.01	0.24 ±0.02
B7	0.54 ±0.02	0.55 ±0.01	0.56 ±0.00	0.53 ±0.02	0.52 ±0.01
B8	0.66 ±0.01	0.67 ±0.00	0.67 ±0.00	0.64 ±0.01	0.64 ±0.02

B9	0.53 ±0.01	0.57 ±0.00	0.56 ±0.00	0.53 ±0.00	0.54 ±0.00
B10	0.46 ±0.01	0.44 ±0.01	0.43 ±0.01	0.42 ±0.02	0.38±0.01

**Values followed by their standard deviations are means of triplicate runs. Control refers to a sample where the moisture has not been adjusted. The actual moisture values are reported in Table5. 2.*

5.4.6. Fluidization behavior of waste coal, pine residues and organic fraction municipal solid waste blends

5.4.6.1. Verification of the fluidized bed system

The fluidized bed was tested by fluidizing sand particles the particle diameter of $d_{50} = 0.54\text{mm}$, and the minimum fluidization velocity was estimated by the pressure drop method (Let et al., 2023) and the results is plotted in Fig. 5.8. The minimum fluidization was estimated to be the velocity at which increasing on the inlet superficial air velocity resulted in an almost constant pressure drop, the values were found to be $0.28 \pm 0.02\text{m/s}$. Some literature works, including the work of (Soanuch et al., 2020 & Taofeeq, 2020), reported the minimum fluidization velocity of sand to be in the range of 0.27 and 0.35 m/s with similar particle size. This test was used to validate the performance of our fluidized bed.

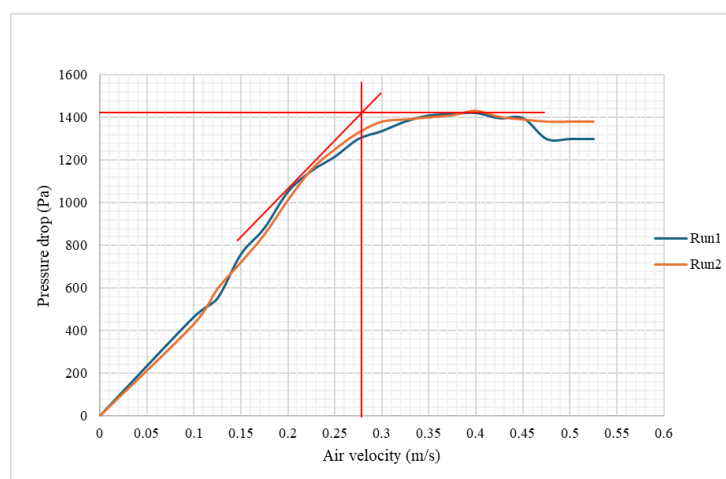


Figure 5.7: Determination of the minimum fluidization velocity of sand particles

5.4.7. Fluidization behaviors of waste coal, pine residues, and organic fraction municipal solid waste

The fluidization behavior of the individual components was first examined by physically observing the evolution and the state of the bed. Fig. 5.9 and 5.10 show fluidization behaviors of PR and OFMSW. It can be depicted that both figures followed a typical fluidization trend where initially, an increase in the superficial gas velocity resulted in a corresponding increase in the pressure drop up to the point where the bed of the material was overcome by the drag force exerted by the incoming gas. As the superficial gas velocity increased slowly, the corresponding pressure drop was recorded across the bed at each flow increment. Initially, the bed of material remained fixed; no bed expansion was observed (Fig. 5.9a and 5.10a), however, the pressure drop increased rapidly as the superficial gas velocity was increased. After a further increase in the superficial gas velocity, the bed began to expand slightly, and lighter particles fluidized near the top of the bed, leaving the bottom of the bed fixed. A similar trend was reported by Kaliyaperumal et al., (2011). A point was reached when an increase in the airflow after a couple of times did not result in a considerable increase in the pressure drop; at this point, the superficial gas velocity was considered as the minimum fluidization velocity (U_{mf}). The minimum fluidization velocity (U_{mf}) was determined at the intersection of the fitting curves in the fluidized bed and the fixed bed, as observed in Fig 5.9b and 5.10b as described by (Let et al., 2023; Reyes-urrutia et al., 2023). At this point, the bed expanded by about 10% to 11% of its original height, suggesting that the bed of material was now supported by the drag force exerted by the air flow. After the gas velocity was increased to about 1.5 times the U_{mf} (Fig. 5.9c and 5.10c), more particles were observed at the top of the bed, while the bed remained dense at the bottom with channeling formation indicating partial fluidization. This was mostly observed for the case of PR. Bigger channels were observed with

OFMSW, as an indication of increased particle agglomeration, leaving some dead zones. The channeling was disrupted by exerting a gentle tap on the wall of the fluidized bed column. This worked in most cases with PR, but for OFMSW, tapping resulted in setting of the bed, and increasing in the air velocity resulted in the bed of material being entrained outside of the bed. In case where channeling persisted, the experiment was stopped and new samples were introduced, to ensure that the data collection was not compromised. With further increase in the air flow velocity, strong particle motions due to bubble growth, coalescence, and eruptions agitated the bed, causing the particles to freely migrate from the bottom to the top and along the bed (mostly observed for PR and WC). OFMSW behaved differently, with chunks of particles erupting from the bed, which sometimes separated the bed into two distinct compartments. These trends become particularly significant when the gas velocity is increased above $2U_{mf}$ (Fig. 5.9d). A similar observation was reported by Kaliyaperumal et al., (2011). When the gas velocity was increased above $2U_{mf}$ for OFMSW, the bed did not fluidize completely; instead, lighter particles moved at the top of the bed, as clusters (no particle separation). As the superficial gas velocity increased to $2.5U_{mf}$, the bed height increased from 8 to 25cm for PR, whereas OFMSW height remained relatively low at about 15cm. The graph of pressure drop vs U_{mf} in Figs 5.9 and 5.10 reveals large pressure fluctuation above the U_{mf} , which may be attributed to strong interlocking and entanglement between particles, which increases resistance to gas flow. This phenomenon was also observed by other researchers such Toschi et al., (2021) and Wu et al., (2017).

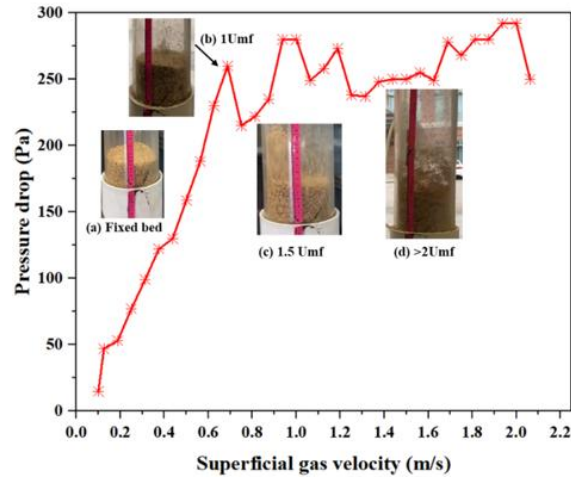


Figure 5.8: Fluidization behavior of pine residue (MC=7.4% wet basis)

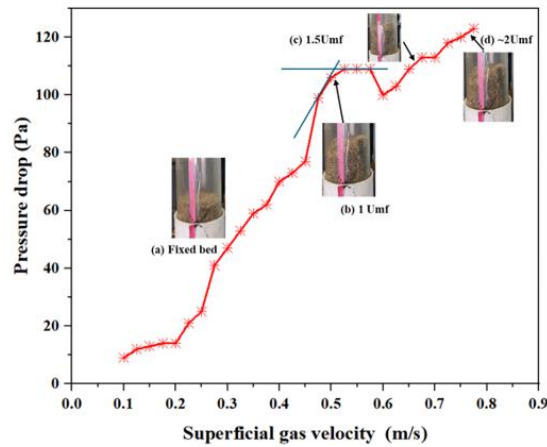


Figure 5.9: Fluidization behavior of OFMSW (MC=6.7% wet basis)

5.4.7.1. Challenges observed during the fluidization of the samples

Figure 5.10 illustrates some of the challenges encountered during the fluidization of PR and OFMSW. Several flow instabilities, including channeling, plug flow, defluidization, and particle entrainment, were observed during fluidization. As air was introduced into the bed and approached the minimum fluidization velocity (U_{mf}), the point at which the drag force exerted by the fluidizing gas balances the weight of the bed, fluidization did not occur uniformly. Lighter particles tended to fluidize first and were occasionally entrained out of the bed, while channeling was also observed. These channels progressively enlarged before complete

fluidization was achieved at the superficial gas velocity as high as $4U_{mf}$. Similar behavior was reported by Olatunde et al., (2017) during the fluidization of loblolly pine grinds, where channeling was found to be predominant for particles larger than 1 mm in nominal size. This phenomenon is attributed to the absence of finer particles, which typically act as a lubricating medium within the bed. Fine particles fill the void spaces between larger particles, thereby redistributing the airflow, minimizing channel formation, and enhancing bed mixing.

More pronounced channeling was observed in OFMSW, which hindered uniform fluidization and prevented full bed expansion. In contrast, WC exhibited relatively stable fluidization behavior, characterized by smooth bubbling and complete fluidization. The observed channeling behavior is primarily attributed to particle shape and packing characteristics. PR particles are elongated and needle-like, leading to interlocking and the formation of void structures that resist uniform gas distribution. Conversely, OFMSW particles were generally flat ($\phi=0.36$), irregular, and fluffy, which further disrupts uniform packing and gas flow pathways. These structural characteristics create preferential flow paths within the bed. As the gas flows upward, it tends to bypass regions of higher resistance and instead travels through zones with a higher concentration of loosely packed or lighter particles, forming channels of varying sizes. The extent and size of channeling are therefore influenced by the spatial distribution and concentration of these lighter, less resistant particles within the bed.

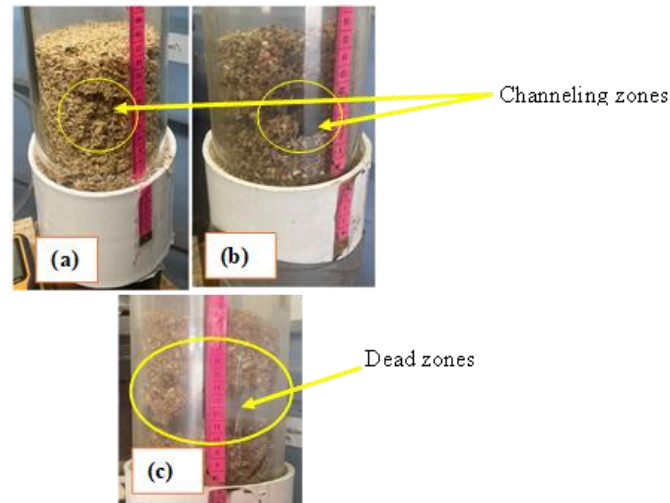


Figure 5.10: Channeling formation during fluidization of a) blend4, 7.3%M; b) blend6, 6.7%MC)

Segregation was observed in the blended samples, as illustrated in Fig. 5.11a, 5.11b and 5.11c. For instance, in B2 (Fig. 5.11a, see blend composition in Table 3.), the smaller WC particles reached their minimum fluidization velocity ($U_{mf} = 0.08 \text{ m/s}$ at 2.5M) earlier and began to fluidize, while the larger particles remained stationary at the bottom of the bed. As the air velocity increased further, these finer WC particles were eventually entrained out of the bed. In B7 (Fig. 5.11b), although it was difficult to visually distinguish between PR and OFMSW, the WC particles remained identifiable. This behavior is primarily attributed to the non-uniform particle size distribution within the bed as well as the sample colour. As observed in Fig 5.11b, WC particles adhered to the walls of the fluidized bed column. PR and OFMSW particles tended to interlock, promoting channeling on one side of the bed, while the WC particles accumulate and remain segregated on the opposite side. Fig 5.11c also reveal another particle to wall adhesion experienced by PR. The adhesion of fine WC particles and PR to the acrylic fluidized bed column can be attributed to their higher surface area ($4.08 \text{ m}^2/\text{g}$) due to their smaller particle size (case of WC), and higher surface energy distribution of 42 - 45 and 32 - 35 e/k for WC and PR respectively compared to OFMSW. Higher surface energy

promotes stronger van der Waals and capillary forces, additionally, the fine particle size (case of WC) increases the relative importance of surface forces over gravitational forces, making adhesion more likely. Also electrostatic interactions between the acrylic wall and these particles may further contribute to particle deposition as explained by Lin et al., (2025). In contrast, OFMSW, which is fluffier and possess lower surface energy distribution (28 – 32 eV/k) tends to favour particle–particle interactions such as interlocking and agglomeration, reducing their tendency to adhere to the column wall.

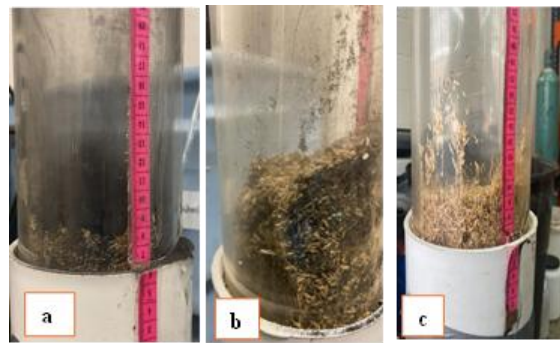


Figure 5.11: Segregation during fluidization of blends: a) blend2, 5.8%M, b) blend7, 5.6%M, and c) blend4, 7.3%MC

Figure 5.12 illustrates another phenomenon observed during the fluidization of the blends. For Blend B5 and blend9, shortly after reaching the minimum fluidization velocity (U_{mf}), approximately at $1.5 U_{mf}$, the bed began to expand collectively from the bottom as a bulk mass. With a further increase in inlet air velocity to around $3 U_{mf}$, only partial fluidization was achieved. Instead of fluidizing as individual particles, the particles moved in clusters. These clusters rose briefly before collapsing and settling back into the bed, after which the behavior recurred intermittently in localized regions. Over time, clusters continuously formed and collapsed in different zones within the bed. This behavior was observed in nearly all the blends. Overall, stable, homogeneous fluidization, with particles fluidizing individually, was not

achieved. This behavior can be attributed to the low density, large particle size, fibrous nature, and cohesive interactions of PR and OFMSW, which are characteristics of Geldart D groups (see Table 5.4). During fluidization, these differences promote particle interlocking, with lighter particles tending to migrate upward while heavier particles remain concentrated near the bottom. As a result, the upward gas flow preferentially fluidizes regions enriched with lighter particles, leading to localized and intermittent fluidization.

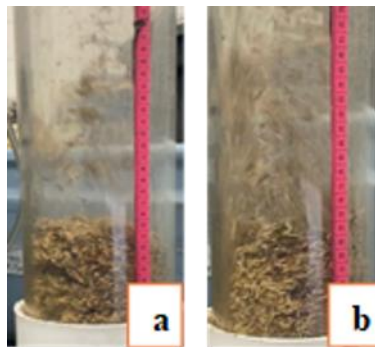


Figure 5.12: Partial and intermittent fluidization behavior observed during fluidization of a) B5, 7.1%MC; b) B9, 5.8%MC

5.4.7.2. Fluidization behavior of moist samples

As the moisture content of the samples increased, fluidization became progressively more difficult. Moisture enhanced interparticle cohesion through liquid bridge formation, which intensified mechanical interlocking, particularly for irregularly shaped particles like PR (Fig. 5.13b) and OFMSW (Fig. 5.13c). For WC (Fig. 5.13a), this behavior was primarily due to particle agglomeration. These effects increased resistance to gas flow through the bed, resulting in an uneven distribution of incoming air because the available paths for airflow were limited. As a result, the bed exhibited plug flow behavior, in which the material moved as a coherent mass (with limited particle mobility) rather than as a freely fluidized system. In this condition, the bed is segregated into distinct regions, with a portion of the material remaining relatively stationary at the bottom. In contrast, another portion accumulates or moves as a

block near the top. Gently tapping the column could disrupt plug formation, facilitate the breakage of the agglomerated structure, and lead to bed collapse. Tapping was most effective for PR where particles rearranged and temporarily improved fluidization. In contrast, for WC (Fig. 5.13a), the bed remained fully settled at the bottom of the column, and no significant particle movement was observed even at higher air velocities. For OFMSW (Fig. 5.13c), tapping caused segregation within the bed, with lighter particles migrating toward the top of the column, and some were subsequently entrained and carried out of the bed by the gas flow.

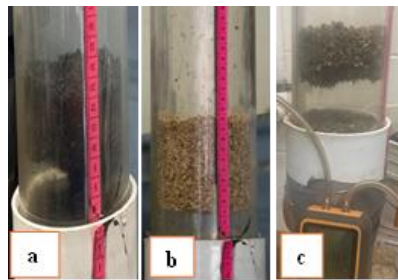


Figure 5.13: Plug flow during fluidization of a) WC, 18.2%MC; b) PR, 40%MC and, c) OFMSW, 40%MC

5.4.8. Effect of moisture on the pressure drop vs superficial gas velocity profile

Figures 5.14 through 5.17 displays the variation of pressure drop with superficial air velocity for the individual samples and B7 at various moisture content (Figures for the rest of the blends are shown in the Appendix1, Fig 8.1). The trend of the curve shows that for an ideal fluidized bed the pressure drops increase with superficial air velocity up to the minimum fluidization velocity (U_{mf}), indicating that the particles are tightly packed. In an ideal scenario after the U_{mf} the pressure drop remains constant with a well-defined fixed bed region, irrespective of the increase in superficial air velocity as reported by Oliveira et al., (2013) and Varghese et al., (2024). In this study, the plot deviated from the ideal constant pressure drop in the sense that, after the U_{mf} reached the bed pressure drop experienced some fluctuations, which could be due to many phenomena such as sudden particle rearrangement,

coalescence formation and bubbles splitting in the unsteady fluidized bed. Additionally, the transition from the fixed bed to the fluidized was not smooth for most of the blends, indicating poor fluidization quality after U_{mf} was reached. Most blends did not exhibit a clear pressure drop plateau or a distinct fluidization point, indicating unstable and incomplete fluidization. Instead, the pressure drop continued to increase with small increments or fluctuated with increasing air velocity or it dropped abruptly at the point of minimum fluidization velocity. This behavior can be attributed to the heterogeneous nature of the blends, which consist of particles with varying sizes, densities, and shapes. Additionally, this abrupt drop of pressure was explained by Clarke et al., (2005) to be due to a brief period of plug formation in the bed. Other factors, such as particle interlocking and defluidization, may have also contributed to this behavior. For example, in B7, the presence of low-density, fibrous biomass particles like PR and OFMSW and denser WC promoted segregation during fluidization (as seen in Fig 5.11b), leading to non-uniform gas–solid interactions. Lighter particles tend to fluidize preferentially (as seen in Fig 5.12a and b), while heavier particles remain at the bottom, resulting in partial fluidization and the absence of a stable fluidized regime. Additionally, phenomena such as channeling and clustering (an example is presented in Fig 5.10), may contribute to the observed fluctuations in pressure drop. These effects are characteristic of systems exhibiting Geldart D group (which is the case of these samples see Table 5.4), where particles do not fluidize uniformly but instead move in bulk or form agglomerates.

It can also be observed from the figures that the pressure drop gradient varied significantly with the moisture content. Steeper gradient was noticed at low moisture levels, and lower gradient was observed at higher moisture content, although the point of minimum fluidization differed for each moisture level. These results could be attributed to the fact that higher moisture levels promoted severe agglomeration between adjacent particles (at moisture

above 20% particle of WC stuck on the surface of PR and OFMSW), resulting in large channeling, and clusters and preferential air flow due to the appearance of empty zone. Additionally, particles also adhered to the wall of the fluidized bed at this moisture (above 20%) all these could greatly decrease the maximum pressure drop in the bed at U_{mf} . Similarly, Clarke et al., (2005) reported a significant decrease in the pressure drop in fluidized bed of sawdust when moisture increased from 45% to 82%, which was highly influenced by the adhesion of the sawdust particles to the sides of the vessel.

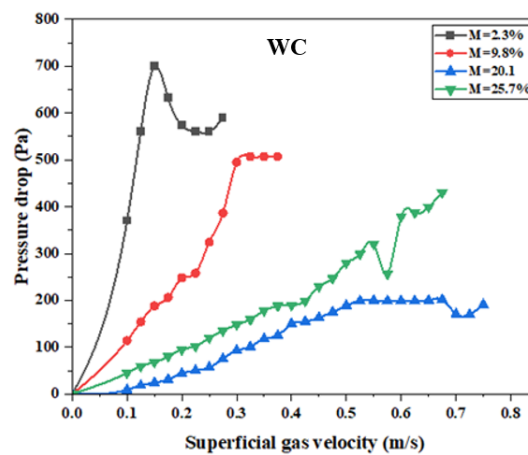


Figure 5.14: Variation in pressure drop and superficial gas velocity at different moisture content for WC

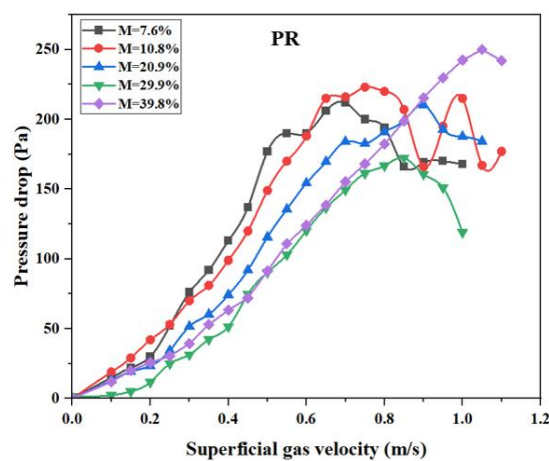


Figure 5.15: Variation in pressure drop and superficial gas velocity at different moisture content for PR

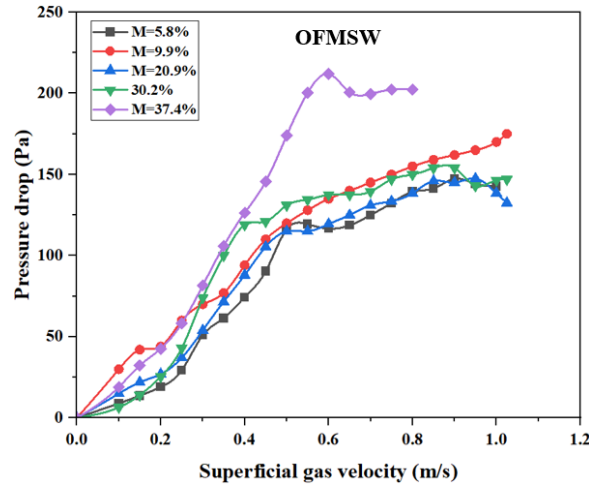


Figure 5.16: Variation in pressure drop and superficial gas velocity at different moisture content for OFMSW

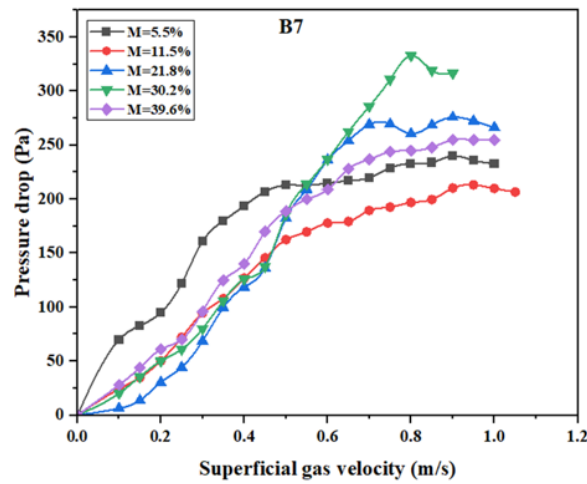


Figure 5.17 : Variation in pressure drop and superficial gas velocity at different moisture content for B7

5.4.9. Effect of moisture content on fluidization quality

The fluidization quality of the blends was evaluated by their fluidization index (FI). The fluidization index is a dimensionless number ranging from $0 \leq FI < 1$ used to measure the quality of fluidization including better mixing, good bed expansion and stable fluidization (Bai & Si, 2020b). A higher ratio of indicates, complete and stable fluidization, while lower ratio is attributed to unstable, incomplete and poor particle fluidization. In this study, the fluidization

index was defined as the dimensionless ratio of the pressure drop and the weight of the bed as follows: $FI = \frac{\Delta P \cdot A}{W}$ where ΔP is the bed pressure drop, A is the cross-section area of the bed and W is the weight of the bed material (Kaliyaperumal et al., 2011; Ram, 2013; X. Wu et al., 2017).

When the bed is fully fluidized, all particles are suspended by the gas; hence, the total particle weight is equal to the pressure drop across the bed, leading $\frac{\Delta P \cdot A}{W}$ being equal to unity, indicating a balance between the drag force and the weight of the bed. This suggests that the effect of particle acceleration and the friction of the wall surface, is negligible. Some studies suggested that when $FI > 1$, the bed of material was considered fully fluidized; when $0.6 < FI < 0.95$, the bed is considered partially fluidized; and when $FI < 0.6$, the bed was regarded as not fluidized or poor fluidization (Bai & Si, 2020b).

Figure 5.18 presents the variation of the fluidization index (FI) of the individual samples and B7 (Figures for the rest of the blends are presented in the Appendix1, Fig8.2) as a function of superficial gas velocity for different moisture contents. It is evident that all samples exhibit similar trends, with FI decreasing as moisture content increases referring to reduced fluidization quality. This observation is consistent with the findings of Wu et al., (2017). Waste coal (WC) demonstrated good fluidization behavior at a low moisture content of 2.5%, with an FI value reaching approximately a value of 1.2, indicating stable fluidization. This behavior is expected, as WC falls within Geldart Group A particles (Table 5.4), which are known for their favorable fluidization characteristics. However, when the moisture content increased to 9.8%, the FI decreased to 0.77, indicating partial fluidization. The fluidization behavior deteriorated even further at higher moisture levels ($\geq 20.1\%$), with FI dropping below 0.2 at 25.7%, regardless of increases in superficial gas velocity, signifying very poor fluidization

at this level of moisture. This decline in fluidization performance is attributed to moisture-induced particle clustering and agglomeration within the bed, which hinders particle mobility and disrupts uniform gas–solid interaction. For PR and OFMSW partial fluidization was predominantly observed across the studied moisture range, with *FI* values between 0.6 and 0.95. OFMSW exhibited a more pronounced decline in fluidization quality at moisture contents above 20%, where *FI* values dropped below 0.6. This behavior can be attributed to the nature of OFMSW, (light, fibrous and fluffy). This resulted in increased particle binding, in addition to the capillary forces produced by moisture. As a result, particles tend to behave as cohesive clusters rather than discrete entities, restricting particle movement and reducing overall fluidization efficiency (Wu et al., 2017; Oliveira et al., 2013). It was interestingly noticed that the fluidization quality slightly improved when these samples were blended, even at high moisture content (examples of B2 and B7). The *FI* of WC was 1.22, 0.8 and 0.45 at moisture content of 2.5, 9.8, and 20.1% wb, that of PR was 0.85, 0.8, and 0.65 at moisture content of 7.8, 10.8, and 20.9% wb, and that of OFMSW was 0.75, 0.70 and 0.56 at moisture content of 5.8, 9.9, and 20.9% wb when blended in B7 the *FI* increased to 1.21, 0.92, and 0.85 at moisture content of 5.5, 11.1 and 20.8% wb respectively. This could be due to the presence of fine waste coal particles, which may acted as lubricants in the bed, resulting in a slight improvement in the gas-solid interaction as explained by Olatunde et al., (2017), although this was not exactly observed during experiments.

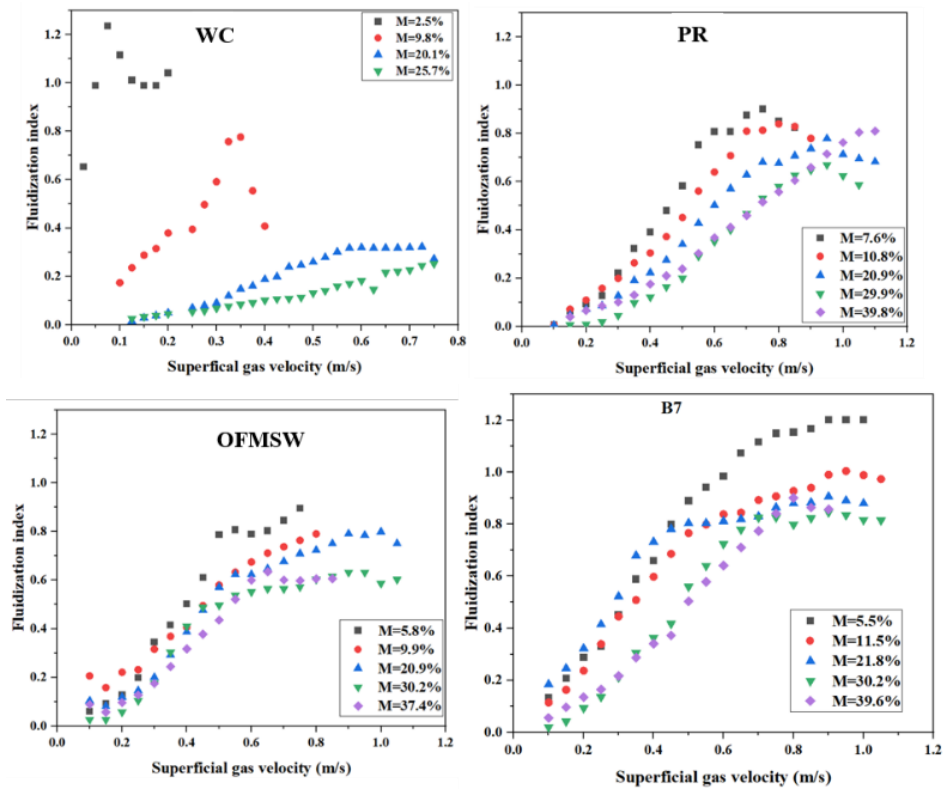


Figure 5.18: Fluidization characteristics curves for WC, PR, OFMSW and B7 at various moisture content

Table 5.7 summarizes the fluidization indexes of the blends calculated at various moisture content (the figures are presented in the Appendix 2), it can be noted that most blend exhibited partial fluidization $0.6 < F_i < 0.95$ especially when moisture content reached 20% and above. few blends (B2, B7 and B8) mathematically exhibited complete fluidization at moisture $< 10\%$, behaviors that were not observed experimentally. Only B1 and B4 exhibited complete fluidization, where particles fluidized individually when the moisture was less than 10% as seen in Fig. 5 .5.

Table 5.7: Summary of the fluidization index of the blends at various moisture contents: (values were taken after the U_{mf})

Blend	Control	10	20	30
B1	1.22	0.80	0.45	0.2

B2	1.11	0.55	0.61	0.65
B3	0.92	0.90	0.90	0.80
B4	0.85	0.80	0.65	0.65
B5	0.91	0.84	0.83	0.83
B7	1.21	0.92	0.85	0.85
B6	0.75	0.70	0.56	0.55
B8	1.11	0.85	0.90	0.83
B9	0.85	0.80	0.74	0.72
B10	1.00	0.92	0.85	0.82

**control" refers to a sample for which the moisture has not been adjusted. The actual moisture values are reported in Table 5.2.*

5.4.10. Effect of moisture content on the minimum fluidization velocity

The minimum fluidization velocity is an important parameter in a fluidized bed, and it can be affected by the physical characteristics of the particles as well as the material's moisture content. Figure 5.19 presents the minimum fluidization velocity (U_{mf}) for individual samples. The results show a linear relationship between moisture content and U_{mf} , with U_{mf} increasing as moisture content rises. This trend is consistent with findings reported in previous studies (Olatunde et al., 2017 & Bai & Si, 2020b). It suggests that added moisture enhances resistance to particle flow, likely due to the formation of capillary films between particles and water molecules. Specifically, as moisture content increased from approximately 2.5% to 25.4%, the U_{mf} values rose from 0.08 ± 0.10 to 0.93 ± 0.42 m/s for WC (B1), from 0.62 ± 0.01 to 1.1 ± 0.29 m/s for PR (B4) when moisture was raised from 7.8% to 40.3%, and from 0.49 ± 0.27 to 0.67 ± 0.25 m/s for OFMSW (B6) when moisture moved from 6.8% to 39.8% respectively. Across the entire moisture range, B4 consistently exhibited higher U_{mf} values

than OFMSW. According to Kumoro et al., (2014), based on particle shape considerations, materials with lower shape (sphericity) factors are expected to have greater particle contact area per unit mass and higher friction coefficients, which should increase resistance to flow and thus U_{mf} . Following this assumption, OFMSW with a sphericity factor of 0.39 would be expected to exhibit a higher U_{mf} than PR (0.56) and WC (0.79). However, the results show the opposite trend, with OFMSW displaying lower U_{mf} values than PR. This could be due to its lower bulk density and fluffy nature, rendering an easier onset of fluidization, pointing out that the U_{mf} does not solely depend on particle shape but also on the material density. The value of U_{mf} obtained in this study for PR (0.62 m/s) was closer to the value of 0.64 m/s reported by Kumoro et al., 2014) for the U_{mf} of rice husk. The U_{mf} value for WC was lower than that of PR and OFMSW at low moisture content, showing that WC with a small particle size, more uniform ($\phi=0.79$), and low moisture content is more suitable for fluidization. However, at moisture content above 10%, the U_{mf} of WC increased sharply above that of PR and OFMSW. This could be attributed to its ability to rapidly agglomerate in the presence of moisture, as demonstrated in Fig. 5 .3. Despite this, PR demonstrated better fluidization quality than OFMWS, as indicated by the fluidization index in Fig. 5 .18 b. This suggests that both the onset and quality of fluidization are strongly influenced by particle properties. Although PR achieved superior fluidization quality ($0.6 < FI < 0.95$), its elongated particle shape combined with the presence of moisture promotes interlocking and channeling, which increases resistance to flow before fluidization and results in higher U_{mf} values. Once fluidization begins, these interparticle structures are more easily disrupted, allowing particles to move more freely and uniformly due to improved gas distribution. In contrast, OFMSW, despite its lower U_{mf} , showed poorer fluidization behavior ($FI < 0.6$ at all moisture ranges, see Fig. 5.18c). This may be attributed to its heterogeneous composition, which can cause particle segregation, increased

channeling, and non-uniform gas-solid interactions, ultimately leading to the formation of dead zones (as illustrated in Figure 5.10c).

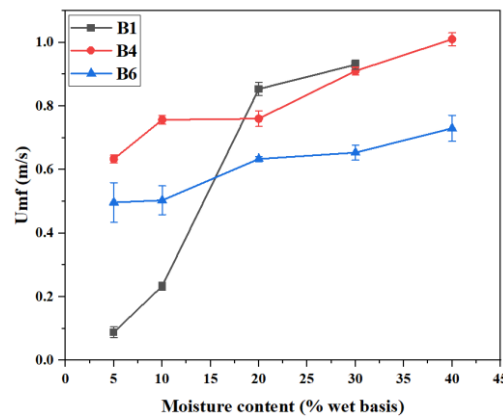


Figure 5.19: Minimum fluidization velocity of the WC (B1), PR (B4) and OFMSW (B6) at various moisture contents

Figs 5.20 and 5.21 depict the minimum fluidization velocity of some blends at various moisture contents. These blends are either binary combinations of PR, WC, WC and OFMSW (B2, B3 and B5) or ternary combinations of the three samples (B7, B8, B9, and B10). The compositions of these blends are presented in Table 5.1. The trends differed slightly from the behavior observed for the individual blends (B1, B4, and B6). Instead of increasing linearly with increasing moisture content, these blends initially exhibited a slight reduction in minimum fluidization velocity (Umf) before increasing at higher moisture levels. Blending increased the heterogeneity of the bed material, especially because the individual samples of the blends have varying particle sizes, with for example, smaller particles enhancing the particle–particle cohesion, interlocking, and entanglement of the bigger particles, particularly at low moisture contents. However, when the moisture content increased to approximately 10%, the added water appeared to act as a lubricant, partially reducing particle adhesion and allowing particles to detach more easily from one another, thereby promoting the onset of fluidization. However, as the moisture content increased further, the minimum fluidization

velocity (U_{mf}) also increased correspondingly. This suggests that the initial lubricating effect of the added water was gradually replaced by the formation of water-induced capillary films, which enhanced particle binding and cohesion within the bed.

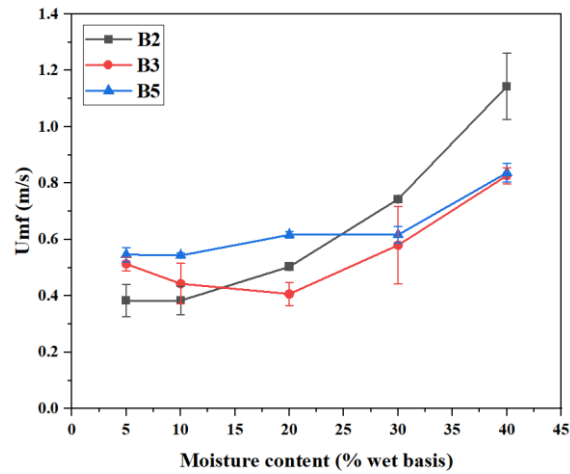


Figure 5.20: Minimum fluidization velocity of B2, B3, and B5 with various moisture contents

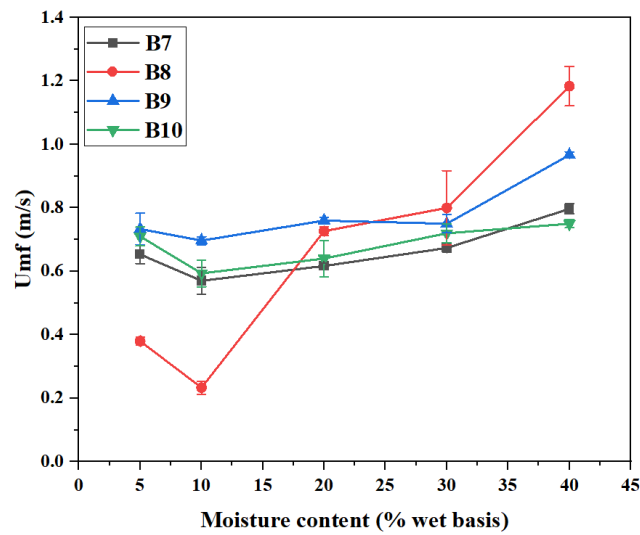


Figure 5.21: Minimum fluidization velocity of B7, B8, B9 and B10 with various moisture

5.4.11. Effect of moisture content of the bed pressure drop at the point of fluidization

The pressure drop at the point of minimum fluidization velocity was obtained by measuring the pressure difference between a point below the distributor and another point above the bed (as seen in Fig. 5.1). This pressure drop is because of the vibrant interaction between the gas and solid particles as well as the interactions with the wall. The results are depicted in Fig 5.22 through 5.24, for the individual samples, for binary (blends of two components) and ternary blends (blends of three components), respectively. A nonlinear relationship was obtained between the moisture content, and the pressure drop profile for the individual samples as well as the blends. High pressure drop was observed at moisture content below 10%wb, then slightly decreased when the moisture content reached 10% and remained constant between 10 and 20% for most blends like B2, B3, and B8. These trends justified the U_{mf} results obtained in Fig 5.21 and 5.22.

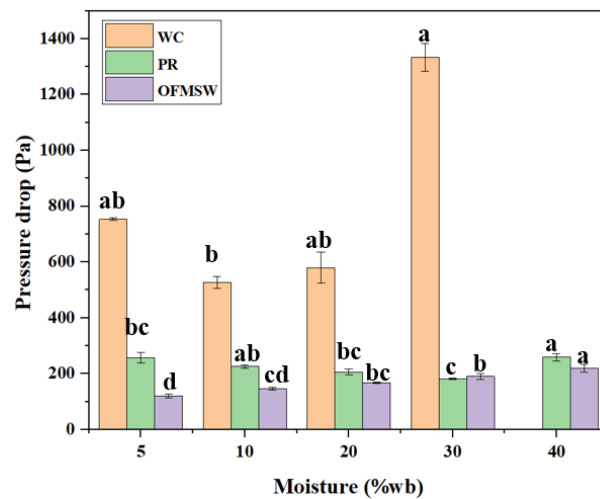


Figure 5.22: Effect of moisture content on pressure drop at minimum fluidization velocity for individual sample (WC, PR and OFMSW)

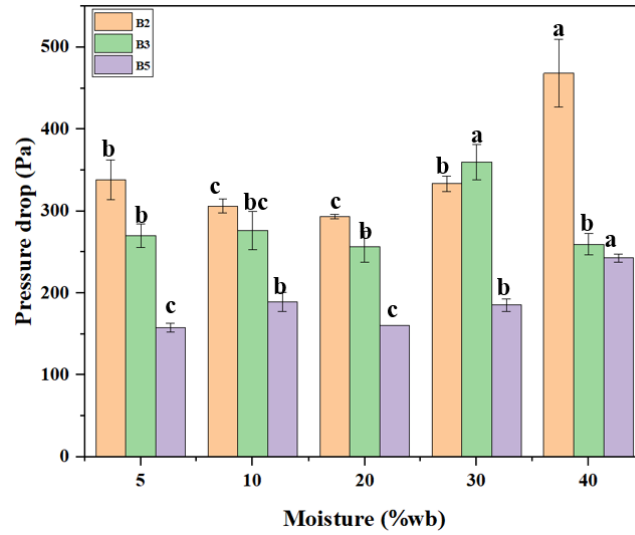


Figure 5.23: Effect of moisture content on pressure drop at minimum fluidization velocity for binary blends (B2, B3 and B4)

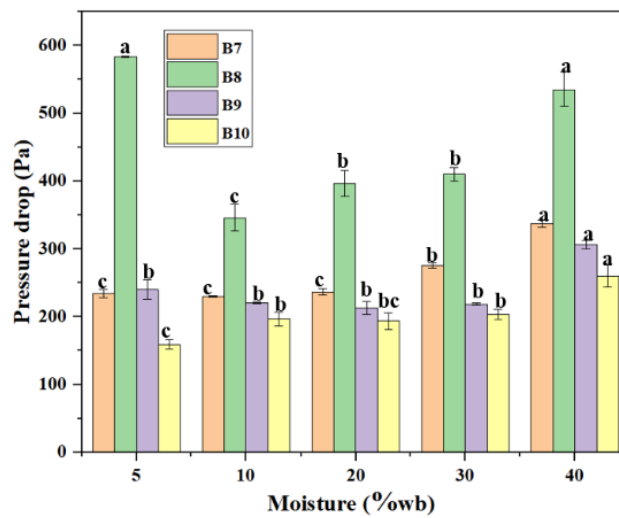


Figure 5.24: Effect of moisture content on pressure drop at minimum fluidization velocity for ternary blends (B7, B8, B9 and B10)

5.4.12. Statistical and machine learning analysis of the key parameter influencing the minimum fluidization velocity and pressure drop

In this section, statistical and machine learning approaches were employed to evaluate the influence of blend composition and moisture content on the minimum fluidization velocity (U_{mf}) and pressure drop. Statistical analysis was performed using a correlation matrix, while machine learning interpretation was conducted using SHAP (SHapley

Additive exPlanations) analysis to quantify the relative importance of the individual blend components and moisture content in predicting the fluidization responses.

5.4.12.1. The Pearson correlation matrix of factors influencing the minimum fluidization velocity and pressure drop prediction

Fig. 5.24 presents the correlation matrix illustrating the relationships among moisture content, blend composition, minimum fluidization velocity (U_{mf}), and pressure drop. The results indicate that moisture content exhibited the strongest positive correlation with U_{mf} ($r = 0.68$), suggesting that increasing moisture significantly increased the U_{mf} ($p < 0.05$). Pine residue (PR) also showed a positive, although weaker, correlation with U_{mf} ($r = 0.35$), indicating that blends with higher PR content tended to require higher gas velocities for fluidization. In contrast, waste coal (WC) and OFMSW displayed weak negative correlations with U_{mf} ($r = -0.21$ and $r = -0.15$, respectively), suggesting a slight tendency to reduce U_{mf} ; however, the correlation between OFMSW and U_{mf} was not statistically significant. Additionally, the interactions between blend components also play a significant role in predicting the U_{mf} . For example, the interactions between PR*WC, OFMSW*WC, PR*moisture, and OFMSW*moisture resulted in an overall decrease in the U_{mf} .

Regarding pressure drop, WC exhibited a strong positive correlation ($r = 0.76$), indicating that increasing the proportion of WC significantly increased the pressure drop across the bed ($p < 0.05$). Conversely, OFMSW and PR showed moderate negative correlations with pressure drop, with correlation coefficients of $r = -0.42$ and $r = -0.31$, respectively, suggesting that increasing the proportions of these biomass components generally reduced the resistance to airflow through the bed.

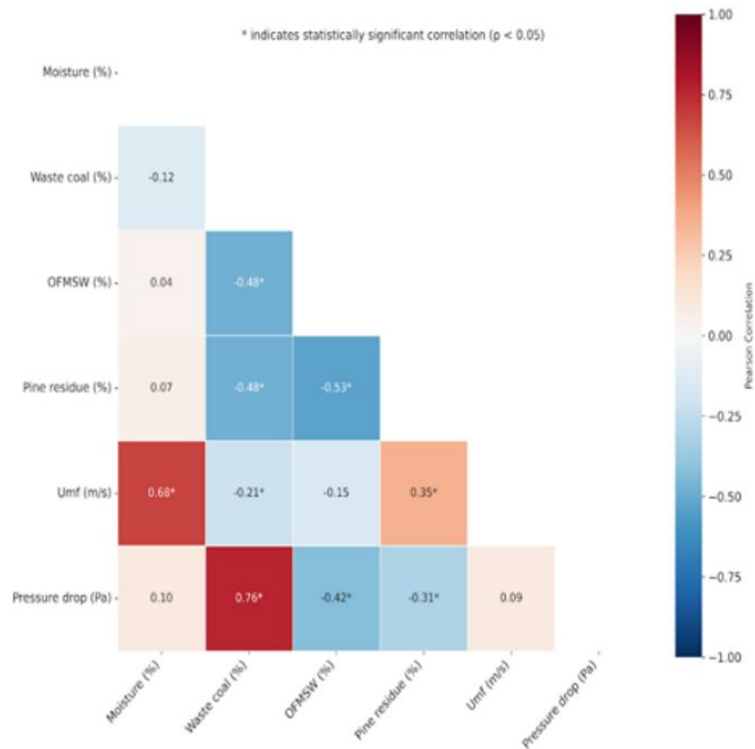


Figure 5.25: Pearson correlation matrix between moisture content, components on the Umf and pressure drop

5.4.12.2. Machine learning approach for prediction Umf and pressure drop

Machine learning (ML) was employed to capture the complex nonlinear relationships between moisture content, blend composition, and fluidization responses. Two machine learning algorithms, Random Forest (RF) and Extreme Gradient Boosting (XGBoost), were developed to identify the most influential variables affecting minimum fluidization velocity (Umf) and pressure drop, with the model performance summarized in Table 5.8. Both models demonstrated excellent predictive capability during training, achieving R^2 values between 0.98 and 0.99 for both responses. For Umf prediction, XGBoost and RF yielded RMSE values of 0.00 and 0.02, respectively, with corresponding MAE values of 0.00 and 0.02. Similarly, for

pressure drop prediction, XGBoost and RF achieved RMSE values of 0.94 and 23.04 Pa, and MAE values of 0.33 and 11.84 Pa, respectively.

The performance of both models decreased slightly when evaluated on the testing dataset, indicating reduced predictive accuracy for unseen data. For Umf, the testing R^2 values were 0.69 and 0.88 for XGBoost and RF, respectively. The corresponding RMSE values were 0.11 and 0.06, while the MAE values were 0.07 and 0.05 for XGBoost and RF, respectively. For pressure drop, both models achieved a testing R^2 of 0.87. The testing RMSE values were 44.65 and 44.23 Pa, and the MAE values were 29.64 and 28.69 Pa for XGBoost and RF, respectively. Overall, RF exhibited superior predictive performance, producing lower prediction errors and more consistent results between the training and testing datasets for both Umf and pressure drop. In contrast, the larger discrepancy between the training and testing performance of XGBoost, particularly for Umf prediction, suggests a tendency toward overfitting. The stronger generalization capability and robustness of RF indicate that it is the more reliable model for evaluating the effects of moisture content and blend composition on fluidization behavior. Consequently, the RF model was selected as the basis for the subsequent SHAP analysis used to quantify the relative importance of the input variables.

Table 5.8: Model fitting test for Umf and pressure drop

Parameter		R^2		RMSE		MAE	
		Training	Testing	Training	Testing	Training	Testing
Umf	RF	0.98	0.88	0.02	0.06	0.02	0.05
	XGBoost	0.99	0.69	0.00	0.11	0.00	0.07
Pressure							
drop	RF	0.99	0.87	23.04	44.23	11.84	28.69

XGBoost	0.99	0.87	0.94	44.65	0.33	29.64

The SHAP analysis presented in Fig 5. 26 reveals that moisture content has the highest impact on the U_{mf} exhibiting a mean SHAP value of 0.130 m/s, substantially higher than OFMSW (0.056), waste coal (mean SHAP value of 0.052 m/s), and pine residues (mean SHAP value of 0.009 m/s). This reveals that increasing moisture generally increased U_{mf} , indicating that wetter materials require higher gas velocities to achieve fluidization due to enhanced interparticle cohesion and capillary forces. This confirms the strong positive correlation ($r=0.68$) observed between moisture and U_{mf} in Fig 2.25.

For the pressure drop model, waste coal (WC) exhibited the greatest influence, as evidenced by the highest mean SHAP value of 117.305 Pa. Moisture content was the second most influential variable, with a mean SHAP value of 56.702 Pa, followed by OFMSW and pine residues (PR), which had mean SHAP values of 14.630 Pa and 2.237 Pa, respectively. These results indicate that WC was the dominant factor controlling pressure drop, while moisture also played a substantial role in determining bed resistance to airflow. In contrast, OFMSW and PR had relatively smaller contributions, suggesting a less pronounced effect on pressure drop compared to WC and moisture.

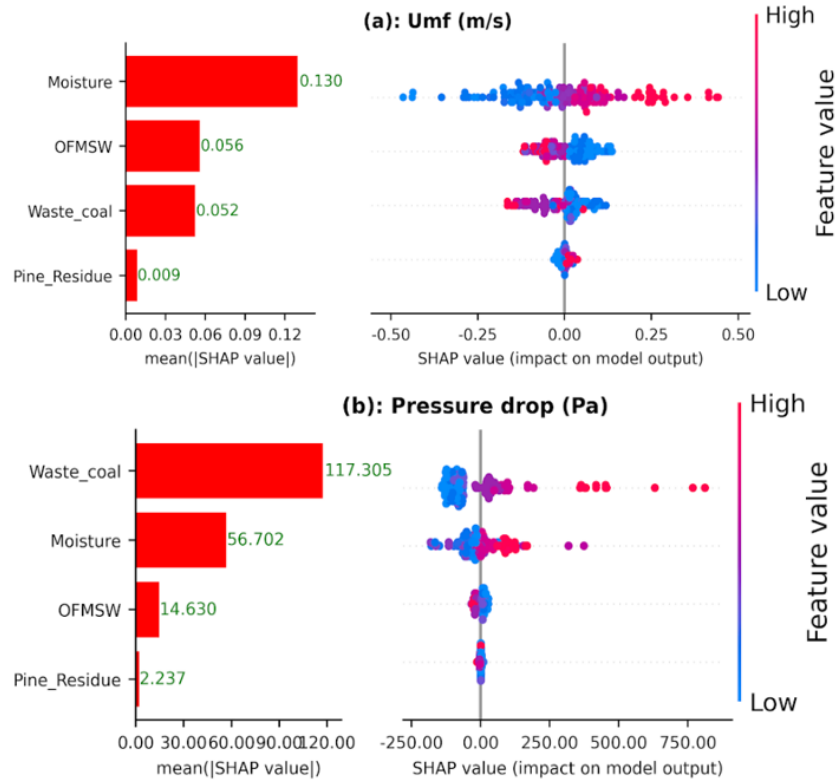


Figure 5.26: SHAP analysis on the key factors affecting the minimum fluidization velocity and the pressure drop

5.4.13. Correlation for minimum fluidization velocity of waste coal, pine residues organic fraction organic fraction municipal solid waste and blends

In this section, new empirical correlations were developed to predict the minimum fluidization velocity of the pine residue, OFMSW and some blends, at different moisture levels based on the existing correlations proposed in literature. The model developed was adapted from correlation proposed by Olatunde et al., (2017) as follows.

$$Umf = k \left[\frac{deff^2 (\rho_p - \rho_g)g}{\mu_g} \left(\frac{\rho_p}{\rho_g} \right)^{1.23} \right]^\alpha \quad (5.7)$$

The effective particle diameter (deff) was correlated using the coefficient of variation, expressed in eqn. 5.8. Where is the mean particle diameter obtained from particle size analysis

$$(5.8) \quad deff = d(1 + \gamma^2)$$

The variation in the particle size was estimated using the coefficient of variation (γ), and was used to represent the distribution of the particle size in the mixture in decimal form, and was expressed as follows:

$$\gamma = 50 \frac{(d_{84} - d_{16})}{d_{50}} \frac{1}{100} \quad (5.9)$$

Introducing the moisture content (ϕ) and the particle sphericity (ϕ) term, the following equation was obtained.

$$Umf = k \left[\frac{d^2 (1 + \gamma^2)^2 \phi^2 \phi (\rho_p - \rho_g) g}{\mu_g} \left(\frac{\rho_p}{\rho_g} \right)^{1.23} \right]^\alpha \quad (5.10)$$

Eqn 5.10 can also be expressed as a linear equation of Umf as a function of k and X

$$Umf = kX^\alpha \quad (5.11)$$

Where X is expressed as follows

$$X = \frac{deff^2 (1 + \gamma^2)^2 \phi^2 \phi (\rho_p - \rho_g) g}{\mu_g} \left(\frac{\rho_p}{\rho_g} \right)^{1.23} \quad (5.12)$$

The value of α in eqn 5.11 can be obtained by plotting the non-linear relationship between Umf and kX. In this work, the relationship between the blend's particle density and moisture content was established by fitting a regression model to the experimental data, and the resulting equation is presented in eqn 5.13.

$$Blends_{particle} = 1680x_{coal} + 1531x_{pine} + 1753x_{MSW} - 1009M \quad R^2=0.99 \quad (5.13)$$

Where x_{coal} , x_{pine} , and x_{MSW} , are the mass fractions of WC, PR, and OFMSW in the blends, and M is the moisture content in decimal respectively.

The blend's coefficient of variation (γ) and effective particle diameter (deff) are expressed as the mass-weighted average of the individual sample γ and deff, as follows

$$\gamma(Blends) = \sum_{i=1}^n x_i \gamma_i \quad (5.14)$$

$$deff(blends) = \sum_{i=1}^n x_i deff_i \quad (5.15)$$

Table 4.9 exhibits the coefficient of variation of the samples blends different moisture levels. The γ of the blend experienced a slight decrease as moisture content increased especially for B4 and B6. The coefficient of variation of B1 could not be determined under wet conditions, as explained in section 5.3. Moreover, B1 showed the highest γ followed by B4 and B6 at dry state, with the γ values of 0.68, 0.34 and 0.29 respectively. The higher γ observed for B1 could be due to the presence of root fibre in the sample as this was collected in a pond. The reduction in γ with moisture content could be attributed to particle agglomeration, as water forms liquid films at particle contact points. This promotes particle-particle attraction and clustering, reduces the proportion of fine particles, and consequently alters the particle size distribution, leading to higher variability, this phenomenon can be seen from the particle size distribution presented in Fig.5.4 and 5.5.

Table 5.9: Coefficient of variation of the blends at various moisture content (Wet basis)

Blends	Control (%)	10%	20%	30%
B1	0.68 ±2.1a	nd	nd	nd
B2	0.51 ±1.8b	0.51 ±4.8bc	0.49 ±9.3bc	0.46 ±4.1 c
B3	0.48 ±2.3c	0.51 ±5.0bc	0.46 ±1.9c	0.47 ±2.3c
B4	0.34 ±4.6e	0.33 ±9.4de	0.32 ±6.8ef	0.25 ±3.1f
B5	0.31 ±8.2f	0.30 ±9.6e	0.29 ±9.1fg	0.25 ±3.8f

B6	0.29 ±1.7g	0.30 ±9.8e	0.26 ±2.1g	0.24 ±5.6f
B7	0.43 ±3.1dc	0.45 ±8.6cd	0.41 ±4.7d	0.39 ±2.6d
B8	0.56 ±1.6b	0.56 ±5.2ab	0.53 ±3.7b	0.53±6.9b
B9	0.42 ±1.4de	0.37 ±2.5 de	0.25 ±6.8ef	0.31 ±6.1e
B10	0.36 ±5.4f	0.37 ±9.2de	0.34 ± 4.6e	0.32 ±5.7e

*** control" refers to a sample for which the moisture has not been adjusted. The actual moisture values are reported in Table 5.2.*

Table 5.10 shows the effective particle diameter of the blends as affected by the moisture content; it was observed that the effective particle diameter increased slightly with increasing moisture content for most of the blends, especially at moisture above 20%. This could be attributed to the swelling effect that was observed in the particle size distribution as the moisture content was increased as explained in section 5.4.1.

Table 5.10: Effective particle diameter of the blends at various moisture content (wet basis)

Blends	Control	10	20	30
B1	0.47 ±0.43	nd	nd	nd
B2	1.13 ±0.73	1.09 ±5.6	1.09 ±9.33	1.15 ±3.37
B3	1.51±2.27	1.55 ±13.1	1.78 ±2.72	1.8 ±3.31
B4	1.80±3.19	1.71 ±9.8	1.72 ±7.18	1.83 ±5.25
B5	2.17 ±8.12	2.17 ±5.53	2.4 ±10.57	2.51 ±5.01
B6	2.55 ±6.17	2.6 ±3.11	3.09 ±3.96	3.19 ±4.76
B7	1.61 ±8.68	1.61 ±7.75	1.7 ±7.75	1.84 ±7.44
B8	1.04 ±50	1.0 ±4.06	1.11 ±9.14	1.15 ±4.02
B9	1.70 ±60	1.6 ±6.35	1.74 ±5.73	1.83 ±4.54
B10	2.1 ±802	2.1 ±18.32	2.42 ±7.75	2.51 ±2.93

*** control" refers to a sample for which the moisture has not been adjusted. The actual moisture values are reported in Table 2.*

Nonlinear power regression analysis was applied to the experimental Umf vs X data to obtain similar equation as in eqn 5.11 ($y = kX^\alpha$) as shown in Figs. 5.27 and 5.28. The effective particle size, sphericity, and coefficient variation used to estimate the X value are reported in Tables 5.10, 5.9 and 5. 9. From the regression plots the K and Alpha values were determined using the power trendline in MS Excel® and are reported in Table 5.10. The slope increased with increasing moisture content; this indicates that fluidization behavior is significantly affected by changes in particle properties (particle swelling) resulting from the presence of moisture.

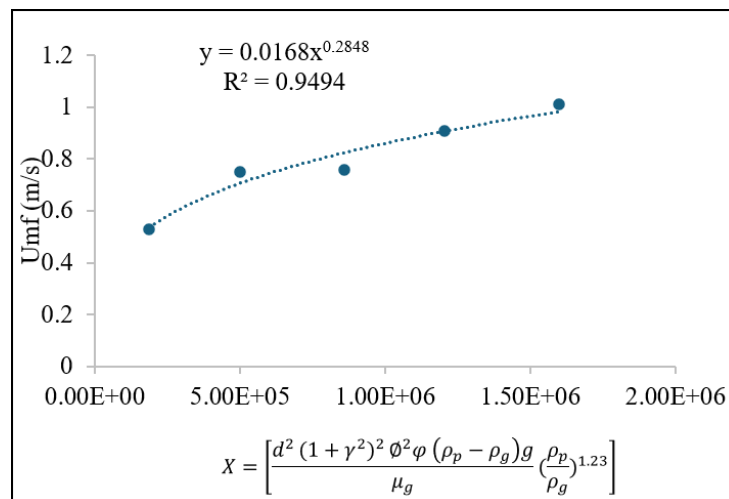


Figure 5.27: Effect of particle properties and moisture content on the Umf of B4

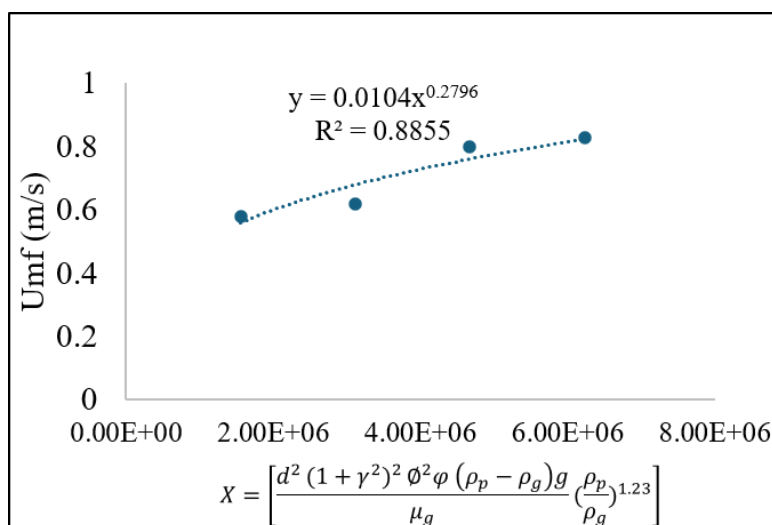


Figure 5.28: Effect of particle properties and moisture content on the Umf of B6

Table 5.11: The estimated values of the coefficient k and α for the blends and their respective R² value

Blends	K	α	R2
B1	8E-6	0.901	0.739
B2	0.0014	0.4558	0.8431
B3	0.3516	0.0236	0.0256
B4	0.0168	0.2848	0.9494
B5	0.1852	0.0859	0.9250
B6	0.0104	0.276	0.8855
B7	0.0077	0.3139	0.6132
B8	0.0002	0.6213	0.7678
B9	0.3493	0.0384	0.3791
B10	0.4815	0.0237	0.0329

5.4.13.1. Model validation for the Umf correlation

To verify the model's suitability, a new set of samples was prepared. Table 5.10 presents the measured parameters used to estimate the Umf for PR (B4), OFMSW (B6), and B7 (see blend composition in Table 5.1) at different moisture contents based on the developed equation, and the predicted values of Umf are shown in Table 10. The accuracy of the model was validated using the mean relative deviation between experimental data and the predicted data.

$$MRD (\%) = \frac{1}{n} \sum_{i=1}^n \frac{(P_i - E_i)}{E_i} \quad (5.15)$$

Where P_i and E_i are predicted and experimental values, and n is the number of experimental replicates.

Table 5.12: Parameters for model verification

		γ		φ				Exp.	Predicted	
		Moisture	Deff		ρ_p			Umf	Umf	MRD
Blends	(% wb)		(mm)		(kg.m ⁻³)	X		(m/s)	(m/s)	(%)
	6.9	0.31	1.75	0.58	1470.43			0.69		
	±0.18	±0.23	±1.23	±0.01	±27.83	420155.6		±0.01	0.7	-1.48
	30.7	0.21	1.78	0.56	1365.61			0.85		
B4	±0.55	±0.02	±2.22	±0.1	±1.34	599978.1		±0.04	0.74	13.65
	11.2	0.35	3.49	0.31	1635.10			0.59		
	±1.23	±0.00	±4.88	±0.5	±45.23	371366.8		±0.01	0.54	8.45
	19.9	0.34	3.38	0.22	1576.73			0.74		
B6	±4.89	±0.01	±5.62	±0.3	±28.44	756525.1		±0.02	0.61	18.21
	9.9	0.59	5.15	0.33	1562.47			0.57		
	±0.11	±0.62	±5.59	±0.02	±62	840649.4		±0.03	0.51	9.97
	21.6	0.48	4.21	0.37	1540.31			0.36		-
B7	±0.11	±0.00	±0.19	±0.01	±16.96	1189123		±0.01	0.62	63.57

The predictive model demonstrated improved accuracy at lower moisture contents, exhibiting good agreement with the experimental data. Specifically, at moisture levels below 10%M, the MRD between the experimental and predicted U_{mf} values were -1.48%, 8.45%, and 9.97% for PR (B4), OFMSW (B6), and B7, respectively, indicating strong agreement with the experimental observations. However, as the moisture content increased, a corresponding increase in prediction error was observed for PR, OFMSW and B7. Similar observed by

Beimesse & Delebarre, (2008), who observed an increase in the error from 34.6% to 82.0% between the experimental and predicted Umf of wood scraps as the moisture content increased from 11.9% to 30.4% using a new model. At higher moisture contents (30.7%, 19.9%, and 21.6% wb), the mean relative errors for PR, OFMSW, and B7 increased to 13.65%, 18.21%, and -63.57%, respectively. The significant deviation at elevated moisture levels is primarily attributed to the increased difficulty in accurately characterizing the physical properties of the blends under such conditions. For example, it was assumed that WC physical properties (PSD, porosity, and sphericity) did not change with moisture variation, that alone might have introduced bias in the calculations. Additionally, moisture-induced effects, such as particle agglomeration and increased heterogeneity, introduce greater variability in key parameters. For example, the effective particle diameter and sphericity of B4 varied from $1.75 \pm 1.23\text{mm}$ to $1.78 \pm 2.22\text{mm}$ and from 0.58 ± 0.01 to 0.56 ± 0.10 , respectively. Although these variations appear relatively small, they can have a pronounced impact on fluidization behavior due to their influence on drag forces and bed hydrodynamics. Consequently, these uncertainties reduce the predictive reliability of the model at higher moisture contents.

5.5. Conclusion

This study investigated the fluidization behavior of WC, PR, municipal solid waste (OFMSW), and their blends under varying moisture conditions. The results demonstrated that moisture significantly influenced the fluidization characteristics of the materials. In general, the minimum fluidization velocity (U_{mf}) increased with increasing moisture content across all blends. This behavior was attributed to moisture-induced particle cohesion, agglomeration, and channeling observed during fluidization. Fluidization quality was evaluated using the fluidization index (FI), which was found to decrease as moisture content increased. For WC, the fluidization index decreased from 1.2 to 2.5% moisture content, indicating complete fluidization, to below 0.2 at 20.1% moisture content, signifying poor fluidization behavior. This indicates that increasing moisture content reduced the fluidization quality of WC by more than 80%. In contrast, PR exhibited partial fluidization at moisture contents between 7.6% and 10.8%, with fluidization indices ranging from 0.85 to 0.65. However, as the moisture content increased further, the fluidization index declined below 0.65, indicating poor fluidization behavior. Organic fraction municipal solid waste (OFMSW), on the other hand, exhibited poor fluidization throughout the entire moisture range investigated, with fluidization indices consistently below 0.65. Interestingly, the blended samples, particularly those containing WC, exhibited slight improvements in fluidization quality at moisture contents below 10%, suggesting a synergistic interaction between the blended materials. For example, blend B2, consisting of 50% WC and 50% PR, and blend B3, composed of 50% WC and 50% OFMSW, showed fluidization indices consistently higher than those of PR and OFMSW alone, especially at moisture contents below 20%. Specifically, blending with WC increased the fluidization index from 0.85 to 1.11 for PR and from 0.75 to 0.92 for OFMSW. This improvement may be attributed to fine and relatively dry WC particles penetrating the void

spaces between pine residue and OFMSW particles, thereby acting as a lubricating medium that improved airflow distribution and facilitated the onset of fluidization at lower moisture contents. The newly developed model showed good agreement with the experimental U_{mf} data. For pine residue blend B4, the mean relative deviation (MRD) ranged from -1.48% at 6.8% moisture content to 13.65% at 30.7% moisture content. For blend B6, the MRD increased from 8.45% to 11.2% moisture content to 18.21% to 19.9% moisture content. Similarly, for blend B7, the MRD varied from 9.97% at 9.9% moisture content to -63.57% at 21.6% moisture content. These results indicate that the model performed better at lower moisture contents, while prediction accuracy declined as moisture content increased.

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Chapter 6. Estimation of the pressure drop in a packed bed of pine residues and organic fraction municipal solid waste using the revised Ergun correlation

6.1. Abstract

The existing Ergun equation was found to be inadequate for predicting the behavior of beds containing non-uniform particles such as PR and municipal solid waste (OFMSW). This limitation arises because the original equation does not account for the unique physical characteristics associated with these materials. In this study, a modified Ergun-based model was developed to predict the pressure drop and minimum fluidization velocity (U_{mf}) of PR and OFMSW in the presence of moisture. The influence of particle size distribution was incorporated through the use of an effective particle diameter, while new void fraction correlations were proposed for both materials. The Ergun equation was further modified by revising the viscous and kinetic energy loss terms to account for the influence of moisture content. In addition, new friction factor correlations relating the Reynolds number to viscous and kinetic energy losses were proposed and evaluated. Using the least squares method, the model coefficients K_1 and K_2 were estimated to be 270.5 and 1.13 for PR, and 381.5 and 3.88 for OFMSW, respectively. Overall, the modified model significantly improved the prediction of bed behavior compared to the original Ergun equation. The mean relative deviations between the predicted and experimental pressure drop and U_{mf} values were 16.78% and -13.36% for PR at 7.04% moisture content, and 23.61% and 17.81% for OFMSW at 6.8% moisture content, respectively.

6.2. Introduction

Various empirical models have been developed in the literature to describe the relationship between pressure drop per unit bed height ($\Delta P/H$) and superficial gas velocity in packed beds used in many industrial applications. These correlations were mostly based on the flow rate, fluid properties, and bed characteristics. The model assumes that the pressure drop across a granular bed is a second-order polynomial function with respect to fluid velocity at low flow rates and to the square of the velocity at high flow rates, as expressed in eqn. 6.1

$$\frac{\Delta P}{H} = aU + bU^2 \quad (6.1)$$

Where a and b are empirical coefficients of viscous and the kinetic energy terms, that is dependent on the particle characteristics. And the values of a and b can be estimated as a function of bed porosity as:

$$a = \frac{(1-\varepsilon)^2}{\varepsilon^3} \quad (6.2)$$

$$b = \frac{(1-\varepsilon)}{\varepsilon^3} \quad (6.3)$$

Among these models, the Ergun equation developed by Leva et al., (1951) has been widely applied for predicting fluid flow pressure drop through packed beds. The equation combines the contributions of both the laminar and turbulent flow regions into a single correlation capturing the transition from viscous-dominated to kinetic-dominated flow regimes (Barros & Regina, 2012; Burke & Plummer, 1928; Kaur & Singh, 2011; Kumoro et al., 2014). The Ergun equation was developed assuming the additive effect of the viscous and kinetic energy losses in a packed bed and a smooth transition from a viscous-dominated to kinetic-dominated effects as fluid flow (Grubecki, 2015; Nemec & Levec, 2005).

$$\frac{\Delta P}{H} = k_1 \frac{(1-\varepsilon)^2}{\varepsilon^3} \frac{\mu U}{\phi dp^2} + k_2 \frac{(1-\varepsilon)}{\varepsilon^3} \frac{\rho U^2}{\phi dp} \quad (6.4)$$

ΔP : pressure drop in the bed (Pa)

H: bed height (m)

ε : bed voidage / porosity at minimum fluidization velocity

μ_g : gas viscosity (Pa. s)

U : Surficial gas velocity (m.s^{-1})

d_p : particle diameter (m)

g : acceleration due to gravity (m.s^{-2})

ρ_p : particle density (kg.m^{-3})

ρ_g : gas density (kg.m^{-3})

k_1 and k_2 are the Blake-Kozeny-Carman and Burke-Plummer constants, and are originally set to be $k_1 = 150$ and $k_2=1.75$ respectively (Mayerhofer et al., 2011). These values are appropriate for particles that are near spherical, and also particles that have uniform size and are obtained experimentally. The Ergun equation has been proven to accurately predict the pressure drop for beds containing spheres, cylinders, and crushed solids over a wide range of flow rates within acceptable engineering accuracy (Nemec & Levec, 2005). Ergun also proposed correlations for the viscous and kinetic energy loss within the bed in terms of bed porosity as follows: $(1 - \varepsilon)^2/\varepsilon^3$ term for the viscous loss part and the $(1-\varepsilon)/\varepsilon^3$ term for the kinetic energy part. However, a small change in porosity has a large effect on the pressure drop, which makes it difficult to predict the latter accurately and to reproduce experimental values after a bed is repacked (Ozahi et al., 2008). Ergun identified the rate of fluid flow, viscosity and density of fluid, closeness and orientation, size, shape, surface area, and bed porosity as factors that influence the relationship between pressure drop and fluid flow velocity. When a bed consists of particles with uniform shape and size distribution, Ergun's

expression has been proven to perform satisfactorily in predicting pressure drop data at different gas flow rates. For example, Ozahi et al., (2008) predicted the pressure drop through a bed of non-spherical particles using the original Ergun equation and reported a maximum deviation over 20% from experimental data, showing that the Ergun equation cannot accurately predict the bed behavior of non-uniform particles; however, when a new correlation was proposed based on the particle Reynold number and the particle friction factor, the deviation was reduced to 4%. Another study by Luckos & Bunt, (2011) concluded that the Ergun equation in its original form fails to predict the pressure drop in a commercial Sasol-Lurgi gasifier because of significant differences in the bed structure and gas flow in individual reaction zones.

The Ergun correlation is generally derived under the assumption that the packed bed should consist of uniformly sized, near-spherical particles, and moderate porosity ($0.35 \leq \epsilon \leq 0.4$) and homogeneous bed material. This assumption becomes problematic when applied to biomass materials, which are inherently heterogeneous in nature and predominantly needle-like in shape, characteristics that deviate significantly from the idealized spherical particle used in the model. Furthermore, biomass feedstocks typically exhibit high moisture content, which further complicates flow behavior within the packed bed. These combined factors impose significant limitations on the predictive accuracy of the standard Ergun equation when applied to biomass systems. Consequently, modifications to the original Ergun equation are necessary to adequately account for the unique physical and structural characteristics of biomass materials like PR and OFMSW.

In this chapter, a modified model derived from the original Ergun equation is introduced to characterize the bed pressure drop during fluidization of PR and OFMSW, both of which contain high moisture content, are non-uniform, and highly heterogeneous. The development

of this model follows a two-step approach. First, an appropriate porosity correlation will be established to predict both the kinetic and viscous fractional void contributions within the bed. Second, the classical Ergun equation will be reformulated using the derived porosity correlation developed for PR and OFMSW by incorporating corrections for particle shape and particle size distribution represented by the effective particle diameter. This approach aims to improve the predictive accuracy of pressure drop estimation for heterogeneous, high-moisture biomass materials that deviate significantly from the idealized assumptions of the standard Ergun equation.

6.3. Material and method

New samples of PR and OFMSW were ground and sieved through 1.91mm. The moisture content was adjusted, and the physical properties were measured using the method explained in Chapter 5.2.

6.4. Statistical analysis

The performance of the modified Ergun model will be evaluated by comparing the experimentally measured pressure drop against the value calculated using the modified equation using the mean relative deviation between.

$$MRD (\%) = \frac{1}{n} \sum_{i=1}^n \frac{(P_i - E_i)}{E_i} \quad (6.5)$$

6.5. Discussion

6.5.1. Physical characteristics of pine residues and organic fraction municipal solid waste at various moisture contents

Tables 6.1 and 6.2 show the particles, bulk densities, porosity, sphericity, effective particle diameter, and coefficient of variation of PR and OFMSW at various moisture contents. It was found that particle density experienced a reduction with added moisture for both samples, similar to the trend observed in Chapter 3. A slight change in porosity was observed for OFMSW, whereas it was not significant for PR.

For OFMSW, the bulk density linearly increased with increasing moisture content, whereas PR' bulk density first increased, and then experienced a sudden decrease at moisture content around 20.3%wb, then increased further with increasing moisture content. This sudden decrease in the bulk density observed for PR at 20.3%M is attributed to the apparent point at which the woody biomass fiber becomes fully saturated with water (fiber saturation point), and has been identified to occur between 20 and 30.8% moisture content wet basis (Lu et al., 2023). At the fiber saturation point, all the moisture is in the cell, but as moisture increases, the cell wall becomes flooded, and causes increase in the overall weight per unit volume (González-prieto et al., 2025). Additionally, as moisture increased in PR, the particles turned toward larger sizes; for example, at 7.4% MC, the effective particle diameter was 1.63 mm, and at 40.2% wb it increased to 1.88mm. Saha et al., (2022) also reported that the particle size of corn stover increased from 0.2mm to 0.37mm as moisture was raised from 10 to 30% wb. The particle sphericity also experienced a significant decrease in the presence of moisture and was more pronounced for OFMSW. The coefficient of variation was also found to decrease with increasing moisture content, showing that as moisture increased, the

number of fine particles reduced as they tended to agglomerate, thereby reducing the relative variability in the effective particle size distribution (Lu et al., 2023).

Table 6.1: Physical properties of PR at different moisture content

Moisture	Particle density kg/m ³	Bulk density kg/m ³	Porosity	Sphericity	Deff (mm)	COV
7.04	1472.5 ^a ± 25.8	287.1 ^b ±0.3	0.80 ^a ±0.0	0.58 ^a ±0.0	1.63 ^c ±0.0	0.39 ^a ±0.002
9.9	1445.2 ^b ±1.0	278.9 ^c ±1.1	0.80 ^a ±0.0	0.58 ^a ±0.0	1.72 ^{cb} ±0.1	0.33 ^b ±0.00
20.3	1408.3 ^{ab} ±4.1	249.8 ^d ±9.7	0.82 ^a ±0.0	0.57 ^b ±0.0	1.83 ^b ±0.0	0.32 ^c ±0.01
29.5	1364.1 ^c ±3.1	255.4 ^d ±0.8	0.81 ^a ±0	0.53 ^d ±0.0	1.88 ^a ±0.1	0.25 ^d ±0.09
40.2	1295.7 ^d ±0.4	311.9 ^a ±2.4	0.75 ^b ±0.7	0.56 ^c ±0.0	1.88 ^a ±0.0	0.23 ^d ±0.013

Values followed by their standard deviations are means of triplicate runs. Means with different letter in a row are statistically significant ($p < 0.05$).

Table 6.2: Physical properties of OFMSW at different moisture content

Moisture	Particle density kg/m ³	Bulk density kg/m ³	Porosity	Sphericity	Deff (mm)	COV
6.8	1815.8 ^a ±13.2	114.6 ^c ±4.8	0.94 ^a ±0.0	0.46 ^a ± 0.0	3.49 ^a ±4.4	0.20 ^b ± 0.0

10.2	1689.5 ^b ±75.0	120.5 ^b ±1.9	0.93 ^b ±0.3	0.41 ^b ±0.7	3.38 ^b ±5.6	0.20 ^b ±0.0
28.6	1630.8 ^c ±28.7	125.9 ^a ±1.2	0.92 ^b ±0.1	0.36 ^c ±0.7	3.49 ^a ±4.8	0.21 ^a ±0.0

Values followed by their standard deviations are means of triplicate runs. Means with different letters in a row are statistically significant ($p < 0.05$).

6.5.2. Expression of the pressure drop and flow rate relationship through packed bed of pine residues and organic fraction municipal solid waste

Fig. 6.1 shows the plot of the ratio of the pressure gradient to velocity against the air mass flow rate at various moisture levels using Eqn. 6.1 for PR. The pressure drop ($\Delta p = p_1 - p_2$) through the bed was measured between two pressure taps located upstream and downstream of the bed using a U-tube manometer as shown in Fig 5.1. The plot shows that an increase in the air flow rate results in an increase in the pressure drop. This plot is similar to those obtained by (Olatunde & Fasina, 2018) for loblolly pine grind, and corroborated with the assumption proposed in literature (Luckos & Bunt, 2011 and Quinn, 2014). Additionally, it can be observed from the plot that increase in the moisture content resulted in the decrease in the pressure drop, although the U_{mf} increased with increasing moisture content. similar trend was observed by Kenghe et al., (2011) who observed that the pressure drop in a bed of Lathyrus seed decreased by 3.10% with every 1% increase in moisture content. The decrease in pressure gradient at higher moisture contents, despite the increasing the U_{mf} , suggests that moisture altered the internal bed structure and gas-flow distribution in the bed, and influenced the packing behavior. As moisture increased, liquid bridges formed between pine residue particles, increasing cohesion and promoting agglomeration, causing particle to clump

together as explained by Wu et al., (2017). For example, the cohesion value increased from 0.34 ± 0.27 to 0.46 ± 0.03 kPa when moisture moved from 11.6% to 40.3%, also the mean particle diameter of increased from 1.55mm at 11.6% to 1.88mm at 40.3%. All these changes created non-uniform packing, with preferential flow channels, and plug flow (an example is shown in Fig 5.11, and 5.14) through which air could pass with reduced resistance, thereby lowering the measured pressure gradient (Olatunde et al., 2017). However, the same moisture-induced cohesion increased the resistance to particle motion, requiring a higher superficial air velocity to initiate fluidization. Therefore, the reduction in pressure gradient reflects non-uniform gas bypassing and structural heterogeneity, while the increase in U_{mf} indicates stronger interparticle bonding and a more difficult-to-fluidize bed.

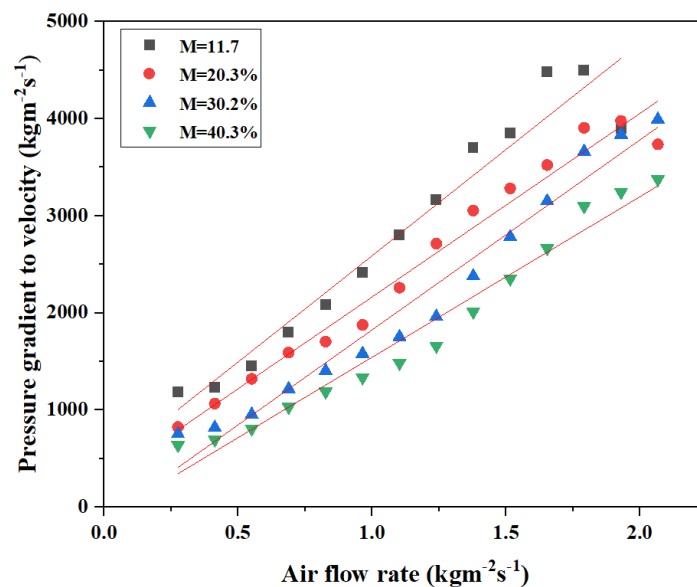


Figure 6.1: Linear form of the pressure gradient and the air flow rate for PR at various moisture content based on Eqn. 5.1

Fig. 6.2 illustrates the relationship between pressure gradient and the air mass flow rate for OFMSW. A generally increasing trend in the pressure drop with increasing air flow rate is observed across the moisture ranges, similar to that observed for PR (Fig.6.1). However, in contrast to PR, the slope of the pressure gradient increased with increasing moisture content.

This difference can be attributed to the heterogeneous nature of OFMSW, which comprises a diverse range of materials, including food and industrial waste, each characterized by varying particle shapes and poor packing behavior. Furthermore, the presence of moisture led to greater interparticle flow resistance in OFMSW beds compared to PR. Similar to PR, moisture in OFMSW promoted interparticle cohesion, which is also one of the dominant factors influencing flow behavior

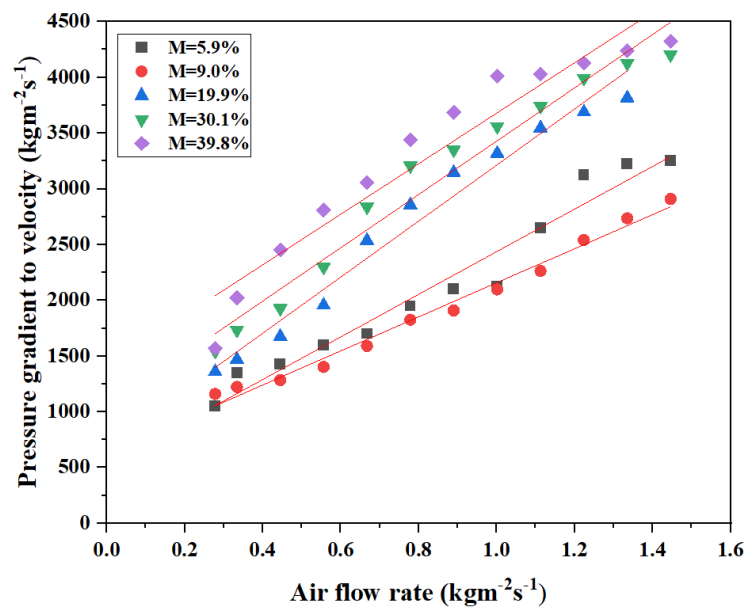


Figure 6.2: Linear form of the pressure gradient and the air flow rate for OFMSW at various moisture content based on Eqn. 6.1

Works by Erdim et al., (2015); Trahana et al., (2014), and Olatunde & Fasina, (2019) revealed that the plot of the pressure gradient to velocity versus gas flow rate (Figs. 6.1 and 6.2) resulted in a straight line where the intercept and slope give the values of a and b in Eqn. 6.1. This assumption was adopted by the work proposed by Leva et al., (1951). Table 6.3 presents the slopes (b), intercepts (a), R^2 values, and the corresponding viscous and kinetic energy loss constants derived from the linear regression plots of the data set shown in Fig. 6.1 and 6.2 and the porosity correlations in eqns. 6.2 and 6.3. The results reveal that the slope

consistently decreases with increasing moisture content, reflecting the effect of moisture-induced channeling and preferential flow, reducing pressure drop in dead zones, which was observed during fluidization at high moisture. Notably, as moisture content increased from 11.3% to higher levels, the slope decreased by approximately 50.7%. In contrast, the opposite effect was noticed for the kinetic energy loss, where the kinetic energy loss increased slightly with increasing moisture content. This behavior can be attributed to the concurrent reduction in porosity, which decreased from 0.83 to 0.79 as moisture content increased from 10.6% to 40.3%. The porosity exerts a disproportionate influence on the kinetic energy loss term through the ε^3 relationship in the denominator of the Ergun equation; consequently, even small reductions in porosity led to significant amplification of inertial energy losses. This is consistent with the findings of Grubecki, (2015), who demonstrated that a modest decrease in porosity from 0.45 to 0.35 resulted in an approximately 150% increase in kinetic energy loss. Furthermore, the same authors noted that in packed beds containing irregular particles such as biomass, turbulent flow conditions prevail, under which kinetic energy losses become increasingly dominant over viscous losses. These findings collectively confirm that while moisture-induced agglomeration reduces viscous resistance (slope), the associated reduction in porosity simultaneously intensifies kinetic energy loss (intercept).

Table 6.3: Estimation of the slope and intercept parameters for PR at different moisture content

Moisture	Slope (b)	Intercept (a)	R ²	Porosity	¹ Viscous loss	² Kinetic loss
11.7	2427.2	213.48	0.98	0.83	0.051	0.29
20.3	1890.6	273.13	0.97	0.84	0.043	0.27
30.2	1555.1	244.24	0.87	0.83	0.046	0.28

4.03	1196.4	294.61	0.99	0.79	0.089	0.42

Value obtained from the plot of pressure gradient vs gas mass flow rate

¹Values calculated from porosity data and viscous energy loss correlation $(1 - \epsilon)^2 / \epsilon^3$ for PR

²Values calculated from the porosity data and the kinetic energy loss correlation $(1 - \epsilon) / \epsilon^3$ for PR

Table 6.4 reveals the values of the slope, the intercept, and the kinetic and viscous energy loss for OFMSW obtained from Fig. 6.2 and eqn 6.2 and 6.3. The slopes increased with increasing moisture content, whereas the intercept decreased with increasing moisture content; this trend again was not constant with that observed for PR. This could be due to the highly heterogeneous, fluffy, and fibrous nature of OFMSW, rendering it very sensitive to moisture, and consequently greatly affecting its porosity and airflow through the bed.

Table 6.4: Estimation of the slope and intercept parameters for OFMSW at different moisture content

Moisture	Slope (b)	Intercept (a)	R ²	Porosity	¹ Viscous loss	² Kinetic loss
5.9	1970.9	561.66	0.966	0.93	0.0048	0.43
9.0	1467.8	616.68	0.9892	0.91	0.0096	0.56
219.9	2421.6	952.92	0.9391	0.88	0.019	0.67
30.1	2696.1	932.05	0.9316	0.86	0.031	0.81
39.8	2769.1	612.94	0.9513	0.83	0.053	1.02

Value obtained from the plot of pressure gradient vs gas mass flow rate

¹Values calculated from porosity data and viscous energy loss correlation $(1 - \epsilon)^2 / \epsilon^3$ for OFMSW

²Values calculated from the porosity data and the kinetic energy loss correlation $(1 - \epsilon) / \epsilon^3$ for OFMSW

6.5.2.1. Porosity correlation development: Ergun's correlation

Work done by Olatunde & Fasina, (2018) revealed that the kinetic energy loss correlation in eqn 6.3 is not adequate for predicting the pressure drop airflow relationship in a bed of irregular biomass like PR; therefore, some modification needs to be done to improve the

prediction. Therefore, an attempt was made to predict the kinetic energy loss in the bed of PR and OFMSW by considering the bed porosity correlation. The kinetic energy loss is related to the bed porosity by the following equation $(1 - \varepsilon)/\varepsilon^3$ proposed by Leva et al., (1951). Figs 6.3 and 6.4 show the plot from the slope and the intercept derived from the pressure gradient vs gas mass flow rate for PR and OFMSW (Fig 6.1 and 6.2) against the viscous $(1 - \varepsilon)^2/\varepsilon^3$ and kinetic energy loss $(1 - \varepsilon)/\varepsilon^3$ constants from the Ergun equation, respectively, as affected by the moisture content. It can be perceived that the viscous energy loss correlation showed an R^2 value of 0.93 and 0.92, while the kinetic energy loss correlation showed a lower R^2 value of 0.85 and 0.88 for PR and OFMSW, respectively. An R^2 value closer to 1 is preferable; values of 0.93 and 0.92 for the viscous energy found for PR and OFMSW suggest that the viscous energy component in the Ergun equation for pressure drop prediction was well modelled. However, values of 0.85 and 0.88 obtained for the kinetic energy loss were not adequately modelled, hence necessitating some modification.

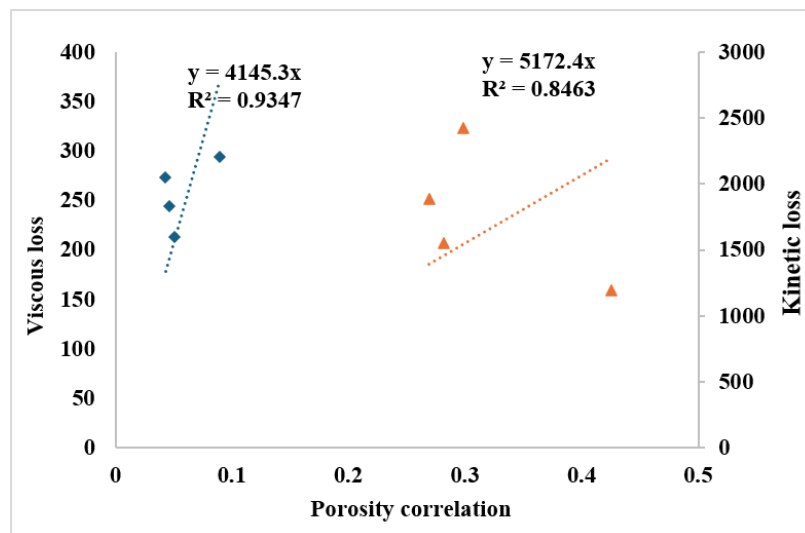


Figure 6.3: Dependence of viscous (blue) and kinetic (orange) energy loss correlations on the porosity correlations at various moisture content used in the Ergun equation for PR

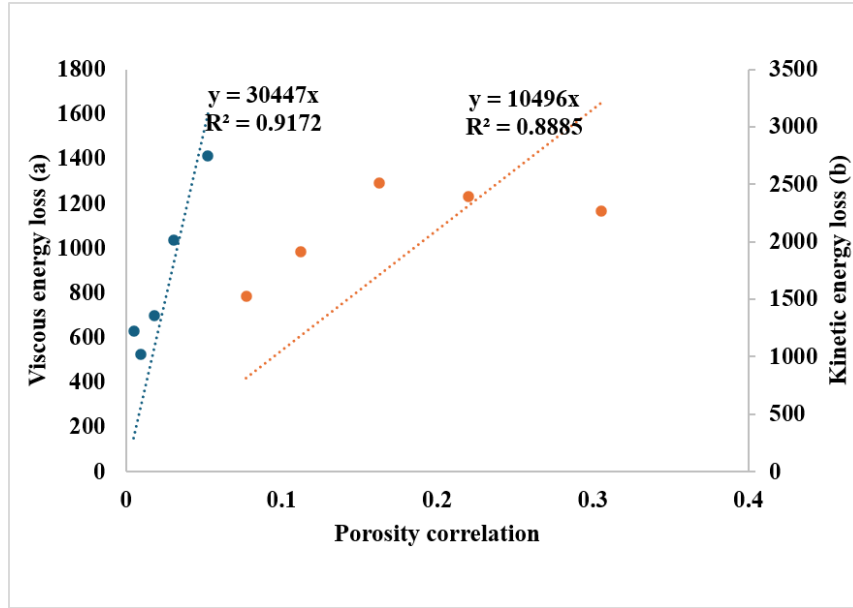


Figure 6.4: Dependence of viscous (blue) and kinetic (orange) energy loss correlations on the porosity correlations at various moisture content used in the Ergun equation for OFMSW

6.5.2.2. Modification of the porosity correlation

Olatunde & Fasina, (2018) proposed a general model to predict the kinetic energy loss through a packed bed of loblolly pine grind as follows:

$$\text{kinetic energy loss} = \frac{(1-\varepsilon)^n}{\varepsilon^m} \quad (6.6)$$

Where the values of parameters n and m were obtained by using a non-linear algorithm based on the generalized reduced gradient algorithm such that the error sum of squares between kinetic and porosity correlation data and the corresponding slopes is minimized. The same approach was utilized in this study to obtain the values for PR and OFMSW. Fig. 6.5 and 6.6 reveal the plot of the kinetic energy loss (slope obtained from Fig. 6.1 and 6.2) against the modified porosity correlation. The values of m and n were obtained to be 0.1 and 3.2, and 0.2 and 3.3 for PR and OFMSW, and the R^2 was improved from the initial value of 0.8463 to 0.9772, and 0.8885 to 0.9772 for PR and OFMSW. Similar values of 0.3 and 3.4 were reported

by Olatunde & Fasina, (2018). These values were considered as the modified kinetic porosity constants of the Ergun equation for subsequent calculations.

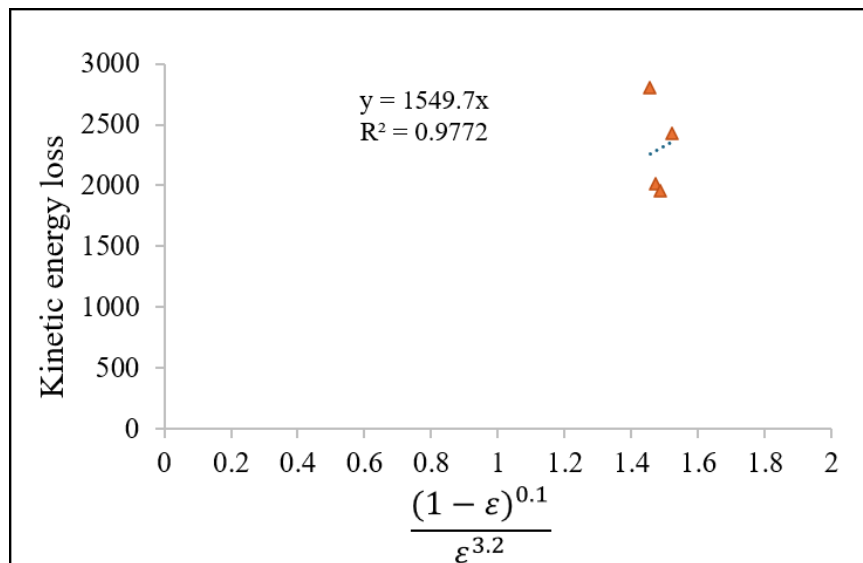


Figure 6.5: Dependence of kinetic energy loss on the modified porosity correlation for PR at different moisture content

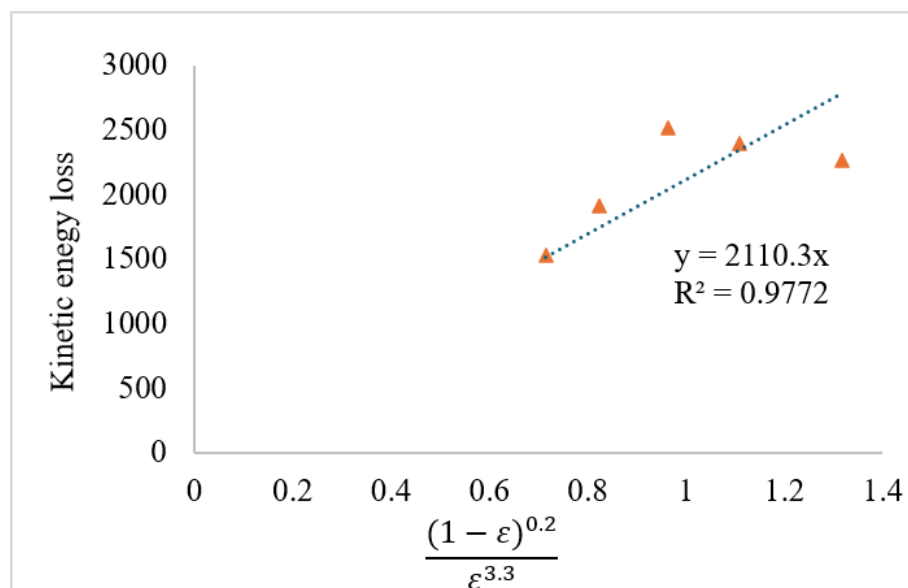


Figure 6.6: Dependence of kinetic energy loss on the modified porosity correlation for OFMSW at different moisture content

6.5.2.3. Modification of the Ergun equation

In this section, the Ergun equation was modified by adding the particle properties specific to PR and OFMSW. The particle size expressed by the effective particle diameter, particle sphericity, the coefficient of variation of the particle distribution, the moisture content, and the new kinetic energy loss model correlation developed by the porosity were included. The effective particle diameter and the coefficient of variation are found in Chapter 5, Eqn 5.8 and 5.9. Accounting for all these properties, a new correlation is proposed as:

$$\frac{\Delta P}{H} = K_1 \frac{(1-\varepsilon)^2}{\varepsilon^3 \varphi^2 d_{eff}^2} \mu U + K_1 \frac{(1-\varepsilon)^{0.1}}{\varepsilon^{3.2} \varphi d_{eff}} \rho_g U^2 \quad (6.7)$$

Adding the effective particle diameter into the Ergun equation, the following equation is obtained:

$$\frac{\Delta P}{H} = K_1 \frac{(1-\varepsilon)^2}{\varepsilon^3 \varphi^2 (d(1+\gamma^2))^2} \mu U + K_2 \frac{(1-\varepsilon)^{0.2}}{\varepsilon^{3.3} \varphi \bar{d}(1+\gamma^2)} \rho_g U^2 \quad (6.8)$$

This equation assumes that there is an additive effect of the viscous and kinetic energy loss in a packed bed, whereby there is a smooth transition between the viscous-dominated effect and the kinetic-dominated effect as the gas flow rate increases (Leva et al., 1951).

The moisture content parameter was introduced in the equation through the porosity term, as in equation

$$\varepsilon_{PR} = 0.822 - 0.101M$$

$$R^2 = 0.99 \quad (6.9)$$

$$\varepsilon_{OFMSW} = 0.948 - 0.00249M \quad R^2 = 0.94 \quad (6.10)$$

M is the wet basis moisture content expressed in decimal

After dividing the left- and right-hand side of eqn. 6.8 by the viscous energy term (first term) the following eqn. 6.11 was obtained.

$$\frac{\Delta P}{HU} \frac{\varepsilon^2 \varphi^2 (d(1+\gamma^2))^2}{\mu_g U (1-\varepsilon)^2} = K_1 + K_2 \frac{\rho U \bar{d} (1+\gamma^2)}{\mu \varepsilon^{3.2} (1-\varepsilon)^{1.9}} \quad (6.11)$$

The left-hand side of eqn. 6.11 can be defined as the ratio of the pressure drop to the viscous energy loss term, which represents the total resistance to flow of the bed designated by f_f (friction factor). The second term on the right-hand side gives the Reynolds Number.

Separating each term in eqn. 6.11 results in eqn. 6.12 and 6.13, where 6.12 is the friction factor and 6.13 is the particle Reynold number.

$$\frac{\Delta P}{HU} \frac{\varepsilon^2 \phi^2 (d(1 + \gamma^2))^2}{\mu_g U (1 - \varepsilon)^2} = f_f \quad (6.12)$$

$$Re = \frac{\rho U \bar{d} (1 + \gamma^2)}{\mu_g \varepsilon^{3.2} (1 - \varepsilon)^{1.9}} \quad (6.13)$$

Combining eqn. 6.12 and 6.13 the final revised Ergun correlation is revised as follows for PR

and OFMSW:

$$f_f = K_1 + K_2 \frac{Re}{\varepsilon^{3.2} (1 - \varepsilon)^{1.9}} \quad (6.14)$$

$$f_f = K_1 + K_2 \frac{Re}{\varepsilon^{0.3} (1 - \varepsilon)^{1.8}} \quad (6.15)$$

Eqn 6.14 and 6.15 reveal a linear relationship between the friction factor f_f and the particle Reynolds number $\frac{Re}{\varepsilon^{3.2} (1 - \varepsilon)^{1.9}}$ and $\frac{Re}{\varepsilon^{0.3} (1 - \varepsilon)^{1.8}}$ for PR and OFMSW where the intercept and the slope result in the values of K_1 and K_2 . 5.14, which summarizes results from previously published studies based on modifications of the Ergun equation.

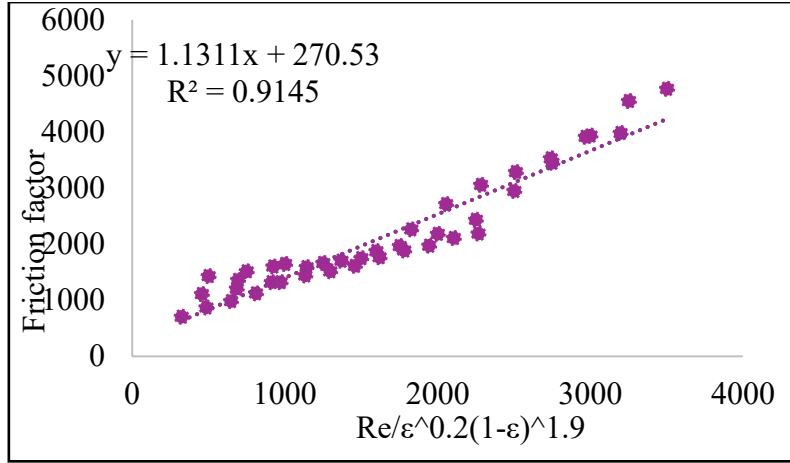


Figure 6.7: Plot of the friction factor vs Reynold number using modified porosity correlation at different moisture content for PR

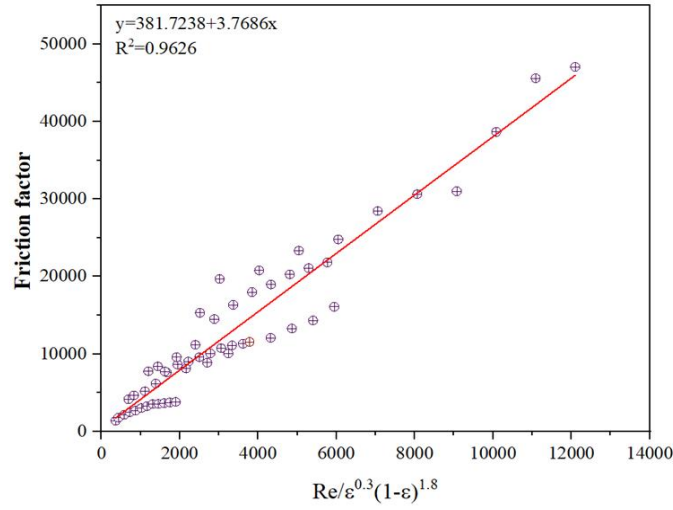


Figure 6.8: Plot of the friction factor vs Reynold number using modified porosity correlation at different moisture content for OFMSW

The final modified Ergun equation for PR and OFMSW are as follows:

$$\frac{\Delta P}{H} = 270.5 \frac{(1-\varepsilon)^2}{\varepsilon^3 \varphi^2 d (1+cv^2)^2} \mu U + 1.13 \frac{(1-\varepsilon)^{0.1}}{\varepsilon^{3.2} \varphi d (1+cv^2)} \rho_g U^2 \quad (6.16)$$

$$\frac{\Delta P}{H} = 381.72 \frac{(1-\varepsilon)^2}{\varepsilon^3 \varphi^2 d (1+cv^2)^2} \mu U + 3.86 \frac{(1-\varepsilon)^{0.2}}{\varepsilon^{3.3} \varphi d (1+cv^2)} \rho_g U^2 \quad (6.17)$$

The estimated values of $k_1 = 270.5$ and $k_2 = 1.13$, and $k_1 = 381.72$ and $k_2 = 3.86$ for PR and OFMSW respectively. These values were compared to those reported by other researchers, as presented in Table 6.5

Table 6.5: Comparison of k_1 and k_2 values between this study and existing literature

K1	K2	Material	Authors
270.5	1.13	PR	This study
381.72	3.86	OFMSW	This study
201.63	2.7	Loblolly wood grind	(Olatunde & Fasina, 2018)
179 -199	1.41- 1.47	Natural Zeolite	(Ruya et al., 2018)
267	2.14	Glass beads	(Quinn, 2014)
160	1.61	Glass beads	(Ozahi et al., 2008)
146.25	1.68	Spherical glass beads	(Kaur & Singh, 2011)

The k_1 and k_2 values obtained for PR and OFMSW differed somewhat from those reported in the literature. This variation is likely attributable to the heterogeneous nature of the waste-derived feedstock used in this study. In addition, the high moisture content introduced considerable variability in the measured physical properties of the materials. These factors likely contributed to the increased complexity and uncertainty associated with estimating the k_1 and k_2 constants

6.5.2.4. Model validation using new experimental pressure drop data

The model was validated by comparing the pressure drop predicted using the developed correlation with those obtained from the original Ergun equation (Eqn. 6.3) under similar bed conditions. For this study, new samples of PR and OFMSW were prepared by grinding and sieving, as described in chapter 3.3. Their physical properties were measured according to the procedures outlined in chapter 3.3. The moisture content was then adjusted to achieve values of 7.0%, 9.9%, 20.3%, 29.5%, and 40.2% wb for PR, and 6.8%, 10.2%, and 18.6% wet basis for OFMSW, respectively. The variation of pressure drop per unit bed length

with superficial gas velocity, predicted using both the newly developed correlations (Eqns. 6.16 and 6.17) and the original Ergun equation (Eqn. 6.3), is presented in Figures 6.9 through 6.13. In all cases, the pressure drop was observed to increase with increasing superficial gas velocity, which is consistent with trends reported in the literature by Grubecki, (2015) during fluidization of wood bark chips. Both the modified Ergun model (new correlation) and the original Ergun equation underpredicted the bed pressure drop; however, the predictions from the new correlation were notably closer to the experimental data. The original Ergun equation significantly underestimated the pressure drop because it assumes spherical, uniform particles, constant bed porosity, and negligible interparticle cohesion, assumptions that are not valid for the heterogeneous and irregular nature of biomass materials. In contrast, the modified model better captures deviations from ideal behavior, including irregular particle shape, variable porosity, and moisture-induced cohesion, resulting in improved agreement with experimental observations. At a moisture content of 20%wb, the new correlation slightly overpredicted the pressure drop across the entire velocity range. Additionally, at higher moisture contents (30%wb and 40%wb), the model underpredicted the pressure drop at low superficial gas velocities but overpredicted it at higher velocities.

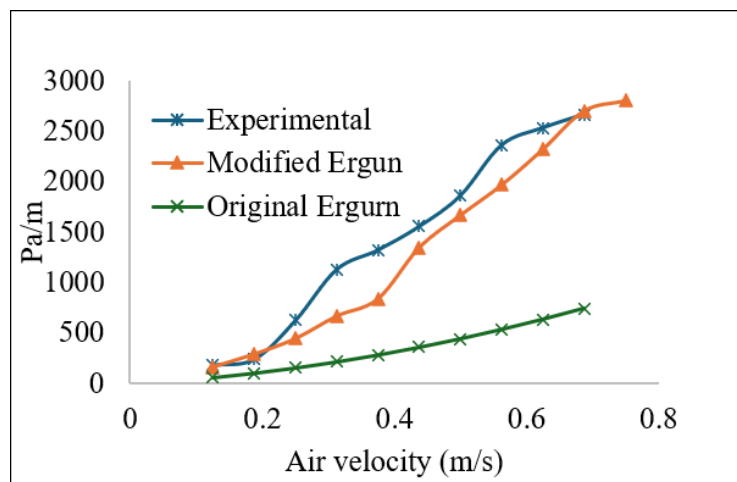


Figure 6.9: Pressure drop per unit length versus superficial gas velocity for PR at 6% moisture content (%wb)

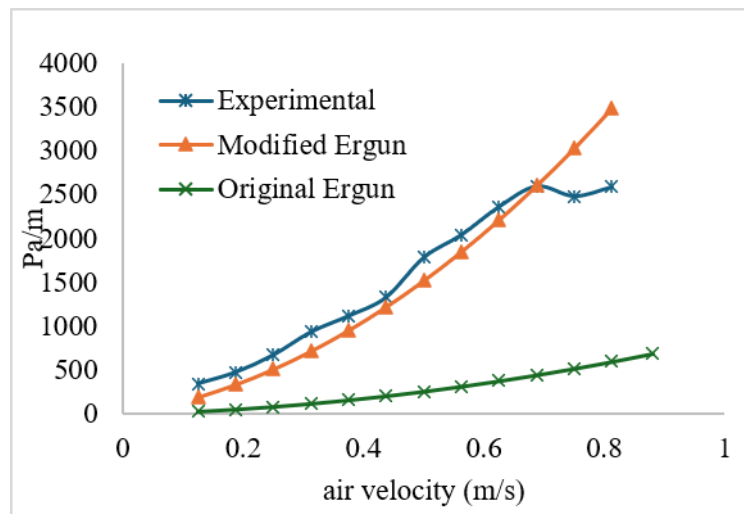


Figure 6.10: Pressure drop per unit length versus superficial gas velocity for PR at 9.9% moisture content (%wb)

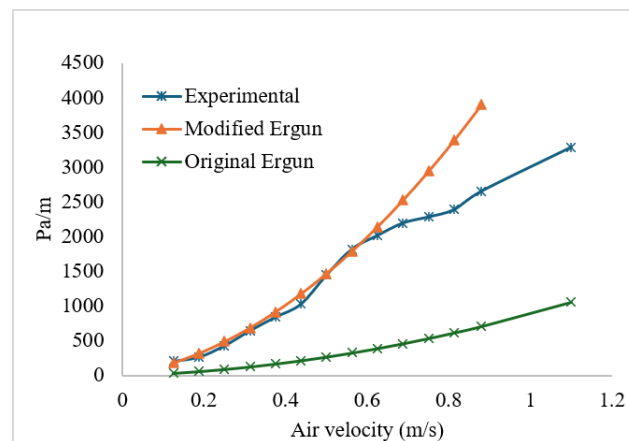


Figure 6.11: Pressure drop per unit length versus superficial gas velocity for PR at 20.3% moisture content (%wb)

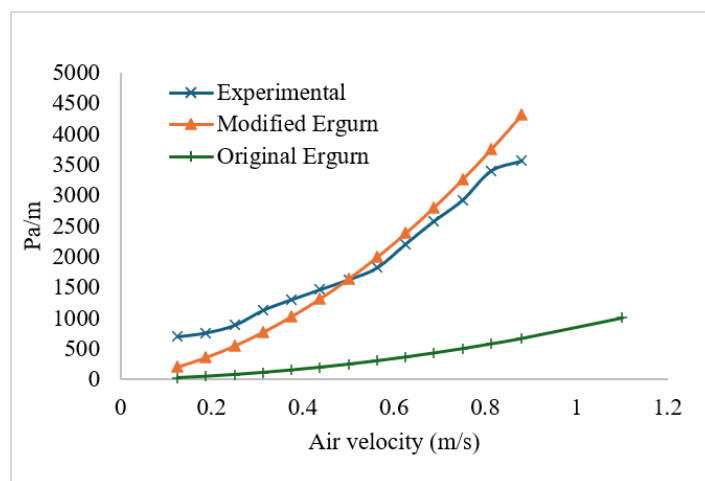


Figure 6.12: Pressure drop per unit length versus superficial gas velocity for PR at 29.5% moisture content (%wb)

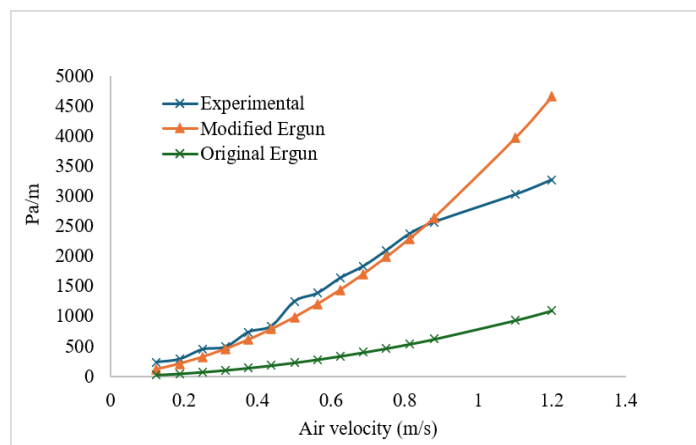


Figure 6.13: Pressure drop per unit length versus superficial gas velocity for PR at 40.3% moisture content (%wb)

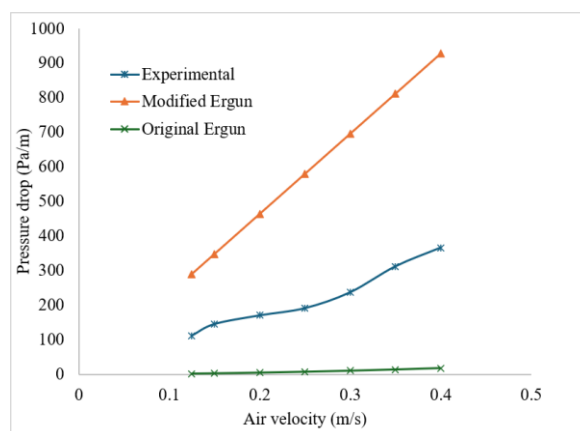


Figure 6.14: Pressure drop per unit length versus superficial gas velocity for OFMSW at 6.8% moisture content (%wb)

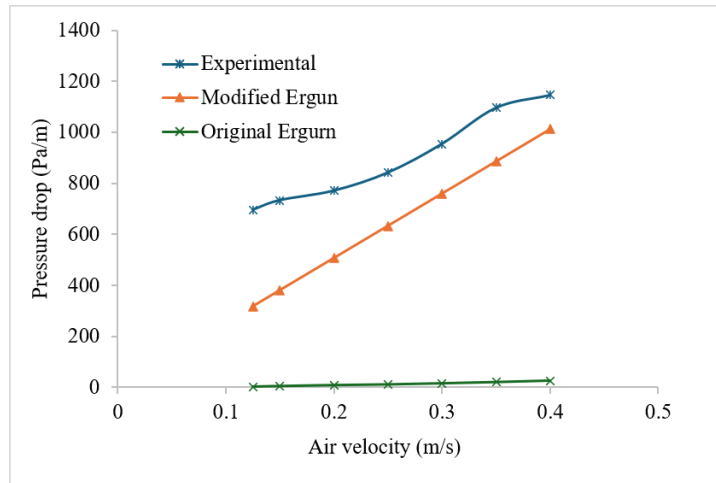


Figure 6.15: Pressure drop per unit length versus superficial gas velocity for OFMSW at 10.2 % moisture content (%wb)

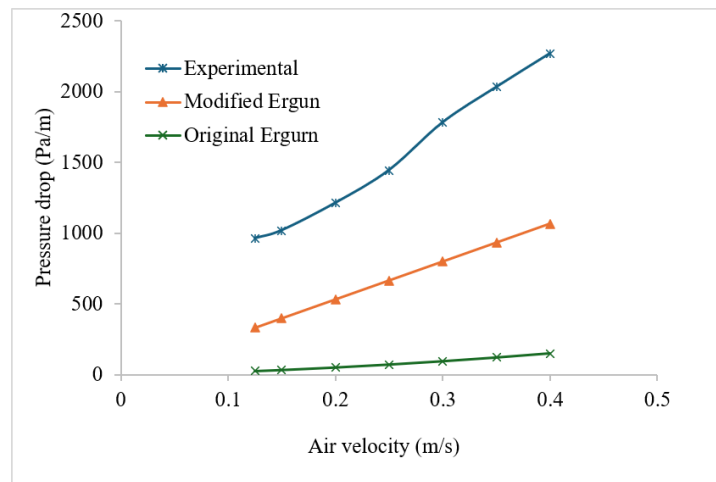


Figure 6.16: Pressure drop per unit length versus superficial gas velocity for OFMSW at 28.6% moisture content (%wb)

6.5.2.5. Performance of the equation on determining the minimum fluidization velocity.

Using the new model proposed in this study (eqn.6 16 and 6.17), predicted values for U_{mf} for PR and OFMSW were obtained at various moisture contents, and the results are presented in Tables 6.6 and 6.7, respectively. It can be observed from the tables that the model developed in this study improved the capability of the Ergun equation to predict the U_{mf} of moist PR and OFMSW by over 50% and 25% for PR and OFMSW, respectively.

Although the MRD obtained in this study was relatively high, comparable or even higher values have been reported in the literature. For instance, Grubecki, (2015) reported root mean square errors ranging from 22% to 41% between experimental measurements and a proposed correlation based on a modified Ergun approach for predicting pressure drop in fluidized beds of moist, irregular wood chips, as the moisture content increased from 8.1 to 64.5% (wet basis)

Table 6.6: % Mean relative deviation of U_{mf} between experimental and the modified Ergun equation for PR

Moisture (%)	Modified Ergun	Original Ergun
7.04	-13.88	36.75
9.9	18.83	28.09
20.33	11.28	24.89
30.11	-5.92	-45.31

Table 6.7: Mean relative deviation of U_{mf} between experimental and the modified Ergun equation for OFMSW

Moisture (%)	Modified Ergun	Original Ergun
6.8	17.91	21.96
10.20	40.90	54.90
18.6	51.32	134.55

In this section, a new model based on the modified Ergun equation was proposed to predict the pressure drop and minimum fluidization velocity (U_{mf}) of PR and municipal solid waste (OFMSW). The model incorporated important physical characteristics, including

moisture content, coefficient of variation (COV) to account for particle size distribution, and sphericity to represent particle shape effects of these samples.

The results demonstrated that the proposed model predicted both the pressure drop and U_{mf} more accurately than the original Ergun equation, highlighting the limitations of the classical Ergun model in describing the behavior of non-spherical and non-uniform particles. In general, the mean relative deviation (MRD) for both pressure drops and U_{mf} predictions increased consistently with increasing moisture content for PR and OFMSW. This trend may be attributed to the difficulty in accurately characterizing the physical properties of these materials in the presence of moisture. For example, OFMSW particles tended to adhere to one another under moist conditions, making the determination of particle size distribution more challenging. Among the materials studied, PR exhibited the lowest MRD across the entire moisture range, whereas OFMSW consistently showed higher deviations.

6.5.3. Conclusion

Moisture content significantly influences the physical properties of biological materials such as PR and municipal solid waste (OFMSW), including bulk density, particle density, porosity, and particle size distribution, all of which play critical roles in determining the minimum fluidization velocity (U_{mf}). The results showed that increasing moisture content led to an increase in bulk density (for OFMSW samples) for PR samples; the bulk density first decreased and then increased with further increase in the moisture content. The particle density and the porosity of both pine residues and MSW decreased with increasing moisture content. In addition, increasing moisture content reduced the coefficient of variation (COV) of the particle size distribution. For example, for PR, the COV decreased from 34% at 10.8% moisture content to 32.2% at 40.2% moisture content, while for OFMSW it decreased from 27% at 10.01% moisture content to 22% at 41.25% moisture content.

New models were developed to predict the minimum fluidization velocity (U_{mf}) of the blends based on existing Ergun correlations. A pressure-velocity model was formulated by modifying the original Ergun equation, which involved developing a new void fraction correlation for PR and OFMSW as a function of moisture content. The concept of coefficient of variation (COV) was also incorporated to account for the wide particle size distribution associated with non-spherical and non-uniform particles such as PR and OFMSW.

Overall, the proposed U_{mf} model showed good agreement with the experimental data, exhibiting a mean relative deviation of less than 20% for blends B4 and B6 at low moisture contents. New coefficients, K_1 and K_2 , of 270.5 and 1.13 for PR, and 381.72 and 3.85 for OFMSW, respectively, were estimated by the model. The results further demonstrated that the modified model provided better predictions of the pressure drop behavior of PR and OFMSW compared to the original Ergun equation.

6.6. References

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Chapter 7. CFD modeling of fluidized bed of coal, pine residues, and OFMSW blends

7.1. Abstract

This study investigated the fluidization behavior of pine residues (PR), waste coal (WC), and organic fraction of municipal solid waste (OFMSW) using computational fluid dynamics (CFD) simulations in a fluidized bed. The samples were ground using a Hammer mill and sieved through a 1.91 mm mesh. The Eulerian–Eulerian multiphase approach coupled with the kinetic theory of granular flow (KTGF) was employed to model the gas-solid interactions. The simulation was carried out using the CFD commercial software package Ansys Fluent R1. Three drag models, namely Syamlal O'Brien, Gidaspow, and Energy-Minimization Multi-Scale (EMMS), were evaluated for their ability to predict pressure drop, bed expansion, and solids distribution within the fluidized bed. The model predictions were validated against experimental fluidization data obtained from a laboratory-scale fluidized bed reactor of 0.1016 m inner diameter and 1 m height. The modeling was carried out at various air velocities ranging from 1 to 4 times the minimum fluidization velocity. The mesh sensitivity analysis was done to optimize the computational domain for accurate numerical calculations, and 3 mm mesh was found to reproduce better gas-solid dynamics, providing the closest agreement to experimental pressure drop and bed expansion with a mean relative error (MRD) of 2.36%. The results showed that the drag models significantly influenced the predicted fluidization behavior. For pine residues and OFMSW, the Syamlal O'Brien and EMMS models produced larger pressure drop fluctuations, while the Gidaspow model predicted more stable bed behavior. Whereas WC exhibited a more stable and smoother bed dynamic using these drag models. The Syamlal O'Brien and Gidaspow models provided the closest agreement with the experimental pressure drop over the investigated velocity range, exhibiting a mean

relative error less than 10% for PR and WC, whereas the EMMS model tended to overpredict pressure drop at higher superficial gas velocities for PR and OFMSW. OFMSW produced the highest MRD of over 20% for pressure drop. Solid volume fraction contours revealed the development of heterogeneous gas–solid flow structures, including dense particle clusters and gas-rich void regions, characteristic of bubbling fluidization, especially for WC particles. In contrast, OFMSW exhibited limited bed expansion and poor solids suspension, with the formation of stable dense regions and gas channels, consistent with experimental observations of poor fluidization quality.

7.2. Introduction

Fluidized bed technology marks a major advancement in the conversion of woody biomass, offering a more efficient and environmentally friendly approach for generating clean power from renewable resources (Mertsoy, 2025). Fluidization is a unit operation in which a solid is subjected to a fluid-like state. This happens when solids come into contact with a fluid or a gas in a long vertical column called a fluidized bed (Adnan et al., 2021). To achieve fluidization, the drag force exerted on the solid by the upward fluid should be sufficiently high to overcome the gravity force exerted on the solid particles. The fluid velocity at this stage is referred to as the minimum fluidization velocity (U_{mf}). It is a critical parameter for governing the hydrodynamic behavior of solid particles within a bubbling fluidized bed (BFB) system. The determination of U_{mf} depends on several key particle properties, including mixing rate, volume fraction, pressure drop, superficial gas velocity, and bed expansion behavior. Fluidization is strongly influenced by particle characteristics and the balance of forces acting between the particles and the fluid flow. As particles interact with neighbouring particles, they are subjected to various forces and shear stresses. Shear stress increases with fluid motion and becomes negligible under stagnant conditions. In contrast, frictional forces between particles are highest when the bed is in a static state (Farhana et al., 2020). Accurately modeling this stagnant solid phase remains a complex challenge. Examples of fluidized beds include bubbling (Luo et al., 2015), turbulent, and circulating fluidized bed reactors (Hossain & Metcalfe, 2023). These reactors are employed in industrial applications such as catalytic cracking (FCC) (Yang et al., 2016), Fisher-Tropsch (FT) synthesis (Gholami & Gholami, 2022), methanol to olefin (MTO) conversion (Tian et al., 2015), coal/biomass combustion, and coal gasification due to their excellent mixing capability, high heat and mass transfer rate, and low emission of pollutants. In a fluidized bed, biomass is

burned at relatively lower temperatures (typically between 800-900 °C, in comparison to 1100 °C of a conventional combustor), thereby reducing the formation of harmful pollutants such as nitrogen oxides (NO_x) and sulfur dioxide in comparison to other combustion technologies (Kwong & Marek, 2021), which generate more thermal NO_x. Additionally, fluidized bed systems can process a wide range of biomass feedstocks, including materials with high moisture or ash content, making them highly adaptable. The improved mixing and uniform temperature distribution within the bed promotes more complete combustion, which enhances overall process efficiency. Some of the drawbacks of fluidized beds include high capital and operating costs, large emissions of particulate matter, and high accumulation of ash, which may result in potentially high maintenance costs (Hossain & Metcalfe, 2023). One of the major challenges in fluidized bed design is improving system efficiency due to the complex interactions between the gas and solid phases, which play a major role in heat, mass transfer, and reaction kinetics. Recent studies have demonstrated the growing importance of computational fluid dynamics (CFD) in understanding biomass fluidization (Luo et al., 2022; Ma et al., 2019; Mertsoy, 2025; M. Yang et al., 2022, 2023). The complex hydrodynamic behavior of a fluidized bed, which cannot be captured experimentally, can be effectively addressed using computational fluid dynamics (CFD) modeling. CFD simulations can significantly reduce the cost and time associated with experimental development and process optimization. However, because fluidized bed systems involve complex physical and chemical interactions between multiple phases, sophisticated mathematical models are required within the CFD framework to accurately describe the system behavior. Various multiphase numerical modeling approaches using both commercial and open-source software are available to investigate the dynamic process within fluidized bed reactors. These models must be carefully verified and validated to ensure their accuracy and reliability for the given process.

Once validated, CFD models can serve as effective tools for evaluating process performance and predicting system efficiency, particularly in situations where experimental investigations are costly, time-consuming, or impractical. Advanced CFD approaches, including Eulerian–Eulerian and Eulerian–Lagrangian coupled with sub-models such as the kinetic theory of granular flow (KTGF) and the dense discrete phase model (DDPM), have been widely applied to simulate the complex gas–solid interactions, heat transfer, and chemical reactions occurring within these systems (Hamidani et al., 2026; Lafta et al., 2026; Lu et al., 2026). In the Eulerian-Eulerian framework, the gas and solids are treated as an interpenetrating continuum. The mass and momentum equation for each phase is calculated from mixture theory or ensemble averaging, and the particle-particle interaction is derived from the kinetic theory of granular flow (Adnan et al., 2021). Modeling the turbulence of a fluidized bed has a significant impact on the overall flow dynamics. Generally, three types of numerical turbulence models are found in the literature, which include the viscous input model, the KTGF model, and the K-epsilon models (Farhana et al., 2020). The basic concept of KTGF is kinetic energy associated with random oscillations of solid particles, also known as granular temperature (Dou et al., 2023). In the K-epsilon model, K is analogous to the granular temperature equation and epsilon is considered as dissipation energy.

The drawback of the Eulerian approach is that the discrete nature of the solid particle is omitted because the solid is modeled as a fluid phase; hence, additional mass and momentum conservation equations are needed for each phase, limiting it to only small-scale systems (Adnan et al., 2021). This limitation is often addressed using the Eulerian-Lagrangian approach, such as the discrete particle model (DDPM) or other models such as the multiphase particle-in-cell model (MP-PIC) or the discrete element model (DEM), in which the solid phase is considered as a discrete entity. Both the Eulerian-Eulerian and the Eulerian-

Lagrangian approaches have been intensively investigated for fluidized bed design (Aboudaoud et al., 2023; Chandimal Bandara et al., 2017; Huang et al., 2022; Luo et al., 2015; Mertsoy, 2025). Recently, Yang et al., (2023) developed a three-dimensional CFD model to investigate the hydrodynamic and combustion characteristics of biomass particles in an industrial-scale circulating fluidized bed (CFB) furnace. The study employed advanced modeling approaches, including the Eulerian–Lagrangian framework and the multiphase particle-in-cell (MP-PIC) collision model, to simulate the complex interactions occurring within the furnace. These modeling techniques provided valuable insights into particle behavior, combustion performance, and flow dynamics. Similarly, a comparative CFD study using a Eulerian–Eulerian two-fluid model (TFM) and a Eulerian-Lagrangian dense discrete phase model (DDPM) framework was developed by Adnan et al., (2021) to predict the hydrodynamic behavior of a pilot-scale bubbling fluidized bed reactor. The study employed two-dimensional simulations to investigate the effects of grid size, the drag force models including EMMS (Energy Minimization Multi-scale), Wen-Yu Gidaspow, and Syamlal O’Brien, timestep (0.002, 0.0005, and 0.0002s), and particle interaction parameters on model performance. The results showed that both models accurately predicted the bubbling bed behavior when the EMMS/bubbling drag model was applied. Although the TFM provided better prediction accuracy, the DDPM generated more detailed solid flow patterns due to its particle-tracking capability. In addition, the DDPM produced a better grid-independent solution and required significantly lower computational time compared to the TFM, making it more suitable for large-scale industrial applications. The results also showed that the time step has no significant effect on the hydrodynamics behavior of a pilot-scale bubbling bed.

Despite the popularity of fluidized bed technology, a detailed understanding of particle flow behavior during fluidization, especially in beds of non-uniform and heterogeneous nature such

as pine residues, OFMSW, and coal, has been lacking. Biomass particles are often irregular in shape, size, density, and pliability, making fluidization behavior difficult to predict due to problems such as channeling, agglomeration, elutriation, and segregation. Unfortunately, researchers have omitted these unique properties of biomass material and focused more on the spherical and uniform particles. The solid-solid and solid-fluid interaction in a fluidized bed are modeled using drag correlations. Drag force is an important parameter for simulating solid and fluid hydrodynamics. Models such as the Gidaspow model, the Syamal-O'Brien model, and the Wen-Yu model are more popularly applied to calculate fluid drag force for a fluidized bed (Chameera K. Jayarathna , Michael Balfe, 2022; Debnath et al., 2021a; X. Wang et al., 2024).

The selection of a drag model is of critical importance for fluidized bed simulations. Agrawal et al., (2018) compared the performance of six drag models, namely Gidaspow, Syamlal–O'Brien, Di Felice, EMMS, BVK, and Ayeni, in CFD–DEM simulations of bubbling fluidized beds containing Geldart D particles using the MFIX–DEM software. The objective of the study was to evaluate the influence of drag model selection on the prediction of fluidized bed hydrodynamics by comparing simulation results with experimental data from a bubbling bed system. The results showed that the Di Felice model provided the closest prediction of average particle height, with discrepancies below 16% compared to experimental measurements, while the Ayeni model showed better agreement for horizontal velocity and granular temperature predictions. It is important to note that a clear understanding of the behavior of different drag models in hydrodynamic tests can contribute to the further development of reaction models in fluidized bed reactors. The study concluded that no single drag model was capable of accurately predicting all hydrodynamic parameters simultaneously; however, the Ayeni and Di Felice models generally performed better than the

conventionally used Gidaspow and Syamlal–O’Brien models in predicting the hydrodynamic behavior of bubbling fluidized beds. Similarly, Estejab & Battaglia, (2014) investigated the performance of seven drag models in predicting the hydrodynamics of Geldart A biomass, coal, and coal–biomass mixtures in bubbling fluidized beds using the MFIX software with an Eulerian–Eulerian approach. The drag models evaluated were BVK, HYS, Koch and Hill, Gidaspow, Gidaspow-Blend, Syamlal O’Brien, and Wen–Yu. Simulation results were validated against experimental measurements of bed height and void fraction distribution. For single solids phases, the Gidaspow, Gidaspow-Blend, Syamlal O’Brien, and Wen–Yu models showed better agreement with experimental bed height predictions, whereas the BVK and Koch and Hill models provided better predictions for the binary coal–poplar mixtures. The study concluded that conventional drag models originally developed for Geldart B particles can also predict Geldart A fluidization behavior when static regions of mass within the bed are considered.

It can be clearly understood from these studies that the selection of drag models often depends on a trial-and-error approach. Furthermore, most previous CFD investigations have focused primarily on conventional Geldart particles, biomass materials with relatively uniform properties, while limited studies have examined the fluidization behavior of heterogeneous materials such as pine residues, municipal solid waste (OFMSW), and waste coal. Therefore, this study investigates the suitability of existing drag models for improving the prediction of gas-solid particle interactions in fluidized-bed reactors for waste-to-energy applications.

7.3. Methodology

7.3.1. Fluidized bed geometry and meshing

In this study, a lab-scale cylindrical fluidized bed made of transparent acrylic was constructed (see Fig. 5.1). The experimental fluidization procedure is explained in Chapter 5.1. Figures 6(a) and 6(b) show the structural diagram and the 3D domain of the fluidized bed reactor used in this study. The fluidized bed geometry was constructed in ANSYS Workbench R1 2025, the computational mesh was generated using the Meshing module within Workbench, and the numerical simulations were carried out using ANSYS Fluent. The gas phase (air was used in this study) was introduced at the bottom of the bed, which has a diameter of 0.1016 m, and the outlet, also 0.1016 m in diameter, was located at the top of the bed, as seen in Fig. 7.1(a). A mesh sensitivity analysis was conducted to determine the mesh size that better reproduces the experimental result. Parameters such as the bed pressure and bed height were compared with experimental data. Mesh quality parameter values are summarized in Table 7.3. For the 3D mesh generation, the Patch Conforming Method was used as the meshing technique in the Ansys Fluent workbench software. The quality of the mesh was subsequently improved by adapting the polyhedral mesh due to its low computational cost and good convergence, which resulted in better residuals compared to the Tetrahedral mesh (Wang et al., 2024). The maximum grid size in solid–fluid CFD simulations should generally exceed 10 to 20 times particle diameters (Benyahia, 2012; Iv et al., 2005). Based on these assumptions, mesh sizes of 2, 3, 4, 4, and 6mm were used for simulation, and parameters such as pressure drop and bed expansion were evaluated with the experimental results. It should be noted that the same mesh configuration has recently been employed by our group for a larger-scale reactive fluidized bed reactor, producing acceptable results (Bhattarai et al., 2025).

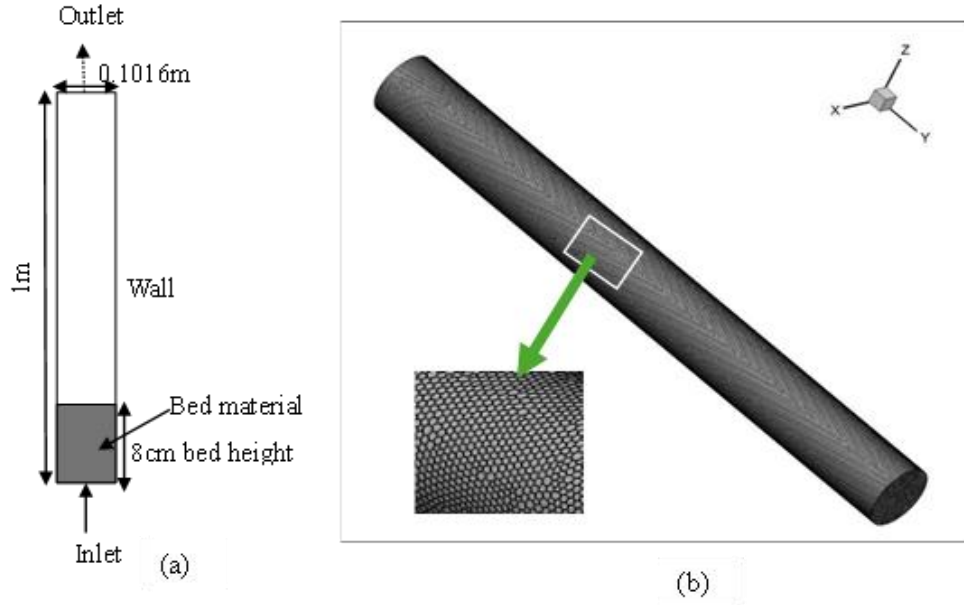


Figure 7.1: Schematic diagram and mesh display of the fluidized bed used for the simulation

7.3.2. Model description and simulation settings

In the present study, the Eulerian multiphase flow models, coupled with the Kinetic Theory of Granular Flow in ANSYS Fluent 2025R1, were developed to study the flow behavior of air and solid phases (pine residues, OFMSW, and waste coal) in the fluidized. In this approach, the fluid and solid phases are modeled as interpenetrating continuous species (Dinh et al., 2021; Wang et al., 2024). Where the solid phase is calculated using the granular temperature to account for particle-particle collision, while the gas phase is calculated using the standard Navier-Stokes fluid dynamics. The sum of the gas (g) phase and solid phase must sum up to unity. The phase volume fraction was used to represent their occupation within the domain. To track the volume occupied by each phase, volume fractions are introduced, where ε_g is the gas volume fraction (void fraction) and ε_s is the solids volume fraction.

$$\varepsilon_g + \varepsilon_s = 1 \quad (7.1)$$

7.3.2.1. Model equations

The governing equations involved in the current simulation include mass and momentum conservation equations for each phase without reaction (Balfe et al., 2022). Each phase is performed and numerically solved independently in the ANSYS Fluent domain. In ANSYS Fluent, each phase equation is solved within the framework of the finite volume method (FVM). The air properties are solved based on the ideal gas laws. Eqn 7.2 and 7.3 represent the mass conservation for the gas (g) and solid phase (s).

7.3.2.2. The continuity equations for the gas and solid phases are

$$\frac{\partial}{\partial t}(\varepsilon_g \rho_g) + \nabla \cdot (\varepsilon_g \rho_g u_g) = 0 \quad (7.2)$$

$$\frac{\partial}{\partial t}(\varepsilon_s \rho_s) + \nabla \cdot (\varepsilon_s \rho_s u_s) = 0 \quad (7.3)$$

where u_s and u_g refer to the velocities of the gas and solid phases, ρ_s , and ρ_g , are the densities of solid and gas phases respectively.

The momentum equations for each phase as shown in eqn 7.4 and 7.5, and it can be stated based on these equations that the rate of change of momentum of a phase is equal to the sum of all forces acting on that phase within the computational domain.

$$\frac{\partial}{\partial t}(\varepsilon_g \rho_g u_g) + \nabla \cdot (\varepsilon_g \rho_g u_g u_g) = -\varepsilon_g \nabla P + \nabla \cdot \tau_g + \varepsilon_g \rho_g g + K_{sg}(u_p - u_g) \quad (7.4)$$

$$\frac{\partial}{\partial t}(\varepsilon_s \rho_s u_s) + \nabla \cdot (\varepsilon_s \rho_s u_s u_s) = -\varepsilon_s \nabla P - \nabla P_s + \nabla \cdot \tau_s + \varepsilon_s \rho_s g + K_{gs}(u_g - u_s) \quad (7.5)$$

Where τ_g , τ_s , and p represent the stress of the gas and solid phases, and pressure, respectively. And $K_{sg}(u_s - u_g)$, $K_{gs}(u_g - u_s)$ are the solid and gas drag forces. K_{sg} and K_{gs} are the interphase momentum drag coefficients, which quantify the interaction force between

the gas and solid particles. The drag coefficient is usually embedded in K_{sg} and K_{gs} and are calculated differently for each drag model.

7.3.2.3. Turbulence model for the air phase

The turbulence model is an important component of CFD simulations because it describes the turbulent characteristics of the gas phase, including mixing, momentum transfer, and the formation of eddies. In fluidized beds, gas flow is highly unsteady due to bubble formation, particle movement, and gas–solid interactions, resulting in complex turbulent structures. Several turbulence models have been developed to represent these flow characteristics, including the standard k - ε , RNG k - ε , Realizable k - ε , k - ω SST model, Reynolds Stress Model (RSM), and Large Eddy Simulation (LES) (Aljuhaishi et al., 2024; Li et al., 2021). In this study, the gas-phase turbulence was modeled using the standard k - ε model, where k represents the turbulent kinetic energy and ε is the turbulent dissipation rate. The standard k - ε model assumes fully developed turbulence and has been widely applied to gas–solid fluidized beds because it provides reasonable predictions of the gas flow field while requiring relatively low computational cost compared with more advanced turbulence models (Wang et al., 2024). The turbulence model was automatically selected within the ANSYS Fluent interface.

7.3.2.3.1. Kinetic Theory of Granular Flow (KTGF) concept

Unlike the turbulence that governs the fluid phase motion, the KTGF describes the solid phase motion and interaction by treating solid particles as granular fluid. It also describes the stresses produced within the solid phase due to collisions, random motion, and deformation within the solid phase (Berzi, 2024). The KTGF is a collection of equations used to close the Eulerian–Eulerian governing equations for the solid phase. It is composed of other models, which include the solid continuity equation, solid momentum equation, solid stress

tensor and the granular temperature equation (Berzi, 2024; Lun et al., 1984; Gholami & Gholami, 2022). The continuity equations for the solid stress tensor (τ_s) in the multiphase model are modeled with the KTGF as follows.

$$\tau_s = -\rho_s I + \varepsilon_s \eta_s (\nabla u_s + \nabla u_s^T) + \varepsilon_s \nabla \cdot u_s I \quad (7.6)$$

The continuity equation for solid pressure (P_s) is also modeled in the KTGF, using the following expression based on Lun et al.

$$P_s = \varepsilon_s \rho_s \theta_s + 2\rho_s (1 + e_s) \varepsilon_s^2 g_o \theta_s \quad (7.7)$$

The solid phase granular temperature is directly related to the kinetic energy of the random motion of the particles, and is it modeled based on the KTGF using the following equation

$$\frac{2}{3} \left[\frac{\partial}{\partial t} (\rho_s \varepsilon_s \theta_s) + \nabla \cdot (\rho_s \varepsilon_s u_s \theta_s) \right] = (-P_s I + \tau_s) : \nabla u_s + \nabla \cdot (k_{\theta_s} \nabla \theta_s) - \gamma_{\theta_s} + \phi_{gp} \quad (7.8)$$

Where $(-P_p I + \tau_p) : \nabla u_p$ represents the energy generated by the solid stress tensor, $\nabla \cdot (k_{\theta_s} \nabla \theta_s)$ is the diffusion energy, γ_{θ_s} is the collision dissipation energy, ϕ_{sg} is the exchange energy between the fluid and solid phases.

Where the granular temperature can be expressed as

$$0 = (-P_p I + \tau_p) : \nabla u_p - \gamma_{\theta_p} + \phi_{gp} \quad (7.9)$$

Various empirical drag models were assessed to understand the solid gas interaction during fluidization of pine residues, waste coal and OFMSW. To calculate the interphase, drag force coefficient, each model uses its own correlations, which will be explained in the following section. Models such as Gidaspow, Syamlal O'Brien and the EMMS (Energy-Minimization Multi-Scale) have been successfully used to model fluidized beds. The aim was to find the most suitable drag model and further validate it against the experimental data.

7.3.2.4. Gidaspow drag model

The Gidaspow model is a hybrid model that combines the Wen-Yu and Ergun models for gas-solid two phase flow (Liu et al., 2022; Wang et al., 2024). The main advantage of the Gidaspow model is that it combines two distinct flow regimes providing a reliable bridge between dense bed $0.2 > \varepsilon_s \leq 0.8$ and dilute bed $0.2 \leq \varepsilon_s < 0.8$ without requiring the user to manually switch models. The overall drag force β exchange coefficient between the phases is calculated continuously using the following general equations.

$$\beta = \varphi \beta_{Wen-Yu} + (1 - \varphi) \beta_{Ergun} \quad (7.10)$$

For Wen and Yu

$$\beta_{Wen-Yu} = \frac{3}{4} C_D \frac{\rho_g \varepsilon_g \varepsilon_s |u_g - u_s|}{d_s} \varepsilon_g - 2.65 \quad (7.11)$$

$$C_D = \begin{cases} \frac{24}{Re_s} (1 + 0.15 Re_s^{0.687}) & Re_s \leq 1000 \\ 0.44 & Re_s > 1000 \end{cases} \quad (7.12)$$

$$Re_s > 1000$$

Where the particle Reynold number is expressed as follows

$$Re_s = \frac{\rho_g \varepsilon_g |\varepsilon_g - \varepsilon_s|}{u_g} \quad (7.13)$$

And for the Ergun correlation

$$\beta_{Ergun} = \frac{150 \varepsilon_s (1 - \varepsilon_g) \mu_g}{\varepsilon_g d_s^2} + \frac{1.75 \rho_s \varepsilon_s |u_g - u_s|}{d_s} \quad (7.14)$$

7.3.2.5. Syamlal-O'Brien drag model

The Syamlal-O'Brien drag model is a semi-empirical gas-solid drag correlation developed for Eulerian multiphase simulations that accounts for particle concentration effects and is widely used to predict momentum exchange in fluidized bed systems. In the

Syamlal-O'Brien drag model, the coefficient of interphase drag force β_g is as follow (Estejab & Battaglia, 2014)

$$\beta_g = \frac{3}{4} C_D \left(\frac{\rho_g \varepsilon_g \varepsilon_s}{d_p v_r^2} \right) |u_s - u_g| \quad (7.15)$$

Where the drag coefficient C_D is

$$C_D = [0.63 + \frac{4.8}{\sqrt{\frac{Re}{v_r}}}]^2 \quad (7.16)$$

Where v_r is the relative velocity correlation, and it is expressed as follows

$$v_r = \frac{1}{2} [A - 0.06Re] + \frac{1}{2} [\sqrt{(0.06Re)^2 + 0.12Re(2B - A) + A^2}] \quad (7.17)$$

Where,

$$A = \varepsilon_g^{4.14} \quad (7.18)$$

$$B = \begin{cases} 0.8\varepsilon_g^{1.28} \\ \varepsilon_g^{2.65} \end{cases} \quad (7.19)$$

$$\begin{aligned} \varepsilon_g &\leq 0.85 \\ \varepsilon_g &> 0.85 \end{aligned} \quad (7.20)$$

7.3.2.6. Energy Minimization Multi-Scale (EMMS) drag model

The EMMS model is derived from an assumption that the particles are heterogeneously distributed in the control volume. The effect of mesoscale structures on fluidization behaviors such as particle clustering and bubble formation is considered, thereby providing a more realistic prediction of gas–solid momentum exchange in fluidized beds than conventional homogeneous drag models (Jiang et al., 2020), which improves the simulation accuracy without more consumption of computing resources. EMMS was originally developed mainly for heterogeneous gas–solid systems such as circulating fluidized beds and risers (Wang et al., 2012). Its performance may be less reliable in dense bubbling beds, near minimum fluidization, or very shallow beds unless the model is specifically modified for those

regimes. Some studies have extended EMMS for bubbling fluidization, but this shows that the original model is not universally valid for all regimes. The EMMS drag model is given as follows

$$\beta = \frac{3}{4} C_D \frac{\rho_g \varepsilon_g |u_g - u_s|}{d_p} \varepsilon_s^{-2.7} H_D \quad (7.21)$$

$$H_D = a(Re_s + b)^c \quad (7.22)$$

Where H_D is the heterogeneity index, and a , b , c are parameters given in Appendix 2.

7.3.3. Simulation setup and boundary conditions

The system was modeled as a cylindrical block along the z-x axis. To obtain a reliable system of equations, reasonable boundary conditions were selected. The phase properties and boundary conditions are presented in Table 6.2. At the inlet boundary condition, the inlet air velocity was assumed to be uniform along the axial direction at the bottom of the fluidized bed, while the inlet solid velocity was set to zero to ensure that no solid leaves or enters the boundary. The outlet boundary is the pressure boundary condition (Bahramian, 2019). The values of the air velocity used are presented in Fig. 6.3. At the inlet and outlet boundaries, the solid volume fraction was set to zero. The outlet pressure was set at zero, which considered the outlet pressure to be the atmospheric pressure (Bahramian, 2019). All the wall boundary conditions were set to no-slip conditions for the air phase, by setting the air velocity at the wall to zero, and the wall was considered stationary (Aboudaoud et al., 2023). For the solid phase, the Schaeffer approach was used for the no-slip boundary condition (Bahramian, 2019, Adamczyk et al., 2014). The Schaeffer viscous model is usually introduced in the KTGF to represent the additional resistance caused by particle friction in the dense bed due to the initial packed bed, like a fluidized bed of PR, WC, and OFMSW. In the computational domain, the gas was taken as the continuous phase while the solid was considered as the dispersed phase inside the column, for interpenetrating and interacting with each other. In this study, we

did not examine the case of heat transfer; both air and solid temperatures were initially set to 300K throughout the bed. The system was modeled as unsteady and non-reactive. Inlet and outlet boundary conditions were also set to this temperature. For the multiphase model, the material was patched to 8cm (bed height used in the experiment) using the solid volume fraction, which varied as follows: 0.25 for OFMSW and pine residues and 0.475 for coal, respectively.

Table 7.1: Phases properties and operating conditions for fluidized bed simulation

	Particle size (mm)	Particle density (kg/m ³)	Moisture content (%) wb
Pine residues	1.63	1462.13	7.6
OFMSW	3.35	1806.19	5.8
Coal	0.27	1643.17	2.5

Table 7.2: Other parameters for boundary conditions

Other parameters	Values
Restitution coefficient	0.9
Packed bed fraction	0.53
Packed bed max fraction	0.55
Granular Viscosity (kg/ms)	Syamlal O'Brien
Granular temperature	Algebraic
Frictional viscosity	Schaeffer
Frictional pressure	Based-KTGF
Radial distribution	Lun-et-al

Gas phase	Air
Density (kg/m ³)	1.225
Viscosity	1.82×10^{-5}

7.3.3.1. Computational solution

The cold fluidization process (or hydrodynamic simulation) in the fluidized bed was simulated using the CFD software ANSYS Fluent 2025R1. The general CFD simulation algorithms used to solve the Eulerian equations in this study is shown in Fig. 7.2. The Eulerian–Eulerian approach was applied to solve the continuity and momentum equations governing the multiphase flow behavior, using the finite volume method, this method was successfully used by other authors (Aboudaoud et al., 2023; Dinh et al., 2021; Sim et al., 2026). All simulations were carried out transiently with a total simulation time of 10s. For the multiphase flow calculations, as the solution method, A first-order upwind scheme and implicit formulation were used to discretize the momentum equations in Ansys Fluent 2025R1 (Bahramian, 2019). Pressure–velocity coupling was carried out using the Phase Coupled SIMPLE algorithms (Sim et al., 2026). The equations for momentum, turbulence kinetic energy, turbulence dissipation, and transient formulation were solved using the first-order upwind scheme. In turbulence calculations, the standard k-epsilon model with standard wall functions was used as the viscous model. A time step of 0.001s, a maximum of 10000-time steps, and an iteration of 20 resulted in a total simulation time of 10s. Convergence between 10^{-3} and 10^{-6} was chosen to ensure numerical stability and accuracy. Given the intricate nature of fluidization, selecting suitable input parameters and submodels for various numerical models presents a significant challenge. Therefore, determining the most appropriate

modeling approach for a specific fluidization often proves to be a complex task. Table 7.2 summarizes the sub-models used in the study.

Table 7.3: Solution Methods

Pressure velocity coupling	
Pressure-Velocity Coupling	Phase coupled SIMPLE
Spatial discretization	
Gradient	Least Squares Cell Based
Pressure	PRESTO!
Momentum	QUICK
Volume fraction	Modified HRIC
Turbulent kinetic energy	First Order Upwind
Turbulent Dissipation Rate	First Order Upwind
Transient Formulation	First Order Implicit
Time step	0.001s

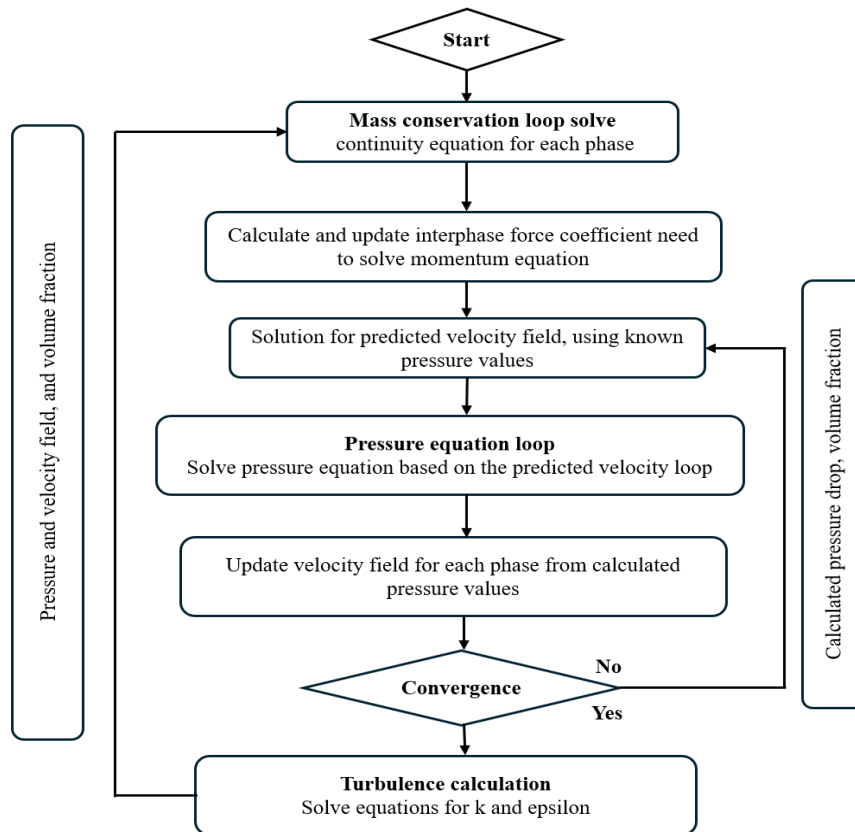


Figure 7.2: SIMPLE algorithms to solve the multiphase model

7.3.3.2. Simulation cases

Fig. 7 .3 summarizes the simulation flowchart based on the experimental studies of the fluidization behavior of pine residues, waste coal, and OFMSW, using different drag models and inlet velocities, and the resulting pressure drop and bed expansion were compared with the experimental data to evaluate the effectiveness of these drag models on predicting the behavior of the fluidized bed. Additionally, a parametric study was conducted for the various superficial gas velocities while keeping the other operating conditions constant, and the simulation results for pressure drop and bed expansion were compared with experimental results. The selected conditions are representative of the experimental operating conditions and provide detailed hydrodynamic measurements under well-controlled conditions, allowing a meaningful validation of the present model.

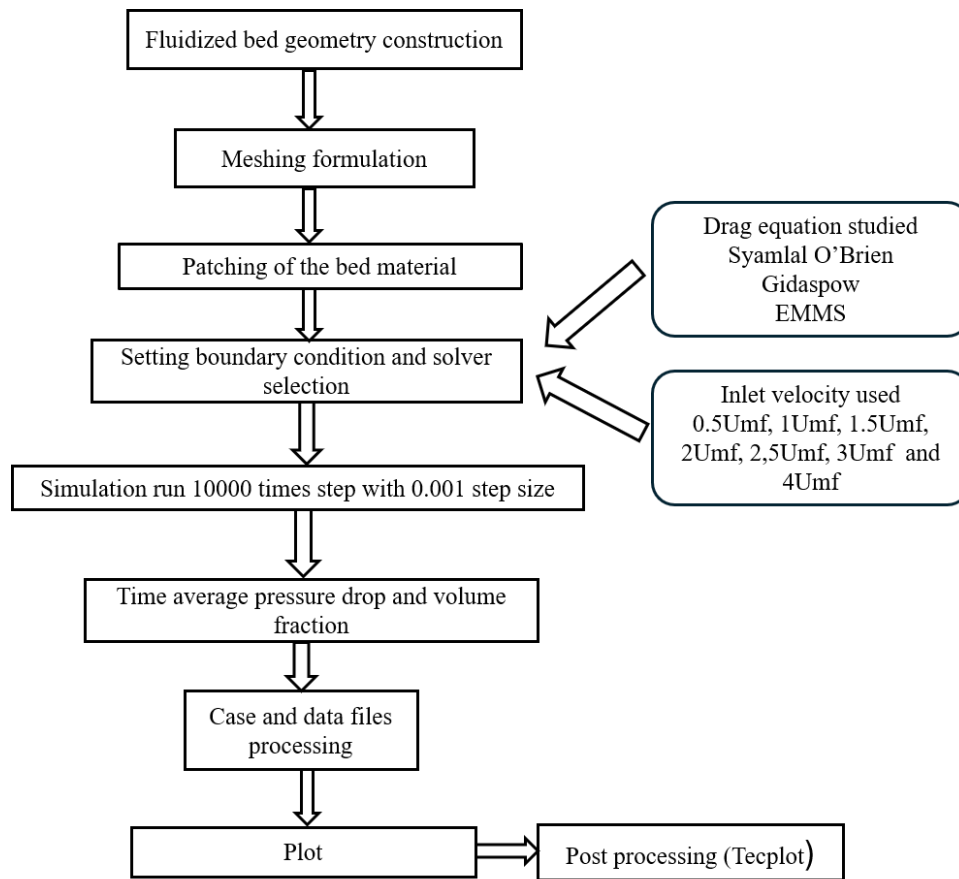


Figure 7.3: CFD simulation workflow

7.4. Results and discussion

7.4.1. Mesh sensitivity analysis

Mesh sensitivity analysis is the first step in any CFD study, as it minimizes numerical errors while optimizing computational time and cost. In this study, a mesh sensitivity analysis was conducted to select the best mesh size that will reproduce results that are consistent with the experimental results, while saving computational cost and time. Since the median particle diameter of pine residue was 1.63 mm, the computational cell size was selected to be larger than the particle diameter to satisfy the continuum assumption in the Eulerian–Eulerian model. For this reason, 5 mesh sizes ranging from 2 to 6mm were selected, as seen in Table 7.3. The bed material was initialized by patching the solids phase to closely replicate the experimental bed, using an initial pine residue solid volume fraction of 0.25. This initialization

produced a bed containing approximately 236 g of pine residue particles, which closely matched the mass used in the fluidization experiments, which was 225g. The bed inlet air velocity was set to $4U_{mf}$ (2.5m/s). The simulation was conducted based on the workflow algorithms presented in Fig. 7.2 and 7.3. The simulation was run for a total time of 10 s, corresponding to 10000-time steps at a 0.001 s time step size, and the resulting bed pressure drop (Pa) and bed expansion (cm) were extracted from ANSYS Fluent and compared to the experimental data.

Table 7.4: Mesh independence assessment

Mesh size (mm)	2	3	4	5	6
Number of cells	8668315	195194	1088955	558071	323192
Number of faces	17436704	1335159	2202834	1131586	657093
Number of nodes	1503071	1139964	195014	101317	59588
Minimum	2.09527e-01	4.72708e-01	2.09639e-01	2.26568e-01	2.25834e-01
Orthogonal quality					
Maximum aspect ratio	1.56467e+01	6.76418e+00	1.51974e+01	1.47904e+01	1.60043e+01

**Meshing method: Path conforming, Improved to Polyhedral in Ansys Fluent*

Figure 7.4 presents the time-averaged solids volume fraction contours obtained using different mesh resolutions under the same operating conditions as the fluidization experiments. Particle clustering near the right wall of the bed was observed in both the simulations and the experimental results. Among the mesh resolutions evaluated, the 3 mm and 6 mm meshes predicted denser particle accumulation near the wall, closely resembling the experimental observations.

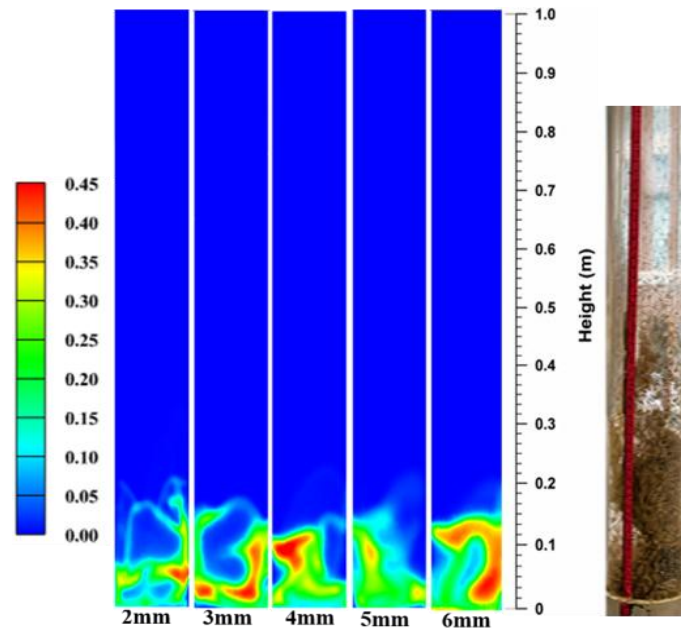


Figure 7.4: Snapshot of time average solids volume fraction representing the bed hydrodynamics for different mesh resolutions

7.4.1.1. Effect of mesh size on the transient pressure drop fluctuations

Fig 7.5 presents the transient pressure drop predicted by the CFD model using mesh sizes ranging from 2 to 6 mm. All mesh configurations exhibit similar pressure drop trends throughout the simulation, characterized by an initial transient period followed by periodic fluctuations associated with particle movement and gas–solid interactions within the fluidized bed. Although minor differences in the instantaneous pressure drop are observed among the meshes, the overall pressure drop behavior remains consistent, indicating that the numerical solution is relatively insensitive to mesh size for the case of this study. The similarity in the pressure drop profiles suggests that mesh-independent results were achieved within the investigated mesh range.

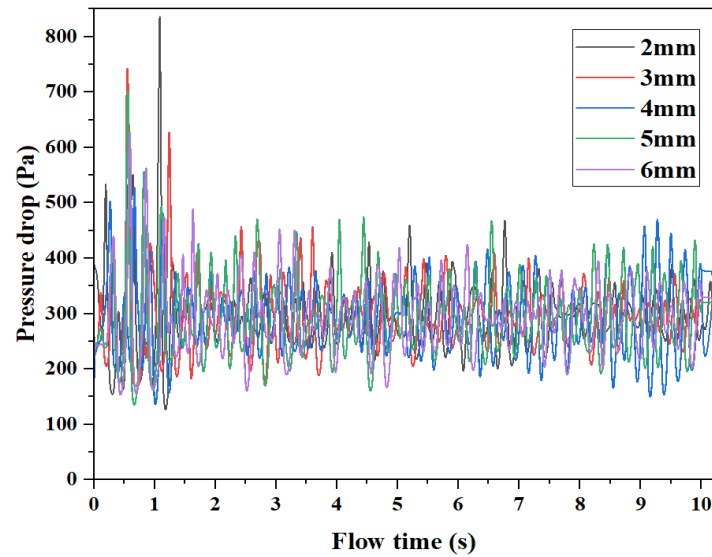


Figure 7.5: Effect of mesh size on the transient pressure drop, with pine residues particles at 4Umf using the Syamlal O'Brien drag model

The pressure drop was calculated experimentally by dividing the weight of the bed material by the cross-sectional area of the bed and was found to be 272.75g. Fig 7.6 establishes the simulated pressure drop for the various mesh sizes. This value was compared by calculating the percentage mean relative deviation (%MRD) between the experimental and simulated data. The percentage mean relative deviation was found to be 0.2%, 2.36%, 9.65%, 3.92%, and 10.76% for 2, 3, 4, 5, and 6mm, respectively. The studied mesh resulted in an error of less than 10% except for the 6mm mesh size. The computational time required for the complete 10s world time was 48, 19, 24, 6, and 4h, respectively, on the Auburn University high-performance computing (HPC - Easley.auburn.edu).

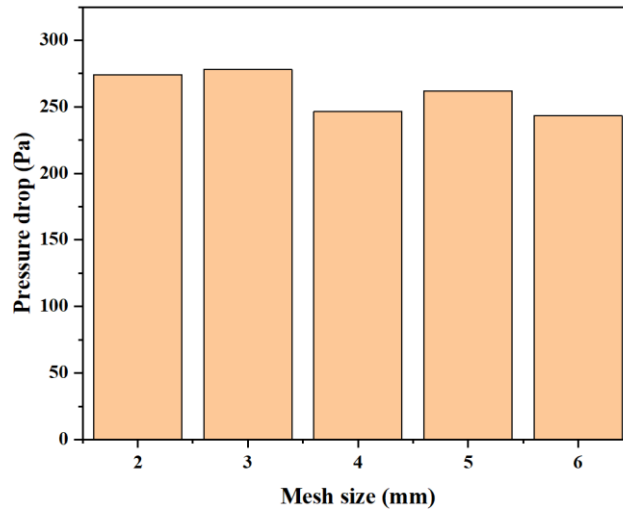


Figure 7.6: Effect of mesh size on the pressure drop

7.4.1.2. Effect of mesh size on the bed expansion

Similarly, the effect of mesh size on the bed expansion was also studied, and the result is shown in Fig. 7.7. The percentage means relative error between the experimental and simulated bed expansion was found to be 31.38, 41.31, 49.27, 44.19, and 46.93% for 2, 2, 5, 5, and 6mm mesh size, respectively. The discrepancy between experimental and simulated bed expansion increased with increasing mesh size. This behavior can be attributed to the reduced spatial resolution of the coarse meshes, which limits their ability to accurately capture local gas-solid interactions and solids concentration gradients within the fluidized bed. As a result, the prediction of suspension of solids and bed surface position becomes less accurate, leading to larger deviations from experimental measurements. The finer mesh (2mm and 3mm) provided better resolution of the fluidization hydrodynamics and consequently produced more accurate bed expansion predictions, although all the mesh sizes underpredicted the bed rise. The bed expansion ratio was calculated by dividing the initial bed height (8cm) by the bed height after simulation. The values were found to be 2.78, 2.38, 2.08, 2.26, and 2.15, resulting in the bed height increase of 178.67, 138.44, 106.06, 126.69, and 115.58%. Compared with the experimental results, the 2mm mesh showed the closest value

to the experimental data. However, although 2mm has the lowest error for pressure drop and bed expansion, the computational time was relatively higher. The 3mm mesh also produced lower errors for pressure drop and the bed expansion compared to the rest of the mesh sizes, although the computational time was slightly higher than for the 5 and 6mm mesh sizes. For this reason, the 3mm mesh was selected as the optimum mesh size and used to for further analysis.

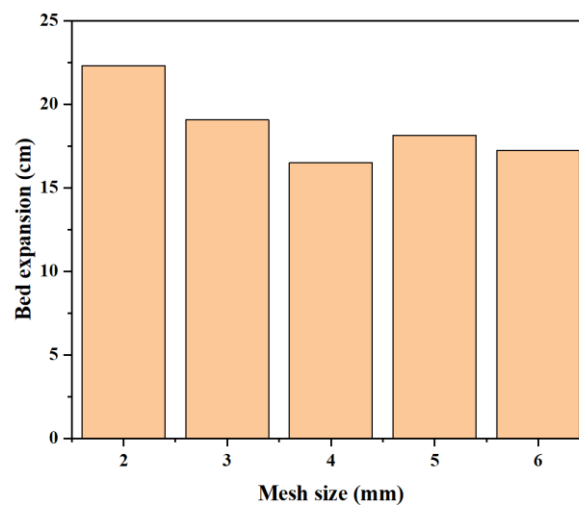


Figure 7.7: Effect of mesh size on the bed expansion

7.4.2. Effect of the drag model on the fluidized bed hydrodynamic

Figures 7.8 through 7.15 present snapshots of the transient contour plot for the solid and gas concentration distribution for pine residues, waste coal, and OFMSW using the Syamlal–O’Brien, Gidaspow, and EMMS drag models. As can be seen in the figures at $t = 0$ s, particles are primarily concentrated at the bottom of the bed near the distributor. Upon gas introduction, a sudden bed expansion is observed at $t = 1$ s, as the incoming drag force exerted by the air overcomes the bed weight, leading to the formation of large bubbles within the bed. This results in the development of distinct dense and diluted regions: low-volume-fraction (light green or blue) areas correspond to gas bubbles and voids, while high-volume-fraction (red) areas indicate particle-rich clusters. As time progresses, the contours exhibit continuous

bubble formation, particle circulation, and redistribution of solids throughout the bed, characteristic features of fluidization. This is mostly observed for pine residues and waste coal using Syamlal O'Brien and Gidaspow drag models. However, a clear distinction was observed between the gas and solid concentration for WC. The persistence of alternating dense and dilute zones reflects a heterogeneous gas–solid flow structure, confirming that the bed has reached a dynamic fluidized state (at $4U_{mf}$). Similar behavior was reported by Aboudaoud et al., (2023) in their hydrodynamic study of glass beads. The Syamlal–O'Brien and Gidaspow drag models show comparable trends in solid volume fraction distribution over time. A closer examination of pine residue behavior (Fig. 7.8 at $t = 1$ s) indicates that the particles fluidize readily, producing a highly diluted bed where smaller particles fluidize freely while larger particles remain relatively stationary. As time advances, more particles accumulate in specific regions within the bed (red zones). This observation could be because biomass particles are not only less dense but also cohesive in nature, exhibiting particle agglomeration and interlocking, which reflects the nature of niddle-like and heterogeneous nature of pine residues. A similar pattern was reported by Battaglia, (2016). In contrast, coal (Figs 7.11 and 7.14) particles exhibited a more uniform mixing with the gas within the bed, with smaller and multiple bubble formation for the Syamlal O'Brien and the Gidaspow drag models. OFMSW (Figs. 7.15 and 7.16), on the other hand, showed less solids circulation and more persistence of localized dense regions, indicating poor fluidization quality and gas channeling. A similar phenomenon was observed during experimental fluidization. Large bubbles were also observed, which were as large as the diameter of the fluidized bed, characteristic of a plug flow. This behavior could be attributed to the irregular particle morphology and the cohesive, fluffy nature of OFMSW, which hindered single particle suspension and promoted stable

agglomerates. These CFD predictions align with experimental observations, where OFMSW exhibited the lowest fluidization performance among the materials studied.

A different trend is observed with the EMMS drag model. For instance, Fig. 7.11 (pine residues) shows larger bubbles comparable to the bed diameter which divided the bed into two distinct compartments, a behavior that was not observed experimentally at this moisture content (7.6% wb). Waste coal (Fig 7.14), on the other hand the EMMS drag model predicted smaller and more uniformly distributed bubble structures, which may be attributed to its ability to account for mesoscale flow structures, such as particle clusters and gas-rich voids, during the calculation of gas–solid momentum transfer (Wang & Lu, 2022). Whereas the Syamlal and the Gidaspow model assume that the particle is uniformly distributed and there is perfect mixture between the gas and the solid which is not the case for the heterogeneous mixture of biomass particles, which are usually characterized by particle cluster and channeling.

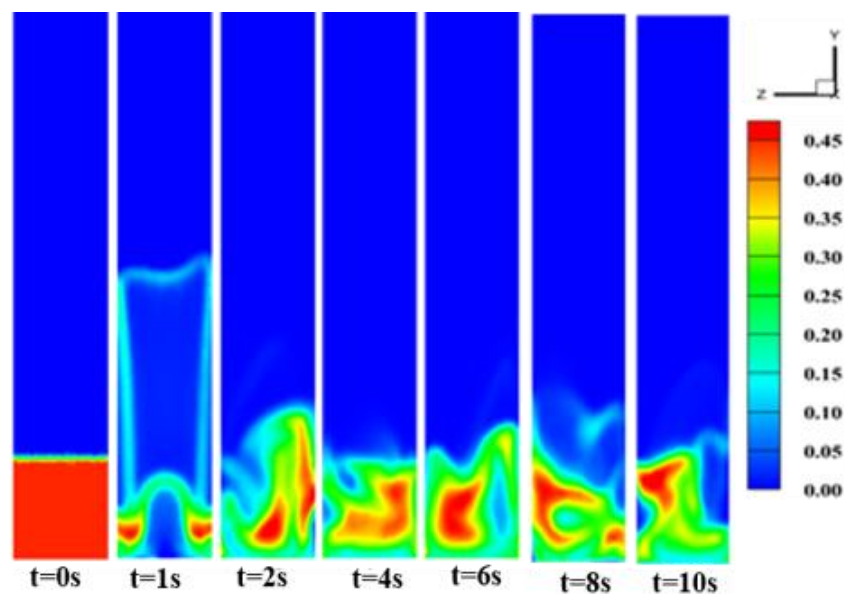


Figure 7.8: Snapshot of the simulated time-averaged solid volume fraction contour of pine residues using the Syamlal O'Brien drag model at the gas velocity of $4U_{mf}$

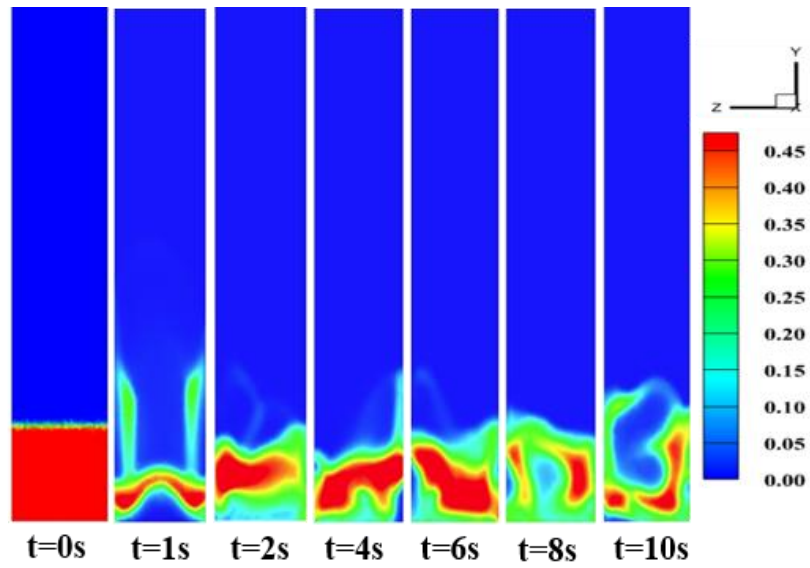


Figure 7.9: Snapshot of the simulated time-averaged solid volume fraction contour of pine residues using the Gidaspow drag model at the gas velocity of $4U_{mf}$

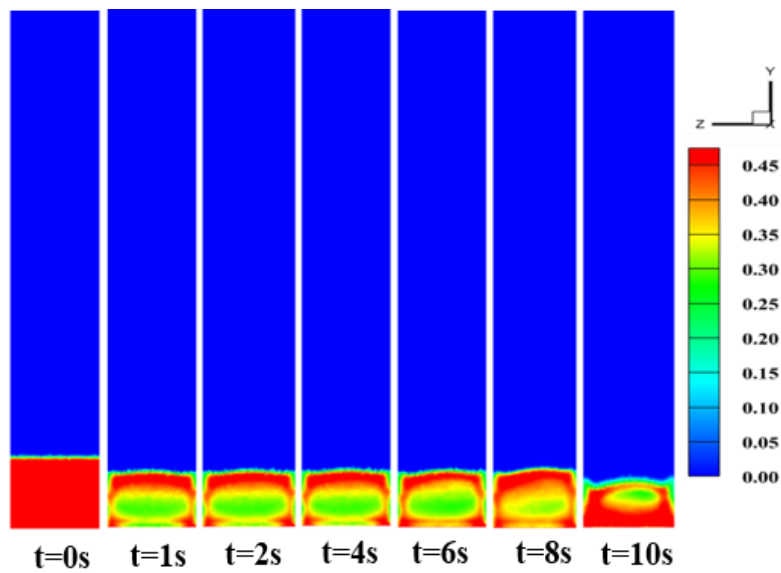


Figure 7.10: Snapshot of the simulated time-averaged solid volume fraction contour of pine residues using the EMMS drag model at the gas velocity of $4U_{mf}$

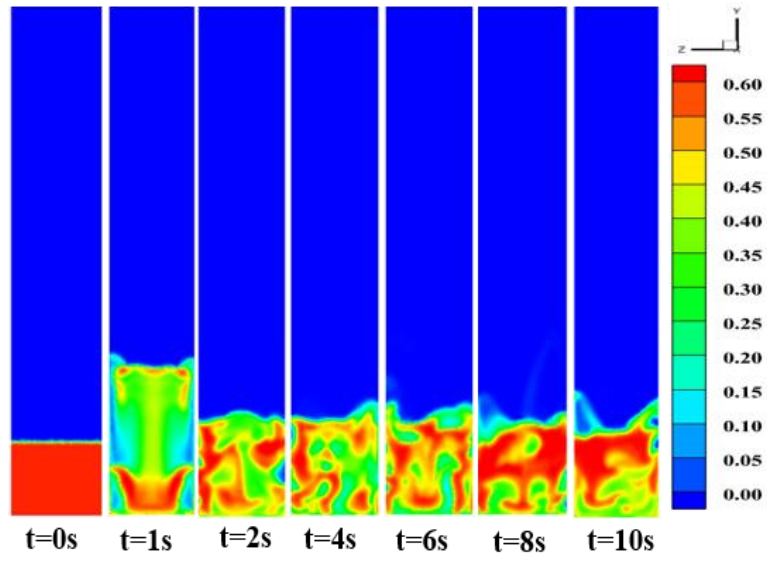


Figure 7.11: Snapshot of the simulated time-averaged solid volume fraction contour of coal using the Syamlal O'Brien drag model at the gas velocity of $4U_{mf}$

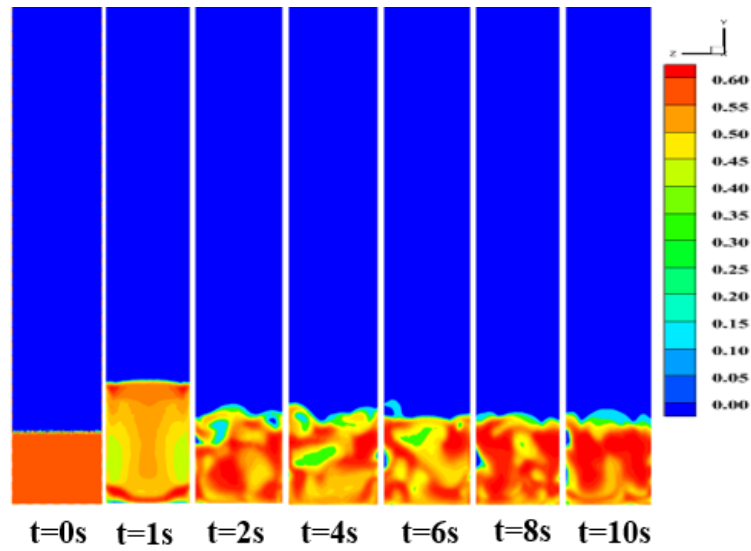


Figure 7.12: Snapshot of the simulated axial time-averaged solid volume fraction contour of coal using the Gidaspow drag model at the gas velocity of $4U_{mf}$

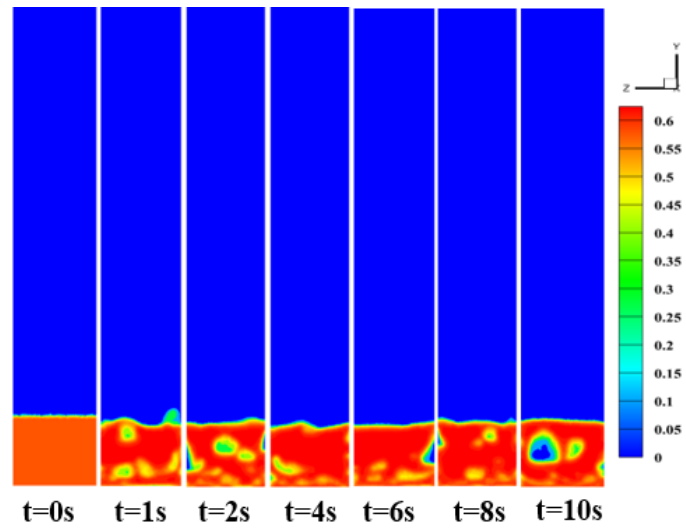


Figure 7.13: Snapshot of the simulated time-averaged solid volume fraction contour of coal using the EMMS drag model at the gas velocity of $4U_{mf}$

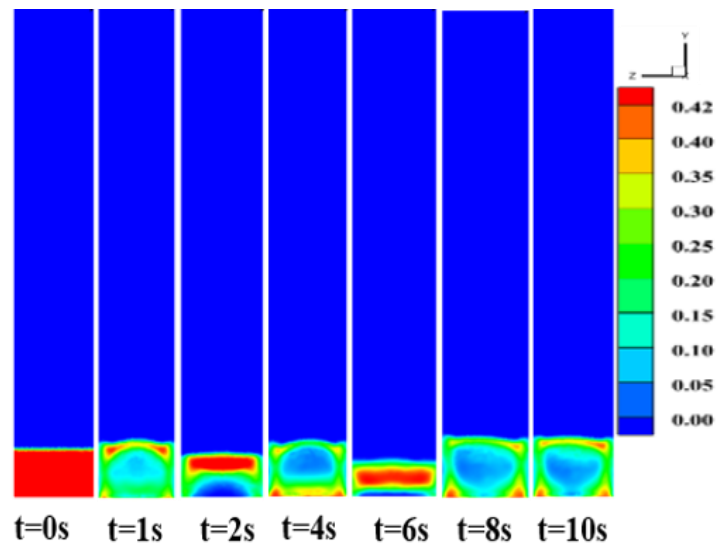


Figure 7.14: Snapshot of the simulated time-averaged solid volume fraction contour of OFMSW using Syamlal O'Brien drag model at the gas velocity of $4U_{mf}$

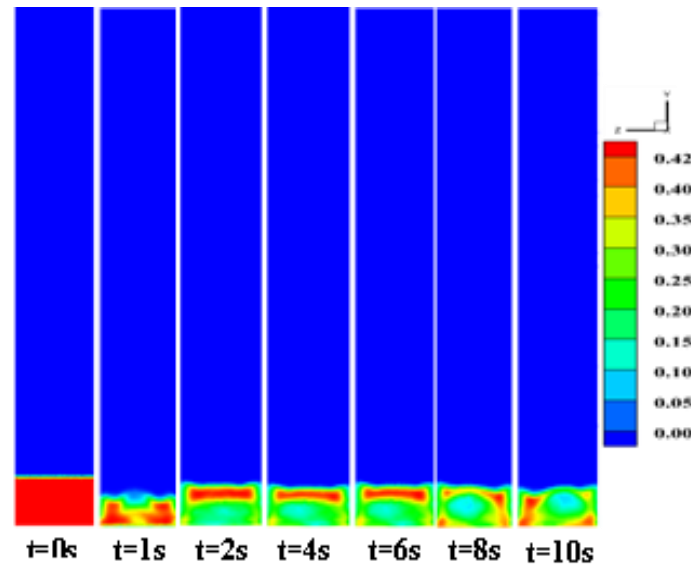


Figure 7.15: Snapshot of the simulated time-averaged solid volume fraction contour of OFMSW using the Gidaspow drag model at the gas velocity of $4U_{mf}$

7.4.3. Prediction of the distribution of solid particles along the fluidized bed

7.4.3.1. Axial distribution of solid volume fraction

In this section, the particle concentration along the bed was numerically evaluated, and the underlying physical behavior was analyzed based on experimental observations. The axial solids profile typically consists of a dense region at the bottom, a dilute region at the top, and an intermediate transition zone between these two layers (Yupeng et al., 2017). Figs 7.16(a) –(c) illustrate the axial solids distribution and the corresponding three-dimensional solids structures predicted by the Syamlal–O’Brien, Gidaspow, and EMMS drag models for pine residues, waste coal, and OFMSW, respectively, at bed heights ranging from 0.2 to 0.5 m after 10 s of simulation. The profiles obtained in this study are consistent with those reported by Yupeng et al., (2017). It can be noticed that the solid volume fraction along the axis of the bed decreased gradually with increasing bed height. This was consistent with the published work of Gu et al., (2023). At the bottom region of the bed (approximately 0.005 cm), a relatively low solids concentration is observed, particularly for pine residues (Fig. 7.16a across all drag models). In this region, particles are readily entrained upward due to the relatively high

inlet gas velocity ($4U_{mf}$), which promotes the formation of large bubbles. Above this region, a higher solids concentration is observed between 0.02 and 0.06 cm, where particles begin to lose momentum. This behavior results from interactions between particles descending from the upper regions and those rising from below. In the upper region (above 0.08 cm), the solids concentration decreases significantly as gas bubbles occupy a larger fraction of the bed volume, leading to greater particle dispersion and overall bed expansion.

Although all three models predicted the formation of a dense solid region and a dilute freeboard region, significant differences were observed in the distribution of solids throughout the bed. The Syamlal–O'Brien model predicts a more extended solids suspension region and a gradual decrease in solids concentration within the bed height, whereas the Gidaspow and EMMS models predicted a more compact dense phase concentrated near the lower section of the bed for all the material studied. Different bed heights were predicted by the drag models, of which Syamlal O'Brien predicted a more expanded bed for waste coal, with the highest reaching about 20 cm, for pine residues about 15cm, and for OFMSW about 11cm. The three-dimensional contours further reveal distinct bed morphologies, indicating that the choice of drag model strongly affects the predicted gas–solid momentum exchange and solids holdup distribution. These results highlight the sensitivity of fluidized bed hydrodynamics to the selected drag correlation and emphasize the importance of drag model validation against experimental observations.

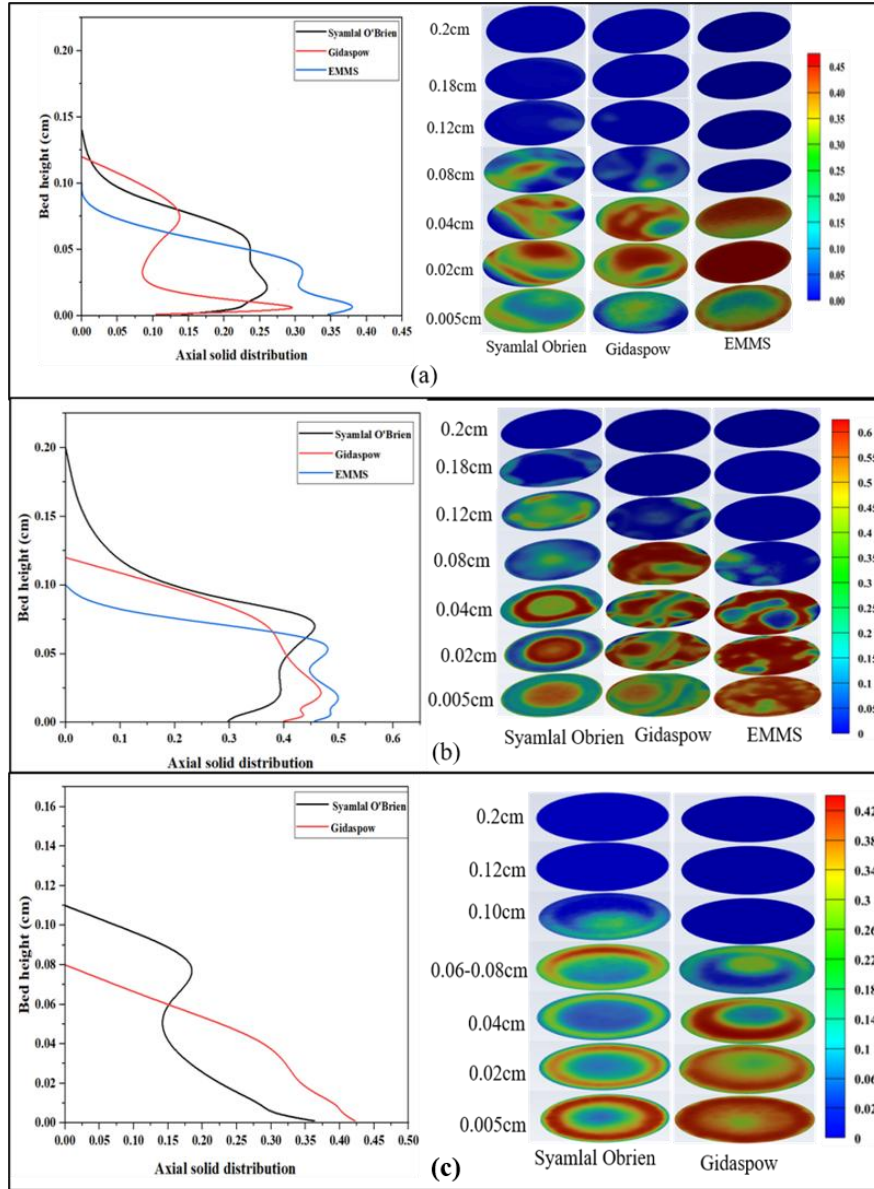


Figure 7.16: Axial average solid holdup for different drag models; a) Pine residues, b) waste coal, c) OFMSW at 4Umf

7.4.3.2. Radial distribution of solid volume fraction

To comprehensively investigate the three-dimensional flow characteristics of pine residues (PR), waste coal (WC), and the organic fraction of municipal solid waste (OFMSW) in the fluidized bed reactor, the solids volume fraction was sampled at several horizontal planes along the bed height. The average radial solids volume fraction at each plane is presented in Fig 7.17–7.19 for PR, WC, and OFMSW, respectively. The Syamlal–O'Brien, Gidaspow, and

EMMS drag models predicted distinct radial solids concentration distributions for all materials, reflecting differences in their representation of gas–solid interactions. At elevations between $y = 0.01$ and 0.10 m, corresponding to the dense bed region, the solids volume fraction exhibited a non-uniform radial distribution, generally characterized by a U-shaped profile regardless of the drag model or material. Higher solids concentrations were observed near the reactor walls, while lower concentrations occurred toward the bed center. This behavior is consistent with the typical hydrodynamics of bubbling fluidized beds, where rising gas bubbles preferentially travel through the central region, displacing particles toward the walls and producing heterogeneous solids distributions rather than uniform concentration profiles.

At $y = 0.01$ m, the solids volume fraction remained relatively high because the particles were densely packed immediately above the gas distributor. As the bed height increased to $y = 0.03$ and 0.05 m, corresponding to the dense bubbling and upper dense bed regions, the radial profiles exhibited pronounced peaks and valleys across the reactor diameter, particularly near the walls. These variations indicate heterogeneous solids distribution resulting from bubble passage, particle circulation, localized clustering, and segregation, which are commonly observed in biomass fluidization due to the irregular shape and low density of the particles. It was interestingly noticed that for PR and the Syamlal O'Brien drag model (Fig 7.17a), the solid concentration at these zones was higher on the left side of the bed, reaching about 0.45 at $y = 0.05$ m. for the case of WC and the EMMS drag model (Fig 6.18c) exhibited an more uniform particle concentration between $y = 0.05$ m and 0.05 , however, at $y = 0.05$ on the right side of the bed a significant drop of solid concentration was observed, which could be due to the formation of large gas bubble at that zone.

At $y = 0.10$ m, the solids volume fraction decreased considerably, indicating the transition from the dense bed to the dilute freeboard, where particle concentration became progressively lower. At $y = 0.12$ and 0.15 m, the solids volume fraction approached zero across most of the reactor diameter, demonstrating that only a small fraction of entrained particles reached these elevations. Overall, none of the drag models predicted a perfectly uniform radial solids distribution. Instead, all three models successfully captured the heterogeneous nature of the fluidized bed, characterized by bubble-induced particle redistribution, wall accumulation, particle clustering, and solids segregation.

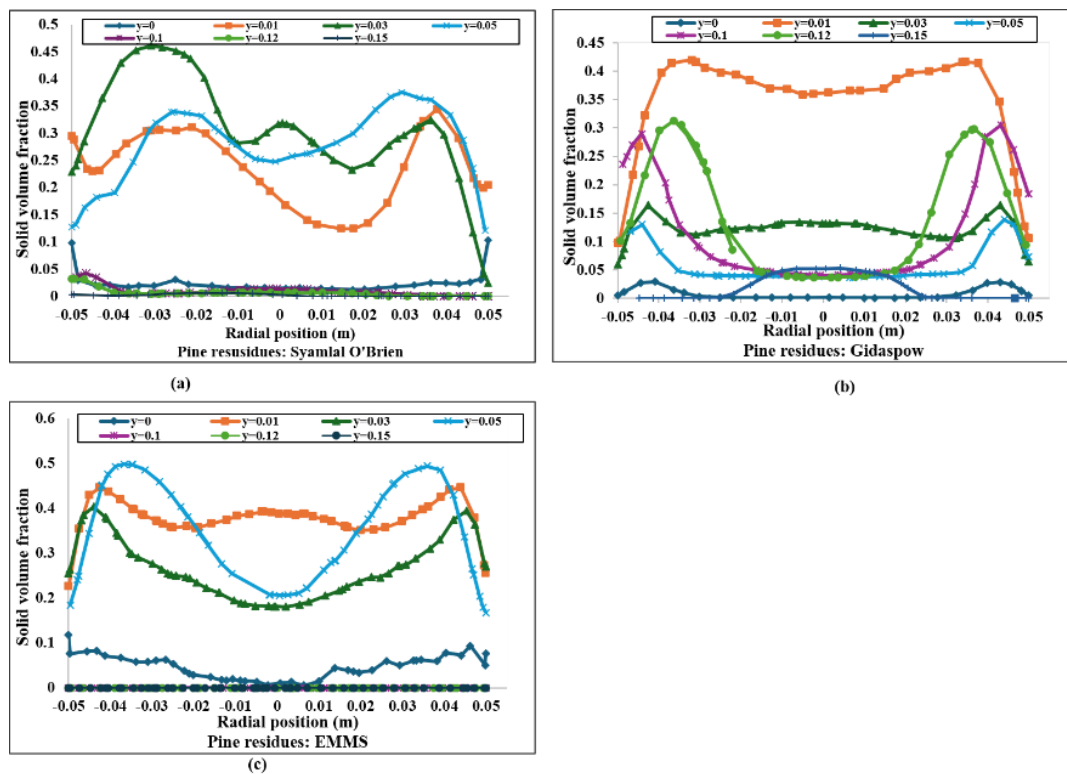


Figure 7.17: Relative position of pine residues particle in the radial direction using: (a) Syamlal Obrien, (b) Gidaspow, (c) EMMS drag models (y in m)

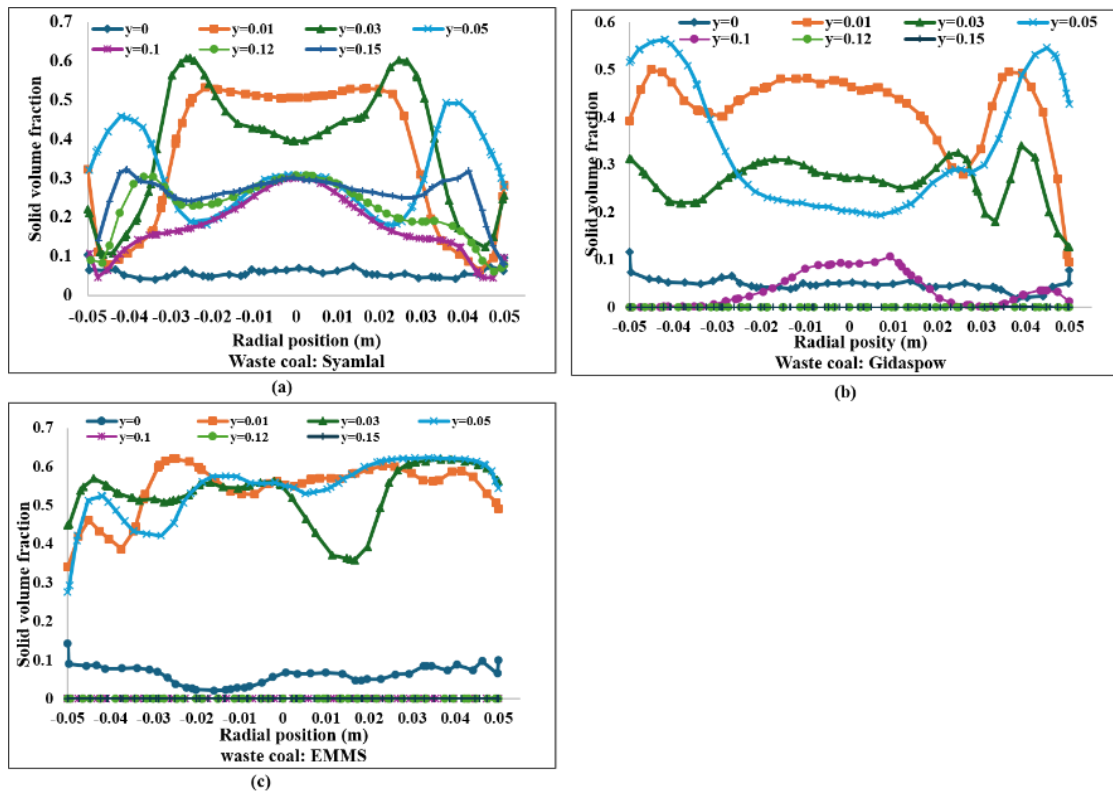


Figure 7.18: Relative position of waste coal particle in the radial direction using: (a) Syamlal O'Brien, (b) Gidaspow, (c) EMMS drag models. (y in m)

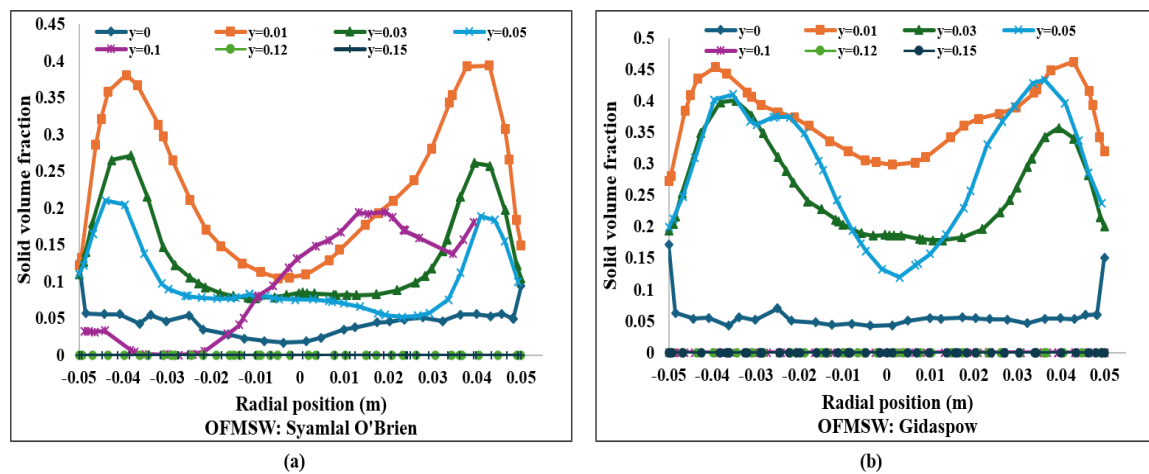


Figure 7.19: Relative position of OFMSW particle in the radial direction using: (a) Syamlal O'Brien, (b) Gidaspow, (c) EMMS drag models. (y in m)

7.4.3.3. Radial distribution of particle velocity

To further investigate the hydrodynamics of the fluidized bed, the mean particle velocity magnitude was extracted along several horizontal planes across the bed diameter for pine residues (PR), waste coal (WC), and the organic fraction of municipal solid waste (OFMSW), as presented in Figures 7.20–7.22. The corresponding radial solids volume fraction profiles (Section 7.4.2.1.2) showed that the solids concentration was generally higher near the reactor walls and lower in the central region for most cases. Such heterogeneous solids distribution influences the gas–solid flow field because the lower solids concentration in the bed center offers less resistance to the upward gas flow than the denser particle regions near the walls. Consequently, one might expect higher particle velocities in the central region due to greater gas–solid momentum transfer. However, this behavior was not consistently observed for all materials and drag models. Instead, the mean particle velocity exhibited significant spatial variations with both bed height and drag model, reflecting the heterogeneous nature of bubbling fluidization.

At the bottom of the bed ($y \leq 0.01\text{m}$), the mean particle velocity remained relatively low for most materials and drag models because this region is located immediately above the distributor, where the particles are densely packed, and their motion is constrained by neighboring particles and frictional contacts. An exception was observed for PR using the EMMS drag model (Fig. 7.20c), where the velocity profile exhibited a parabolic distribution with the maximum velocity occurring at the bed center and reaching approximately 0.27 m/s. This profile suggests that the EMMS model predicted stronger particle acceleration in the central region than the other drag models under the same operating conditions.

As the particles moved upward into the lower and middle dense beds at $y=0.03$ and 0.05m , substantially higher particle velocities were predicted. For WC, the Syamlal–O'Brien model

predicted the highest particle velocities, reaching approximately 0.65 m/s at $y = 0.05$ m near the center of the bed. In contrast, the Syamlal O'Brien model predicted relatively uniform velocity profiles for OFMSW at these elevations (Fig. 7.22a). These heights generally corresponded to the regions of greatest particle motion, although the radial location of the maximum velocity differed among the drag models. Localized high-velocity regions coincided with zones of lower solids concentration, whereas lower particle velocities generally occurred where the solids concentration remained relatively high, indicating that particle motion was strongly influenced by the heterogeneous distribution of solids throughout the bed.

At $y = 0.10$ m, corresponding approximately to the transition region (from dense to dilute bed), the particle velocity profiles became less uniform, and their magnitudes generally decreased because fewer particles occupied this elevation. Only the Syamlal–O'Brien and Gidaspow models predicted appreciable particle velocities at this height. In contrast, the EMMS model predicted nearly zero particle velocity for PR (Fig. 7.20c) and WC, which is consistent with the corresponding solids volume fraction contours (Sections 7.4.2.1 and 7.4.2.2), where little or no solids were observed at this elevation, indicating limited bed expansion.

At the highest sampling elevations $y = 0.12$ and 0.15 m, the velocity profiles differed considerably among the materials because these planes were located within the freeboard region. For OFMSW (Fig 22a), both the solids volume fraction and particle velocity approached zero across most of the bed diameter for both Syamlal O'Brien and Gidaspow models, indicating that only a small number of entrained particles reached these elevations. A different behavior was observed for PR and WC. PR exhibited localized velocity peaks at $y = 0.10$ and 0.15 m, with the maximum velocity approaching 0.85 m/s near the left side of the bed (Fig. 7.20a). Similarly, WC exhibited its highest localized velocity at $y = 0.12$ m near the

right side of the bed, reaching approximately 0.58 m/s (Fig. 7.21b). Because these high velocities occurred only within narrow regions of the bed cross-section, they most likely represent localized particle entrainment or intermittent upward transport rather than uniform particle motion throughout the bed.

Overall, all three drag models captured the heterogeneous nature of the bubbling fluidized bed; however, they differed in the predicted location and magnitude of the high- and low-velocity regions. These differences reflect the influence of the drag formulation on gas–solid momentum exchange and solids redistribution and are consistent with previous numerical and experimental studies, which have shown that particle velocity in bubbling fluidized beds is highly non-uniform because of bubble-induced solids circulation, particle clustering, and heterogeneous gas–solid interactions. (Miao et al., 2011; Lundberg & Halvorsen, 2008; Upadhyay et al., 2020).

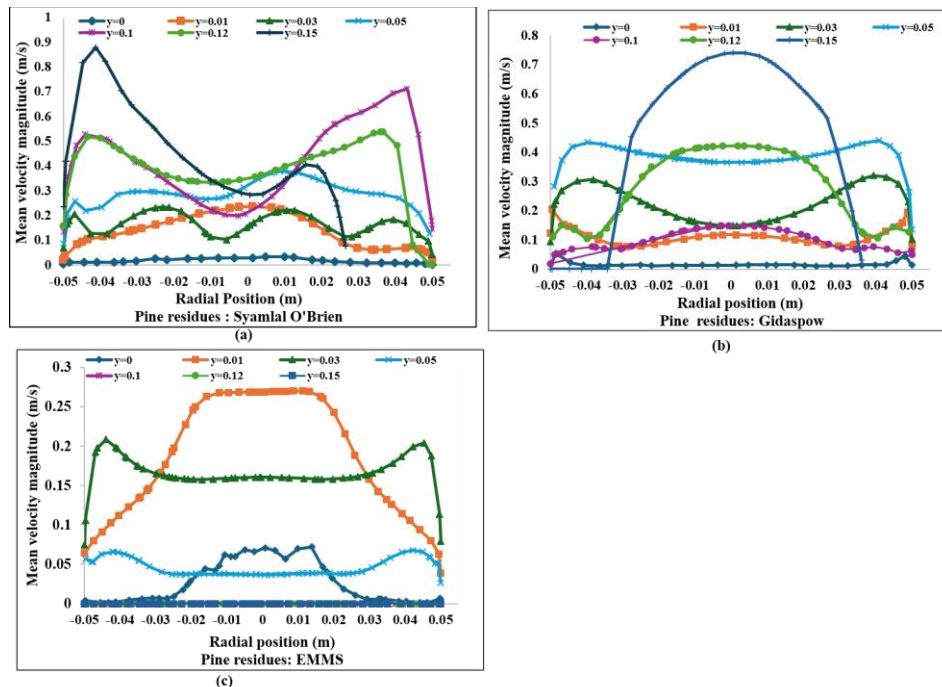


Figure 7.20: Radial mean velocity magnitude of pine residues using various drag models: (a) Syamlal O'Brien, (b) Gidaspow, (c) EMMS

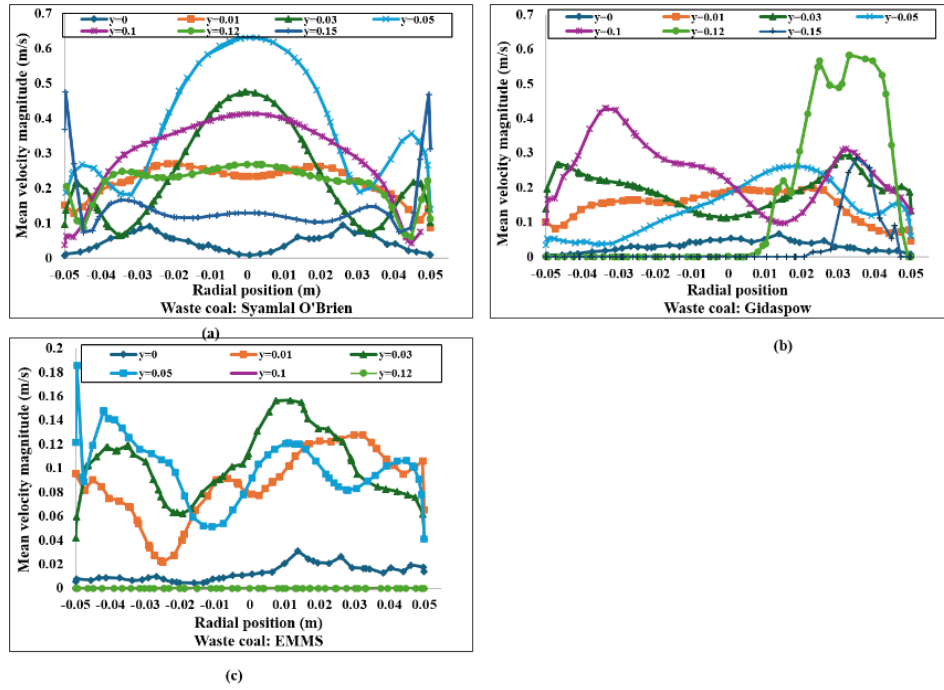


Figure 7.21: Radial mean velocity magnitude of waste coal using various drag models: (a) Syamlal O'Brien, (b) Gidaspow, (c) EMMS

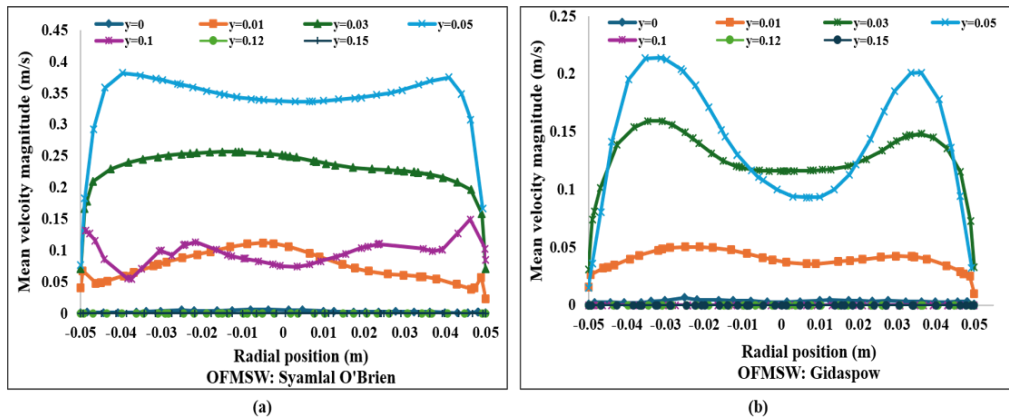


Figure 7.22: Radial mean velocity magnitude of OFMSW using various drag models: (a) Syamlal O'Brien, (b) Gidaspow

7.4.4. Effect of drag model on pressure drop profile

The pressure drops occurring in the fluidized bed are because of the interaction between the solid and the gas. Fig 7.23(a)-(c) compares the transient pressure drop profile predicted by the Syamlal–O'Brien, Gidaspow, and EMMS drag models for pine residues, waste coal and OFMSW. While Fig 7.24 through 26 reveal snapshots of the pressure drop contour for the

materials as predicted by the various drag models. As revealed in Fig 7.23(a)-(c), at the start of fluidization, there is a sudden rise in the pressure drop, usually because a higher drag force is needed to overcome the initial weight of the bed. After the bed was overcome, the bed experienced significant pressure fluctuations; however, significant differences were observed in the magnitude of the fluctuations. The Syamlal–O'Brien and EMMS models predicted the highest fluctuation amplitude of ~20 Pa and 220 Pa for PR and 105 Pa for OFMSW, respectively. This could be due to indicating vigorous particle activity and enhanced solids movement within the bed. The higher-pressure fluctuations indicate greater resistance to gas flow through the bed caused by particle interlocking and the particle cohesive forces that need to be overcome. The Gidaspow model, however, produced a relatively smaller fluctuation of ~10 Pa for PR and 240 Pa for OFMSW, respectively, suggesting a more stable fluidization regime. Consistent with the present findings, Han et al., (2025) reported that the Syamlal–O'Brien drag model generated larger inlet pressure drop oscillations during the fluidization of non-spherical biomass particles, while the Gidaspow drag model resulted in a more stable pressure drop profile with reduced fluctuation amplitudes. Waste coal (WC) exhibited a more stable pressure profile with smoother fluidization of the coal particles (oscillation magnitude of 5 Pa for Syamlal O'Brien, 3 Pa for Gidaspow, and 2 Pa for EMMS). These results demonstrate that the selected drag model significantly influences the predicted gas–solid hydrodynamics and pressure fluctuation characteristics of the fluidized bed.

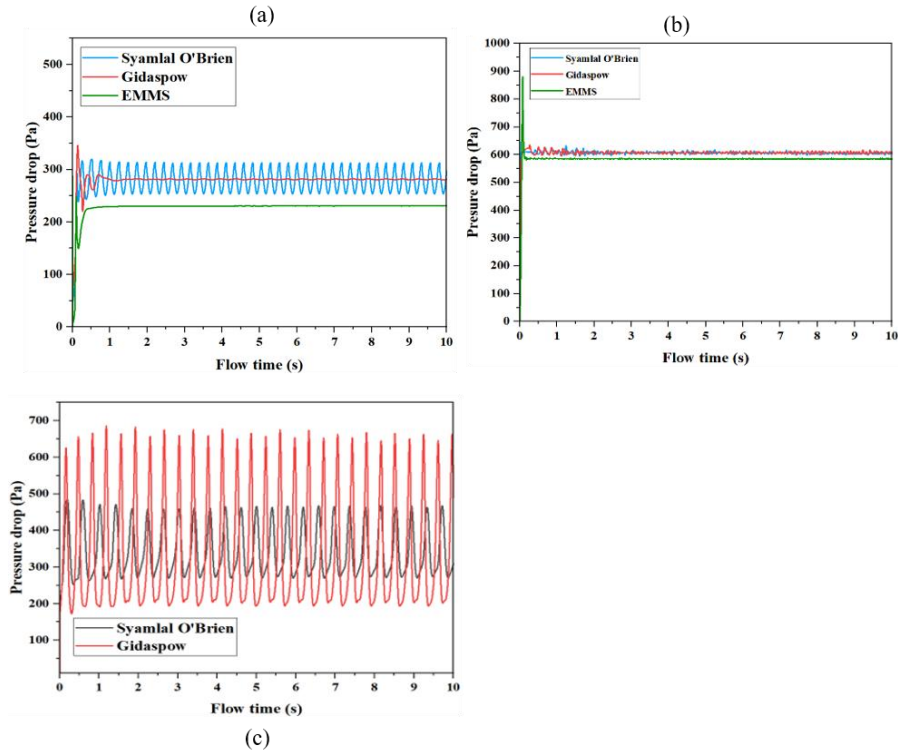


Figure 7.23: Effect of drag model on transient fluidized bed pressure drop: (a) pine residues, (b) waste coal, (c) OFMSW at $2.5U_{mf}$

The pressure drop contour snapshots shown in Figs 7.25–7.27 indicate that the highest pressure drop occurred near the bottom of the bed for all drag models. This behavior is attributed to the high solid concentration in the lower bed region, which increased the resistance to gas flow, as demonstrated by the solids volume fraction distributions discussed in Section 7.4.2.1.

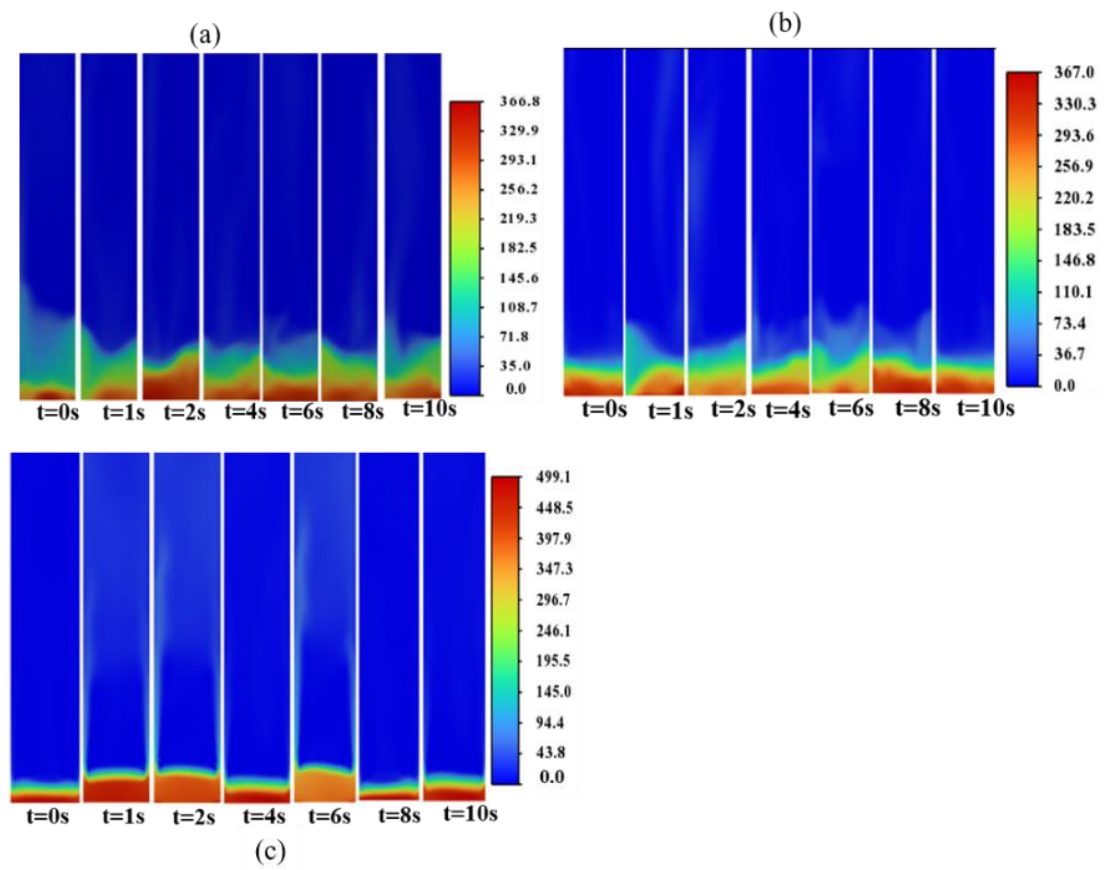


Figure 7.24: Snapshot of the transient pressure drop profile for pine residues using various drag models, at $4U_{mf}$: (a) Syamlal O'Brien, (b) Gidaspow, (c) EMMS

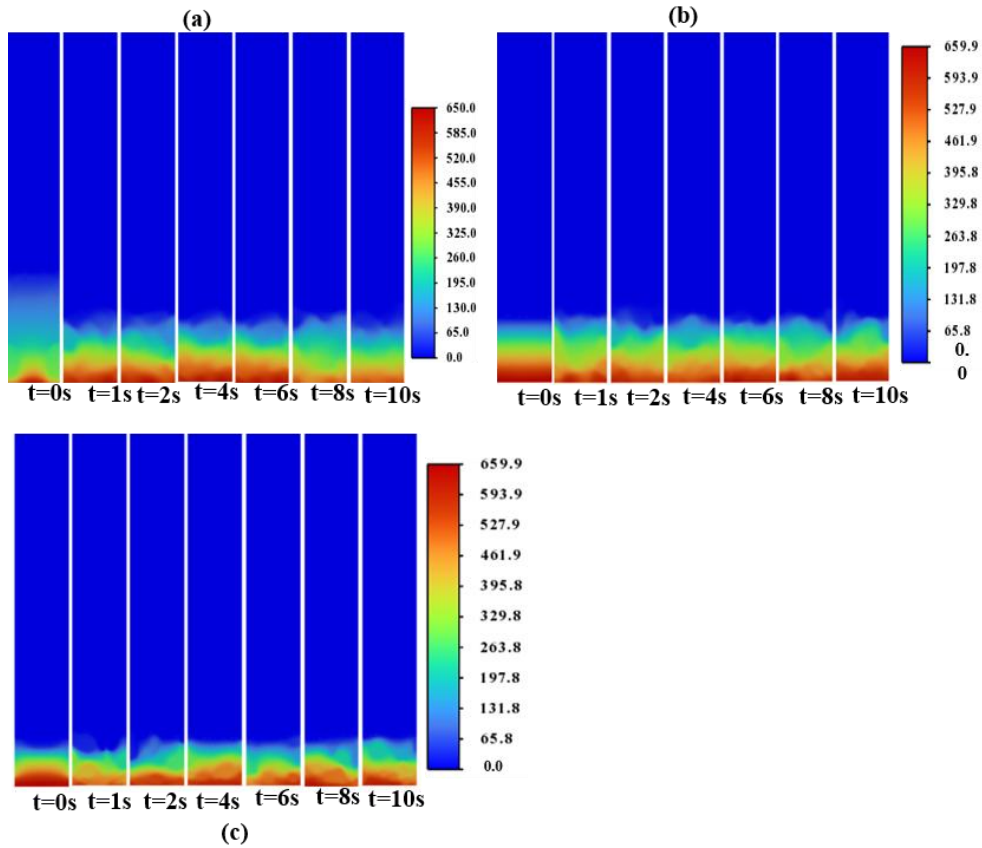


Figure 7.25: Snapshot of the transient pressure drop profile for waste coal using various drag models, at 4Umf: (a) Syamlal O'Brien, (b) Gidaspow, (c) EMMS

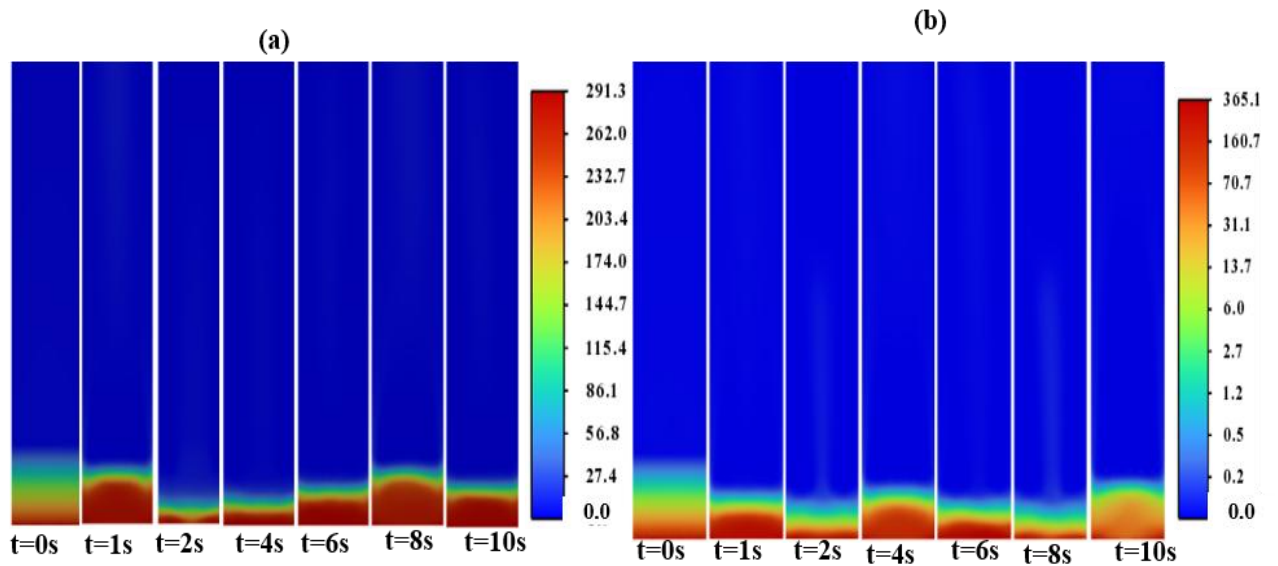


Figure 7.26: Snapshot of the transient pressure drop profile for OFMSW using various drag models, at 4Umf: (a) Syamlal O'Brien, (b) Gidaspow

7.4.4.1. Axial total pressure drops distribution prediction

This section explores how the drag model affects the pressure distribution along the fluidized bed. Fig. 7.27 (a-c) represents the variation of the total pressure drop for pine residues (a), waste coal (b), and OFMSW (c) along the bed. It can clearly be seen that the pressure drop follows the same pattern for all the simulated drag models, decreasing progressively along the bed height, with a maximum pressure drop at the bottom of the bed and a minimum at the top of the bed. Debnath et al., (2021) explained that at the lower regions of the bed, where particle packing is denser and interparticle cohesion forces are more pronounced, the gas must overcome significant resistance, which requires a high drag force. These cohesive interactions hinder the gas flow, increasing resistance and drag forces, and consequently resulting in a higher pressure drop (Debnath et al., 2021). As the gas velocity increases and particles begin to disengage and expand, the bed structure becomes more porous (fewer particles in the freeboard), reducing flow resistance. This leads to a gradual decline in pressure drop along the bed height. This pressure drop pattern resembles the trend obtained by Banik et al., (2025) in their simulation of biomass coal mixture in a dual fluidized bed reactor. Furthermore, the similarity in pressure drop trends across all drag models suggests that, although the magnitude of drag forces may vary slightly depending on the model, the overall hydrodynamic behavior of the system remains consistent.

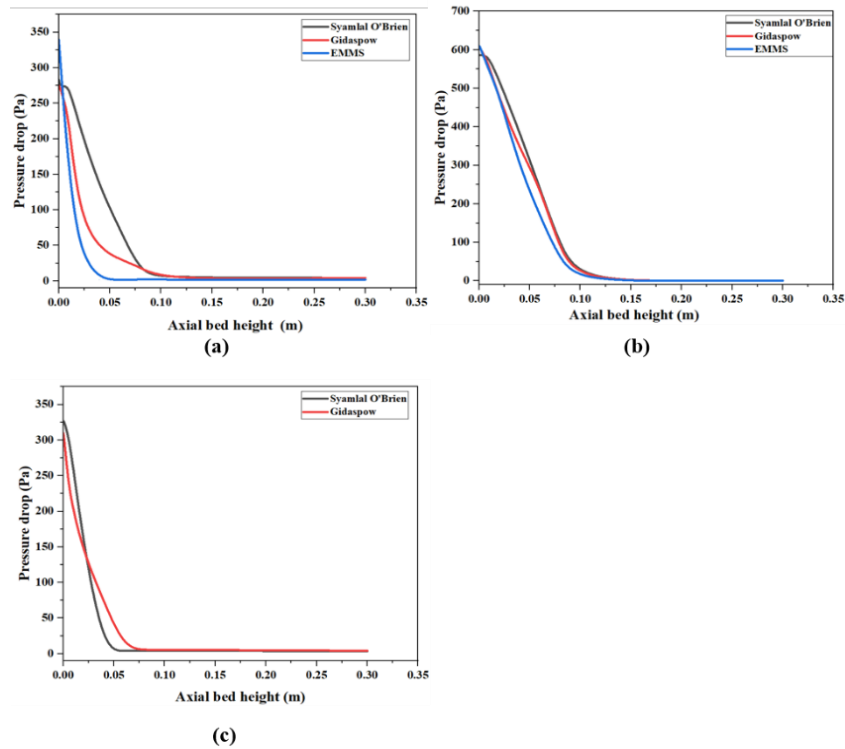


Figure 7.27: Pressure drop distribution across the zx-plane bed height for Syamlal Obrien, Gidaspow and EMMS drag model at $4U_{mf}$: (a) pine residues, (b) waste coal, (c) OFMSW

7.4.5. Comparison of the CFD simulation and experimental results

7.4.5.1. Effect of superficial gas velocity on pressure drop

In this section, the experimental pressure drop was determined as the ratio of the bed material weight to the bed surface area, and it was compared with simulated pressure drops predicted by the Syamlal–O’Brien, Gidaspow, and EMMS drag models over a various inlet air velocity range of $0.5 U_{mf}$ to $4 U_{mf}$. The simulated pressure drop was calculated as the difference between the inlet total pressure drop and the pressure measured on the zx-plane where the solid volume fraction approached zero. Figs 7.28 through 7.30 present the experimental and predicted pressure drop values for pine residues, waste coal, and MSW across the different drag models. It is evident that all three models successfully capture the characteristic pressure drop behavior of a fluidized bed as a function of superficial gas

velocity. Specifically, the pressure drop initially increases linearly with increasing gas velocity until the minimum fluidization velocity is reached, at which point a transition is observed, characterized by a sudden change in the pressure drop trend. Beyond this point, the pressure drop exhibits only minor variations with further increases in velocity, indicating stabilization of the bed. Furthermore, the Gidaspow and Syamlal O'Brien models generally better predicted the bed pressure drop across the investigated velocity range for all materials, whereas the EMMS model tended to underpredict it. Among the models evaluated, the Syamlal O'Brien and Gidaspow models showed the closest agreement with the experimental data over most of the velocity range, suggesting a more accurate representation of gas–solid momentum exchange. In contrast, the EMMS model exhibited the largest deviations at higher gas velocities, where it predicted pressure drops significantly higher than those measured experimentally.

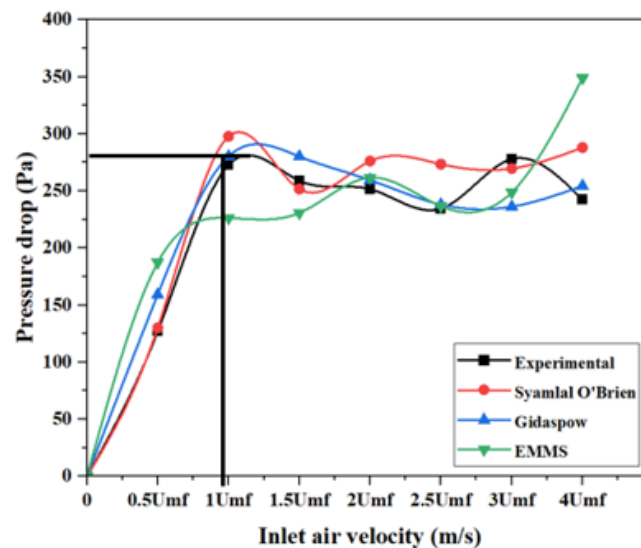


Figure 7.28: Effect of inlet air velocity on the pressure drop in fluidized bed of waste coal using various drag models

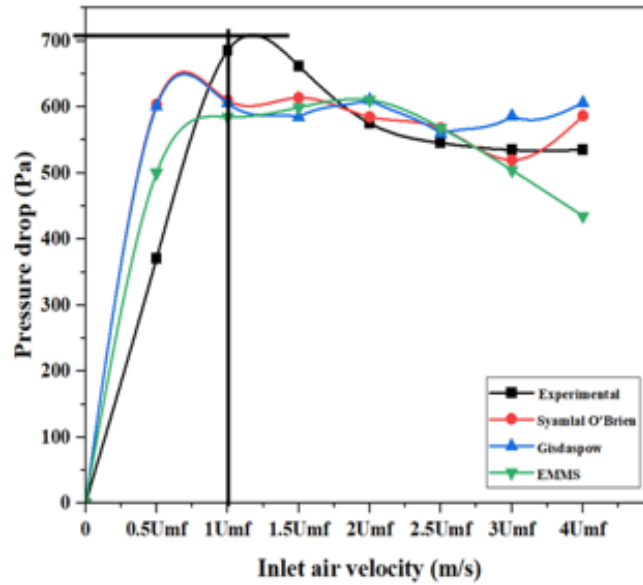


Figure 7.29: Effect of inlet air velocity on the pressure drop in fluidized bed of waste coal using various drag models

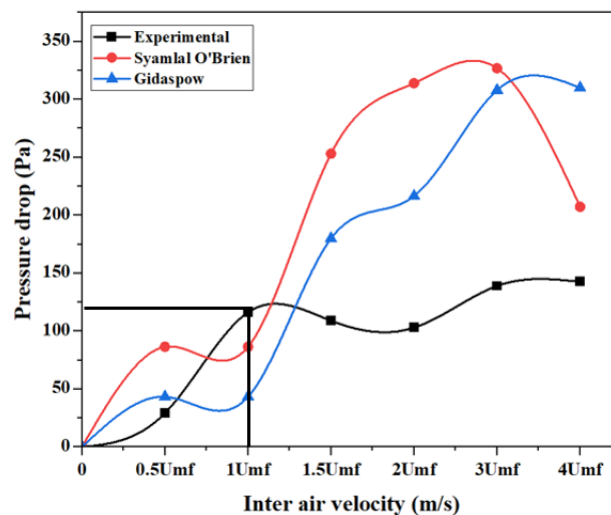


Figure 7.30: Effect of inlet air velocity of the fluidized bed pressure drop of OFMSW using different drag models

Tables 7.4–7.6 reveal the mean relative deviation (MRD) between the experimental and simulated pressure drops for pine residues, waste coal, and OFMSW. For all three materials, the EMMS drag model exhibited an increasing deviation with increasing inlet gas velocity. In contrast, the Syamlal–O'Brien and Gidaspow drag models maintained consistently low deviations over the entire velocity range, indicating their superior ability to capture the complex gas–solid interactions occurring within the fluidized bed. Among the materials

investigated, OFMSW showed the highest deviation across all drag models, with MRD values exceeding 20% (Table 7.6). This behavior is attributed to its poor fluidization characteristics, even at elevated gas velocities, resulting from its high particle cohesion, low bulk density, and highly fluffy structure, which promote agglomeration and hinder stable fluidization.

Table 7.5: % Mean relative error between experimental and simulated pressure drop for pine residues using Syamlal O'Brien, Gidaspow, and EMMS drag models

Gas velocity	Syamlal O'Brien	Gidaspow	EMMS
1Umf	-9.17	-2.79	17.01
1.5Umf	2.84	-8.17	10.90
2Umf	-9.79	-3.20	-4.06
2.5Umf	-5.89	-1.49	-0.91
3Umf	2.98	15.04	10.49
4Umf	-18.8	-4.93	-43.84

Table 7.6: % Mean relative error between experimental and simulated pressure drops for coal using Syamlal O'Brien, Gidaspow and EMMS drag model

Gas velocity	Syamlal O'Brien	Gidaspow	EMMS
1Umf	10.93	11.50	14.65
1.5Umf	7.25	11.65	9.51
2Umf	-1.70	-6.15	-6.15
2.5Umf	-4.08	-2.66	-4.20
3Umf	2.83	-9.64	5.72
4Umf	-9.69	-13.36	18.69

Table 7.7: % Mean relative error between experimental and simulated pressure drop for OFMSW using Syamlal O'Brien, and Gidaspow drag model

Gas velocity (m/s)	Syamlal O'Brien	Gidaspow
1Umf	25.61	62.77
1.5Umf	-132.31	-65.13
2Umf	-204.85	-110.21
3Umf	-135.21	-121.58
4Umf	-45.32	-117.34

7.4.5.2. Effect of the superficial gas velocity on the bed expansion

The primary objective of fluidization is to impart fluid-like behavior to solid particles through the introduction of an upward gas flow. The quality of fluidization is commonly evaluated by the degree of particle suspension within the bed, as greater suspension enhances gas–solid contact and improves momentum transfer between phases. In general, bed expansion increases with gas velocity because higher velocities generate sufficient drag force to counteract the weight of the bed material, leading to bed dilation. Figs 7.31–7.33 illustrate the evolution of bed contours at varying inlet air velocities. Notably, for pine residues, WC, and OFMSW (Figs 7.21 and 7.23), a bed contraction was observed between 1 and 1.5 Umf for pine residues, while OFMSW exhibited shrinkage across nearly all velocities and drag models. This behavior was not observed experimentally. The contraction can be attributed to the high void fractions of these biomasses ($\varepsilon = 0.81$ for pine residues and 0.91 for OFMSW), which correspond to very low solid volume fractions ($\varepsilon_s \approx 0.19$ and 0.09, respectively). Although a value of 0.25 was used in the simulations to approximate experimental conditions, the inherently low solid fractions likely contributed to the

discrepancy. While the Syamlal–O’Brien and Gidaspow models are generally capable of capturing hydrodynamics in dilute systems ($\epsilon_s < 0.2$), they did not adequately predict the behavior of pine residues and OFMSW at low velocities. Under such dilute conditions, particles have substantial spacing, and gas flow can induce particle rearrangement, resulting in temporary bed contraction before sufficient drag develops to promote expansion. This effect is further intensified by the irregular shape and interlocking nature of biomass particles, which encourage compaction before fluidization features that are not well represented in the Eulerian framework. At higher gas velocities (above 1.5 U_{mf} for pine residues and 3 U_{mf} for OFMSW), the bed eventually expands as expected. In contrast, waste coal exhibited a more conventional response, with bed height increasing approximately linearly with air velocity, particularly above the minimum fluidization velocity, consistent with findings reported by Debnath et al., (2019). Unlike biomass materials, coal particles are more uniform in size and shape and possess a higher solid volume fraction ($\epsilon_s \approx 0.48$). These properties align well with the assumptions of the Eulerian and KTGF models, which are based on spherical or near-spherical particle behavior (Ullah et al., 2019). The observed increase in bed height with increasing air velocity can be attributed to the rise in gas volume fraction at higher velocities, leading to the formation of larger bubbles and, consequently, greater bed expansion

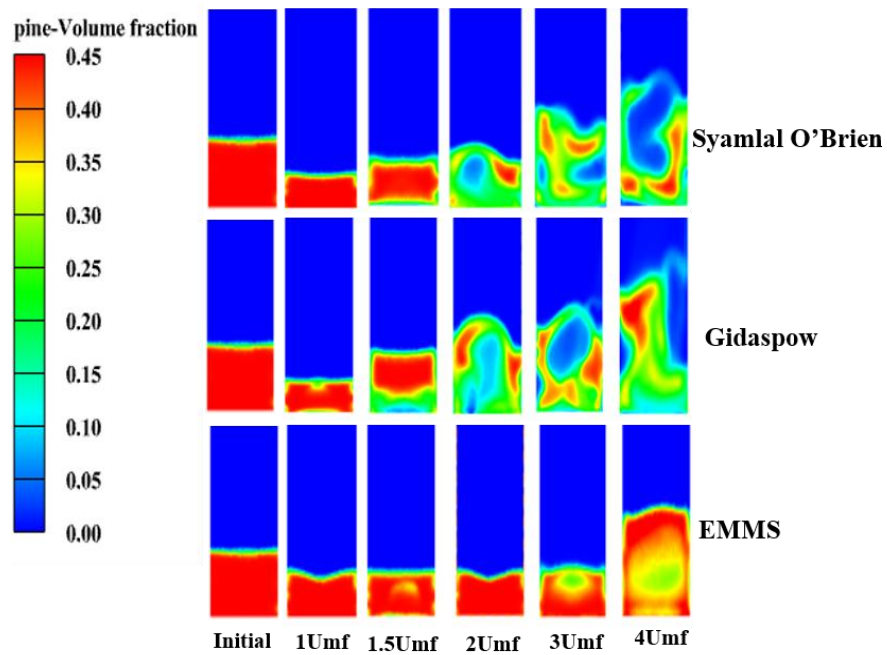


Figure 7.31: Snapshot of the pine residues bed evolution at different air velocity using Syamlal O'Brien, Gidaspow, and EMMS drag models

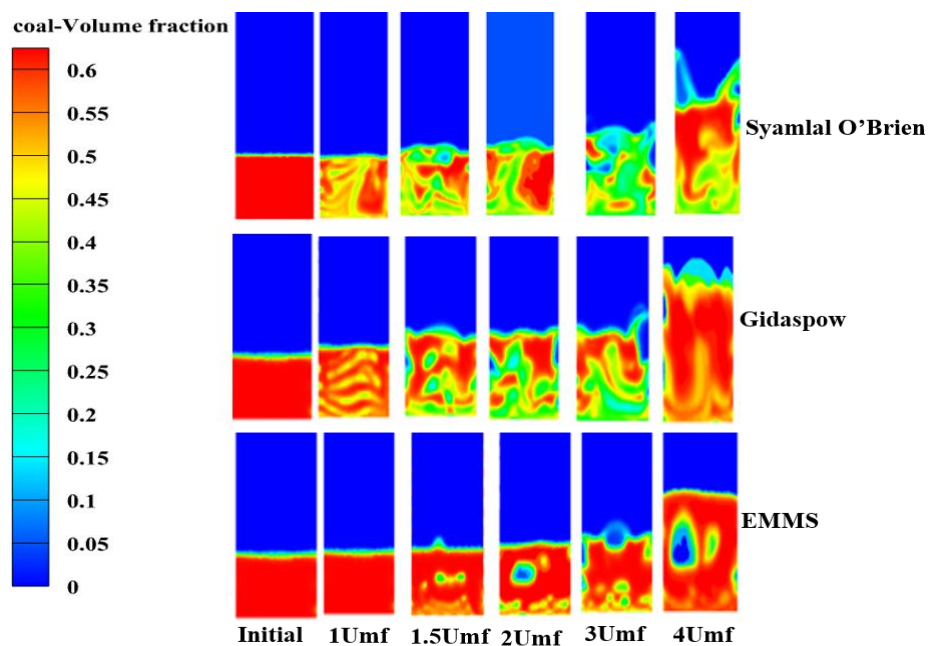


Figure 7.32: Snapshot of the coal bed evolution at different air velocity using Syamlal O'Brien, Gidaspow, and EMMS drag models

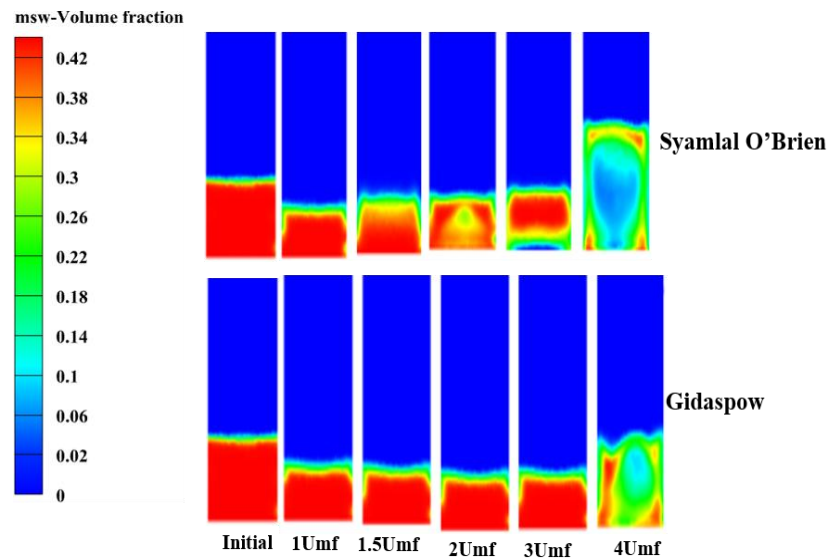


Figure 7.33: Snapshot of the OFMSW bed evolution at different air velocities using Syamlal O'Brien and Gidaspow drag models

Figs. 7.34, 7.35 and 7.37 illustrate the experimental visualization of the bed expansion at different inlet air velocities. The same bed expansion pattern was noticed for all the studied materials; the bed expanded significantly as the inlet air velocity was increased, similarly to the finding of Debnath et al., (2021), which was due to the larger volume fraction of the air introduced. However, for waste coal at 1Umf, for example, the predicted bed height was equal to the experimental value (it is worth mentioning that during the experiment no noticeable bed elevation was observed at the minimum fluidization velocity; only bubbles were seen in the bed at that velocity). The percentage increase in the bed height for all the materials is presented in Table 7.7.

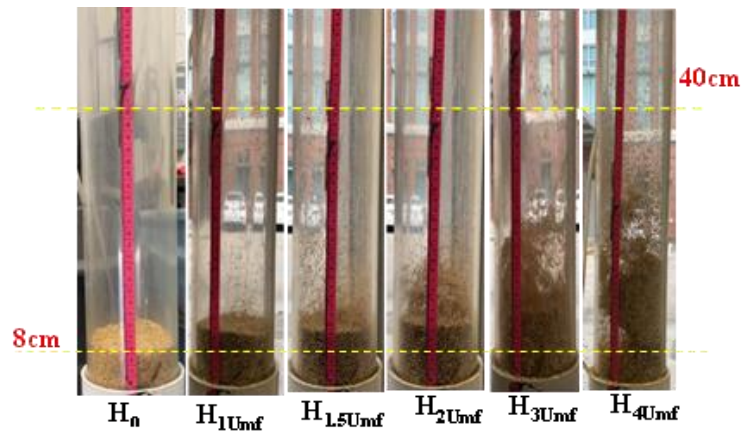


Figure 7.34: Experimental visualization of the pine residues bed expansion at different inlet air velocity

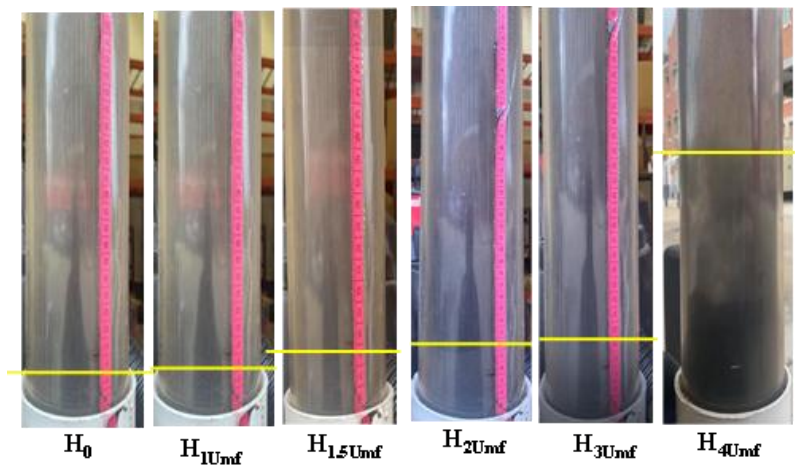


Figure 7.35: Experimental visualization of the waste coal bed expansion at different inlet air velocity

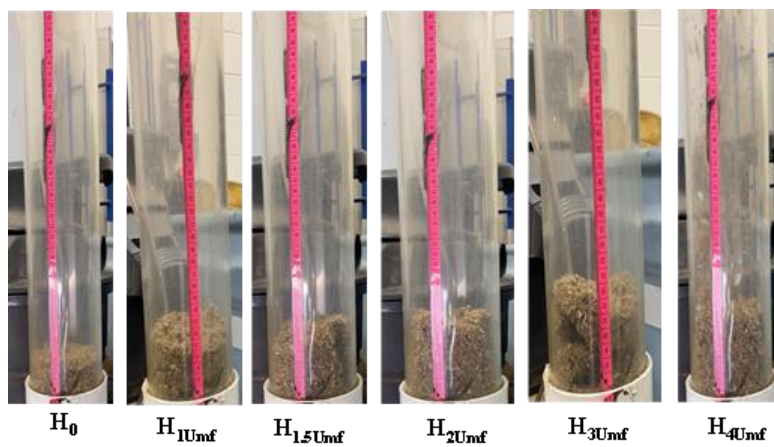


Figure 7.36: Experimental visualization of the pine residues bed expansion at different inlet air velocity

Table 7.8: Comparison of static and expanded bed heights (%increase in bed height)

Air velocity (m/s)	pine residues	waste coal	OFMSW
1Umf	25	0	25
1.5Umf	112.5	37.5	25
2Umf	150	50	56.25
3Umf	212.5	212.5	75
4Umf	425	375	100

The predicted bed heights for pine residues, waste coal, and OFMSW obtained using different drag models at varying air velocities are compared with the experimental data, and the results are in Figs 7.37, 7.38, and 7.39, respectively. To facilitate this comparison, a dimensionless parameter was defined as the ratio of expanded bed height to the initial bed height, expressed as $ER = \frac{H_{Umf} - H_0}{H_0}$, where ER , H_{Umf} , and H_0 is the bed expansion ratio, the bed height at a specific inlet velocity, and the initial bed height, respectively. The error bars represent the standard deviation between different experimental measurements. As shown in the figures, all drag models tend to underestimate the bed height, with the discrepancy becoming more pronounced at higher air velocities, consistent with the observations of Battaglia, (2016). In the case of waste coal, the predicted bed heights were closest to the experimental values across all velocities and drag models. However, bed expansion for coal was only observed when the air velocity reached 1.5 Umf and above across all models considered. Overall, the Syamlal–O’Brien drag model provided the most accurate predictions of bed height across all samples and velocities, followed by the Gidaspow and EMMS models. The mean relative deviation (MRD) between experimental and simulated bed heights for pine

residues, waste coal, and OFMSW is reported in Tables 7.8 to 7.10, respectively. Deviations exceeding 10% were observed for all samples, increasing with air velocity regardless of the drag model used. Among the materials, OFMSW exhibited the highest deviation, reaching values up to 82%, followed by pine residues and waste coal. A part of this deviation is due to the non-uniform size of the biomass and also the large size of particles.

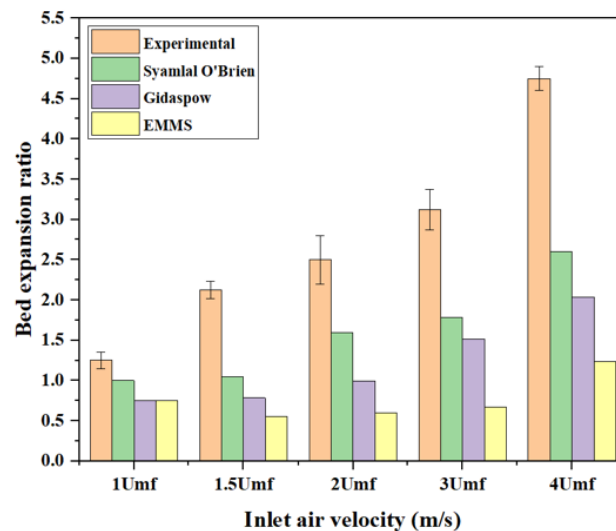


Figure 7.37: Effect of inlet air velocity on the predicted bed height of pine residues using different drag models

Table 7.9: %MRD between experimental and predicted bed height for pine residues

Velocity (m/s)	Syamlal O'Brien	Gidaspow	Emms
1Umf	20	40	60
1.5Umf	50.88	63.11	74
2Umf	36.15	60.25	76
3Umf	43	51.5368	79
4Umf	50.47	61.16	76.42

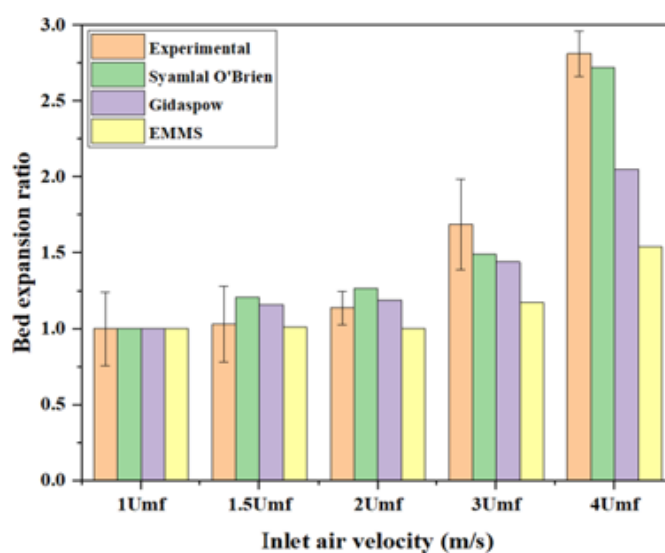


Figure 7.38: Effect of inlet air velocity on the predicted bed height of waste coal using different drag models

Table 7.10: %MRD between experimental and predicted bed height for waste coal

Velocity (m/s)	Syamlal O'Brien	Gidaspow	Emms
1Umf	0	0	0
1.5Umf	15.25	15.71	26.34
2Umf	15.55	20.62	32.5
3Umf	52.25	55.76	62.51
4Umf	22.28	41.39	56.00

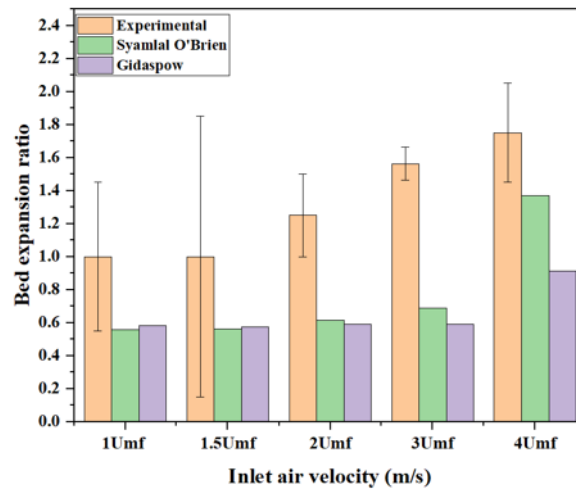


Figure 7.39: Effect of inlet air velocity on the predicted bed height of pine residues using different drag models

Table 7.11: %MRD between experimental and predicted bed height for OFMSW

Velocity	Syamlal	Gidaspow
(m/s)	O'Brien	
1Umf	37.13	40.94
1.5Umf	49.70	52.75
2Umf	60.58	62.20
3Umf	60.63	47.93
4Umf	31.43	82.06

7.5. Conclusion

CFD simulations were employed to investigate the fluidization hydrodynamics of pine residues, waste coal, and OFMSW in a fluidized bed, and the results were compared to the experimental data. The Eulerian–Eulerian approach coupled with KTGF was used to capture the key fluidization phenomena, including pressure drop development, bed expansion, and solids redistribution within the bed. In the first part of this study, the effect of mesh size on the predictive capabilities of the Eulerian approach to predict the gas-solid interaction within the fluidized bed was evaluated. For the computational domain, mesh sizes of 2, 3, 4, 5, and 6mm were evaluated. The simulated pressure drop and the bed evolution profile were compared with experimental data using pine residues. For the pressure drop, the MRD for each mesh was 0.2, 2.36, 9.65, 3.92, and 10.76% for 2, 3, 4, 5, and 6 mm, respectively. In addition, the percentage MRD between the experimental and simulated bed expansion was found to be 31.38, 41.31, 49.27, 44.19, and 46.93% for 2, 3, 4, 5, and 6mm mesh size, respectively. The mesh selected did not predict comparable bed expansion; however, the predicted pressure drop showed good agreement with experimental data. Although the 2mm mesh size showed the least error for pressure drop prediction, the simulation time was higher than all the rest of the mesh sizes, hence 3mm mesh size, which was the second best, was selected for subsequent study.

The simulation results demonstrated that the choice of drag model significantly affects the predicted gas–solid hydrodynamics. The models predicted larger pressure fluctuations for pine residues and OFMSW, which can be attributed to the formation of large channels and particle clustering within the bed, leading to increased resistance to airflow. Waste coal, on the other hand, exhibited smooth and stable bed behavior for all the drag models used. Among the drag models evaluated, the Syamlal O’Brien and Gidaspow models generally provided the

closest agreement with the experimental pressure drop data and produced realistic predictions of bed behavior over the investigated velocity range, especially for pine residues and waste coal with MRD less than 10% in most cases. However, OFMSW predicted higher pressure drop MRD across the velocity range studied. The solid volume fraction contours revealed distinct fluidization characteristics for the three materials. Pine residues and waste coal exhibited significant bed expansion and solids circulation for Syamlal O'Brien and Gidaspow models, whereas the EMMS model predicted a relatively dense bed with bubbling behavior. In contrast, OFMSW displayed limited bed expansion and poor solids suspension. Overall, all the drag forces studied underpredicted the bed expansion for all three materials across all velocities.

7.6. References

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Chapter 8. Conclusion and recommendation

8.1. Conclusions

This study systematically investigated the effects of moisture content and blend compositions on the physical, flow, and fluidization behavior of pine residues (PR), waste coal (WC), and the organic fraction of municipal solid waste (OFMSW) through a combination of experimental characterization, thermal analysis, machine learning, and computational fluid dynamics (CFD). The research established the relationships between particle physical properties, flowability, drying behavior, and gas–solid hydrodynamics to improve the understanding of biomass-coal blend fluidized bed systems.

In chapter 3, the physical characterization demonstrated that moisture significantly altered the packing and flow behavior of the PR, WC, and OFMSW blend. Increasing moisture generally increased particle cohesion, adhesion, compressibility, and flow index and reduced the overall flowability of the blends. Waste coal exhibited the most favorable flow characteristics at low moisture content $\leq 10\%$, whereas OFMSW consistently displayed poor flowability owing to its low density and flat shape. Additionally, statistical analysis revealed that the properties of the blends cannot be adequately explained by the characteristics of individual components alone but rather arise from complex interactions among feedstocks with differing physical attributes, including particle size distribution, particle shape, porosity, and moisture retention capacity. SHAP analysis identified moisture content and high OFMSW proportions as key contributors to reduced flowability. Conversely, blends with higher waste coal content demonstrated improved bulk density and lower compressibility, facilitating better handling characteristics. Among the machine learning models evaluated, XGBoost, Random Forest (RF), and Support Vector Regression (SVR) exhibited strong predictive performance for

the physical and flow properties. XGBoost achieved the highest overall accuracy, with R^2 values exceeding 90% for six of the ten properties assessed. RF accurately predicted two properties, while SVR showed strong performance for one property.

Chapter 4 addresses the effect of moisture content and the blend ratio on the energy requirement for drying the blends. Inverse gas chromatography revealed substantial differences in surface properties among the feedstocks. Waste coal exhibited the highest BET surface area and surface energy, whereas pine residues and OFMSW possessed lower surface energies but greater concentrations of oxygen-containing functional groups. Differential scanning calorimetry further demonstrated that drying energy increased nonlinearly with the moisture content, reflecting the increasing contribution of bound water at lower moisture levels. Statistical analysis further indicated that drying energy in the blends is predominantly governed by the structural characteristics of the feedstocks and their interactions, rather than moisture content alone. Specifically, no significant correlation was observed between drying energy and the linear moisture term, whereas strong correlations were identified with non-linear moisture effects and component interactions

The fluidization experiments conducted in Chapter 5 showed that moisture content strongly influenced the minimum fluidization velocity (U_{mf}), pressure drop, and fluidization index (FI). Increasing moisture content significantly increased the U_{mf} of the blends and reduced the FI . It was found that incorporating waste coal into biomass blends improved the overall fluidization performance by increasing the bulk density of the mixtures and reducing interparticle cohesive forces. Also, increasing moisture content significantly decreased the particle density and bed porosity what play a significant role in fluidization behavior. Using a machine learning approach, we were able to successfully capture the nonlinear relationships between moisture content and blend composition. Both Random Forest and XGBoost

accurately predicted minimum fluidization velocity and pressure drop, with coefficients of determination exceeding 0.98. Feature importance analysis further demonstrated that moisture content was the dominant variable controlling fluidization behavior, while blend composition primarily influenced packing characteristics and density-related properties. Additionally, a new model was developed based on the original Ergun equation to predict the bed pressure drop and the U_{mf} . A new void fraction correlation was developed by accounting for the moisture effect, and model fitting was carried out by including terms for the coefficient of variation and particle shape that were originally lacking in Ergun's equation. Overall, the proposed U_{mf} model showed good agreement with the experimental data, exhibiting a mean relative deviation of less than 10%. New coefficients, K_1 and K_2 , of 270.5 and 1.13 for PR, and 381.72 and 3.85 for OFMSW, respectively, were estimated by the model. The results further demonstrated that the modified model provided better predictions of the pressure drop behavior compared to the original Ergun equation.

The fluidization behavior of PR, WC, and OFMSW was investigated using computational fluid dynamics in Chapter 6. The Eulerian–Eulerian CFD simulations coupled with the kinetic theory of granular was carried out using the commercial code Ansys Fluent software R1. The interaction between the gas and solid in the fluidized bed was assessed using the Syamlal O'Brien, Gidaspow and the energy minimization multiscale (EMMS) drag models. Among the drag models investigated, the Syamlal–O'Brien and Gidaspow models provided more accurate predictions of pressure drop, bed expansion, and solids distribution than the EMMS model under the operating conditions considered. The simulations demonstrated that solids distribution within the bed was highly heterogeneous, with higher concentrations occurring near the reactor walls and lower concentrations within the central bubbling region. Similarly, particle velocity distributions varied considerably with bed height and drag model, reflecting

localized gas–solid interactions, particle clustering, and bubble-induced solids circulation.

The CFD results further confirmed that drag model selection significantly influences predicted gas–solid hydrodynamics, emphasizing the importance of selecting appropriate closure models for biomass fluidization.

8.2. Original contributions

This study provided:

- a) Detailed investigations on the effect of moisture content and blend component ratio on physical and flow behavior of pine residues, organic fraction of municipal solid waste, and waste coal blends using statistical analysis and machine learning approaches
- b) Detailed understanding of the importance of blend component interaction effect and the moisture content on the overall drying energy requirement of pine residues, waste coal, and OFMSW
- c) Developed pressure – velocity model by modifying Ergun’s equation, which also required proposing a void fraction correlation by accounting for the moisture content in pine residues and OFMSW feedstocks
- d) Developing a Eulerian-Eulerian model for the numerical simulation of pine residues, waste coal and OFMSW fluidized bed and validating the simulation results with experimental data. The impact of airflow velocity on bed inventory was also scrutinized.

8.3. Future recommendations

Although this study significantly advances the understanding of biomass waste-coal fluidization, several areas require further investigation to improve both experimental characterization and numerical prediction.

- 1) Future work should investigate larger reactor scales and pilot-scale fluidized beds to evaluate whether the hydrodynamic trends observed in the laboratory reactor remain valid under industrial operating conditions.
- 2) Since this study was conducted under cold-flow conditions, future work should investigate fluidization behavior at elevated temperatures, where thermal decomposition and volatile release progressively reduce particle mass and modify particle properties. These changes are expected to influence particle buoyancy, segregation, and overall bed hydrodynamics. Consequently, further studies are needed to evaluate the effects of thermal decomposition on particle trajectories, bubble formation, particle entrainment, and segregation over a range of fluidizing gas velocities
- 3) Further investigation of moisture migration and evaporation during fluidization is recommended by coupling CFD with heat and mass transfer models. Such simulations would improve understanding of how free and bound moisture influence particle cohesion, drying kinetics, and subsequent fluidization behavior.
- 4) This study demonstrated that the physical property of the feedstock blends significantly influenced their fluidization behavior and the accuracy of fluidization predictions. Therefore, future research should focus on developing improved methods for accurately characterizing the physical properties of heterogeneous feedstocks, particularly the organic fraction of municipal solid waste (OFMSW). Given its highly heterogeneous composition and variable physical characteristics, more representative characterization techniques are needed to improve the prediction of its hydrodynamic behavior and enhance the accuracy of fluidized-bed models

Appendix 1: additional graphs for Chapter 4

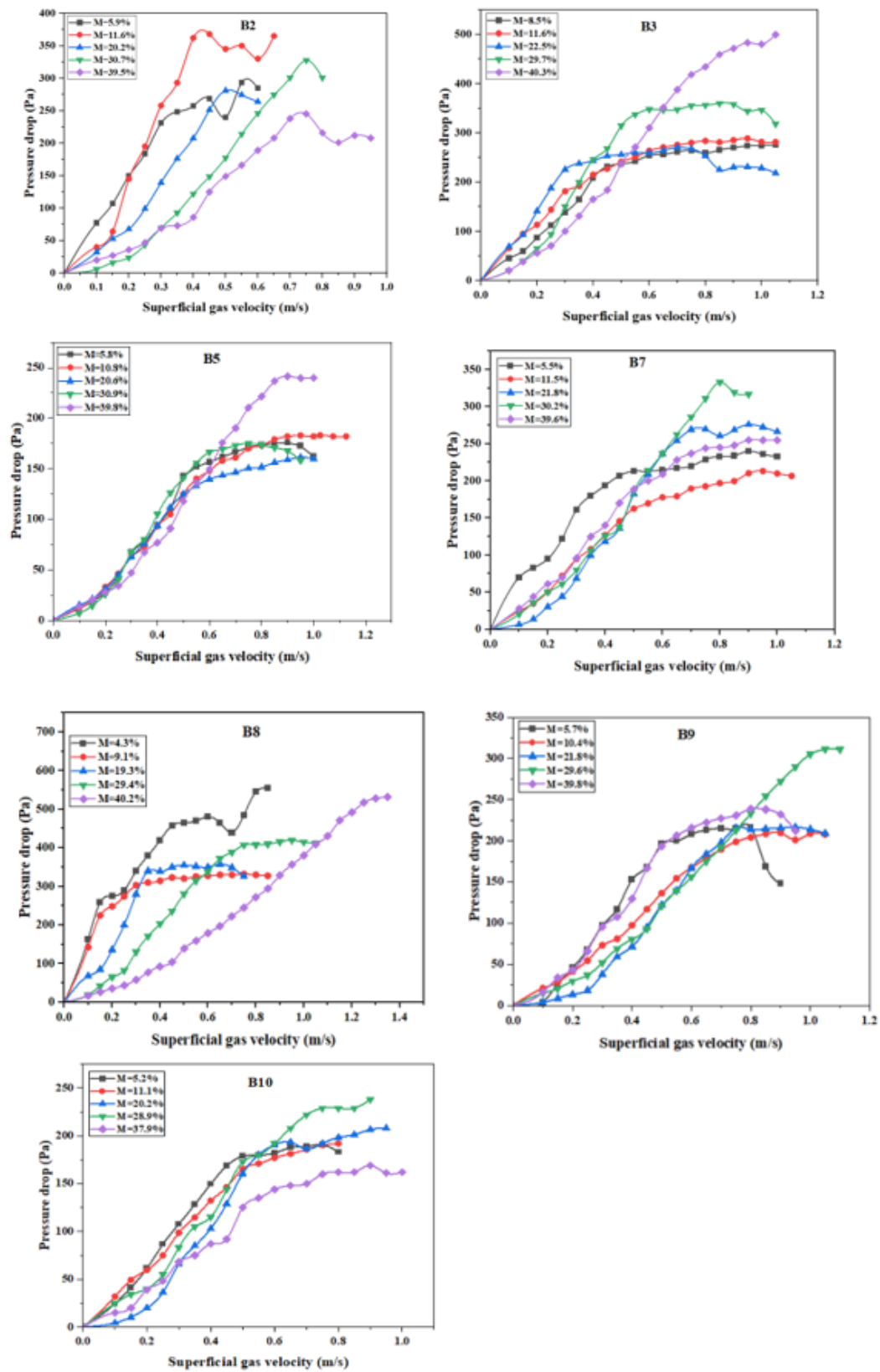


Figure 8.1: Pressure drop versus superficial gas velocity at various moisture contents

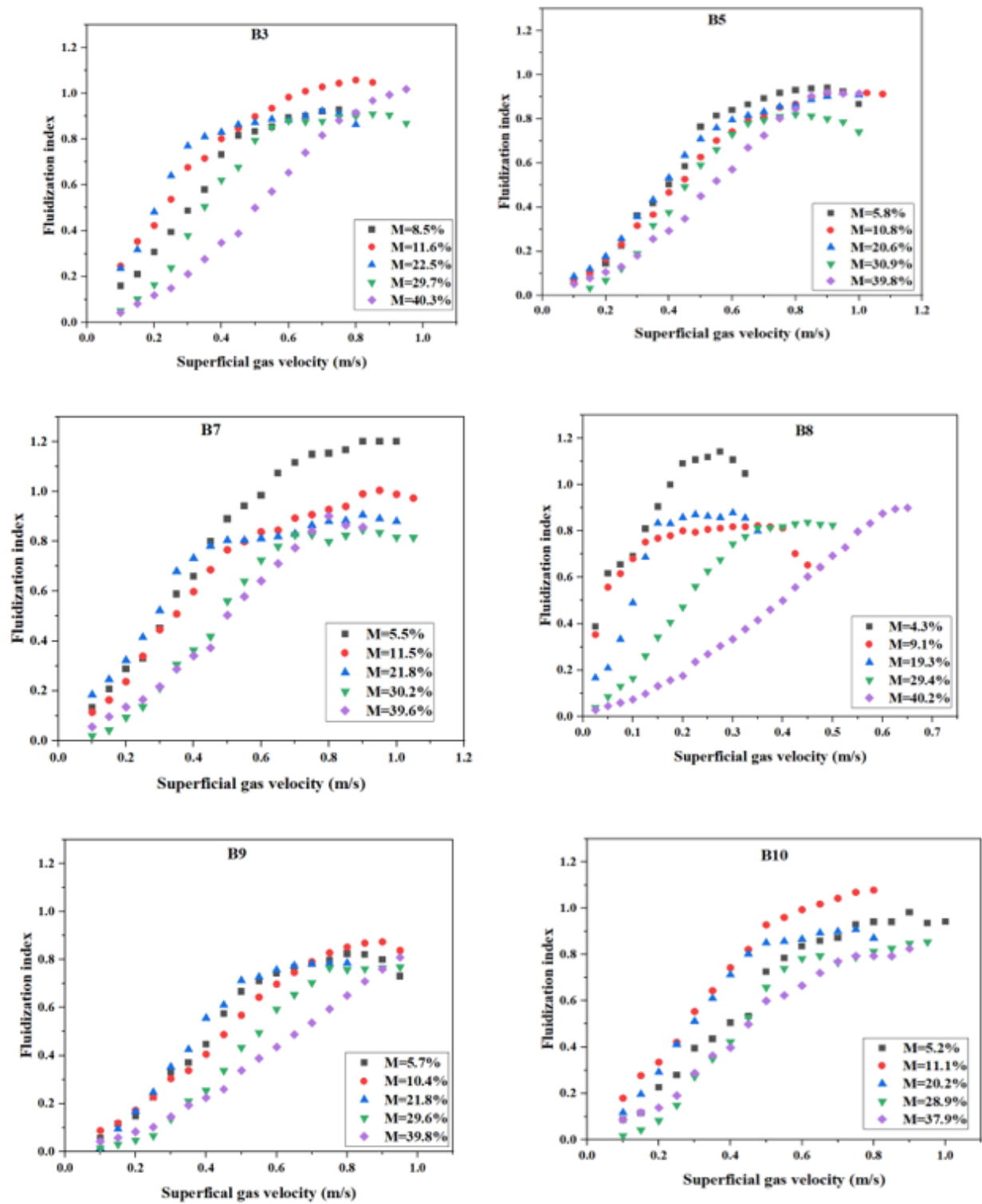


Figure 8.2: Effect of moisture content on fluidization index

Appendix 2: Constants used in the Energy Minimization Multi-scale drag model

$$\begin{cases}
 a = 0.8526 - \frac{0.5846}{1 + (\frac{\epsilon_g}{0.4325})^{22.6279}} \\
 c = 0
 \end{cases} \quad (0.4 \leq \epsilon_g < 0.46)$$

$$\begin{cases}
 a = 0.0320 + \frac{0.7399}{1 + (\frac{\epsilon_g}{0.4912})^{54.4265}} \\
 b = 0.00225 + \frac{772.0074}{1 + 10^{66.3224(\epsilon_g - 0.3987)}} + \frac{0.02404}{1 + 10^{53.8948(0.5257 - \epsilon_g)}} \\
 c = 0.1705 - \frac{0.1731}{1 + (\frac{\epsilon_g}{0.5020})^{37.7091}}
 \end{cases} \quad (0.46 \leq \epsilon_g < 0.545)$$

$$\begin{cases}
 a = (2124.956 - 2142.3\epsilon_g)^{-0.4896} \\
 b = (0.8223 - 0.1293\epsilon_g)^{13.0310} \\
 c = \frac{\epsilon_g - 1.0013}{-0.06633 + 9.1391(\epsilon_g - 1.0013) + 6.9231(\epsilon_g - 1.0013)^2}
 \end{cases} \quad (0.545 \leq \epsilon_g < 0.99)$$

$$\begin{cases}
 a = 0.4243 + \frac{0.8800 \exp(\frac{0.9989 - \epsilon_g}{0.00003})}{1 + \exp(\frac{0.9942 - \epsilon_g}{0.00218}) + \exp(\frac{0.9989 - \epsilon_g}{0.00003})} \\
 b = 0.01661 + 0.2436 \exp(-0.5(\frac{\epsilon_g - 0.9985}{0.00191})^2) \\
 c = 0.0825 - 0.0574 \exp(-0.5(\frac{\epsilon_g - 0.9979}{0.00703})^2)
 \end{cases} \quad (0.99 \leq \epsilon_g < 0.9997)$$

$$\begin{cases}
 a = 1 \\
 c = 0
 \end{cases} \quad (0.9997 \leq \epsilon_g < 1)$$

Figure 8.3: Coefficient for the Energy Minimization Multi-Scale model