Optimization methods incorporating statistical and machine learning models in traffic safety

by

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Abstract

In this dissertation, we investigated the optimization and statistical models regarding the safety aspects of trucking operations. A significant gap in the literature has been identified concerning the interaction between these two kinds of models. The majority of the optimization models in the discipline of transportation safety are related to hazardous transportation with the specialty of high consequence and low probability. For general risk on the road and truck drivers, statistically significant risk factors have been extensively used in optimization approaches. The first chapter is concerned with describing the relevant literature and corresponding gap. To address this disparity, a dynamic model that is easy to combine with the statistical risk modeling approaches has been developed to help the driver schedule the rest stops and select the optimal speed during the route under different conditions in the second chapter. Here, the objective of the dynamic model is to minimize the cumulative travel time and the risk on the road simultaneously by using the averaged weighted method to combine the two objectives. Another approach to incorporating risk factors into trucking routing, referred to as the bi-objective k-shortest paths problem has been studied in the third chapter. This method's framework comprises three major steps: finding the k-shortest paths, predicting the total travel time and risk for each path, and applying Pareto ranking to find the non-dominate sets of paths. The risk and travel time are time-related factors due to time-dependent weather and speed. With the help of the bi-objective model, the driver can determine the optimal route by taking into account multiple factors. Both approaches in dynamic model and bi-objective ksp model rely on explicitly constructed risk models, arrived at through either statistical or machine learning modeling. Another possible framework for incorporating driving-related data into decision-making is inverse reinforcement learning (IRL). IRL is a method to allow us to learn from the expert's data from decision-making. More specifically, by building a Markov Decision Processes (MDP) model, the purpose of IRL is to find the reward for each state-action

pair. The reward is structured according to those features variables related to the state and action variables in the MDP model. Thus, it gives us an opportunity to understand how those experts determine the best action given various driving conditions. The results show that the weather features are significant factors in determining the mean speed. Consequently, the derived reward function can be employed in a Q-learning framework to determine the optimal policy.

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Chapter 1

A Review of Data Analytic Applications in Road Traffic Safety

1.1. Research gap between the descriptive and prescriptive models

A lot of researches have been done to improve the safety issue of trucker drivers during the past few years. However, the interaction between the statistical model and the optimization model is not obvious. For the statistical analysis, a robust predictive model could help people estimate the risk accurately with the given condition. More specifically, a reliable risk model could be used to predict the probability of accidents or the number of accidents. However, the optimization model usually emphasizes on obtaining the optimal solution with the minimum or maximum objective(s) and we know that the solution could change as the different objectives. When we search for the papers in the discipline of vehicles safety involving the decision-making, the majority of those papers are related to hazmat transportation. The speciality of hazardous products is the low probability and high consequence, so the risk models usually take the consequence into account while it is not common when the risk is for the general vehicles. As a result, the review on the optimization part will be conducted from all the components made up for a decision model. In this way, we can bring the benefits of those existing hazmat optimization models to the general truck transportation. The result implies that the current optimization models related to the hazardous products are able to extend their use to other types of vehicles by replacing the risk models. Specifically, the major difference between the hazmat transportation and non-hazmat transportation is the way to evaluate the risk. As we mentioned before, the purpose of statistical models in risk estimation is trying to predict the risk accurately. Hence, the more accurate risk models can lead to more reliable optimization solution. In recent years, the statistical analysis has become more mature than before owning to the easier access of lots of data and the advanced statistical methods and tools. Now it is the time to integrate the predictive modeling and decision model to have a more reliable result.

In the next sections, we review and categorize the optimization/ prescriptive analytic models that focus on minimizing crash risk. While the majority of works in this segment of the literature is related to the hazardous materials (hazmat) trucking problems, we show that (with some exceptions) many can also be utilized in non-hazmat scenarios. In an effort to highlight the effect of crash risk prediction model on the accumulated risk obtained from the prescriptive model, we present a simulated example where we utilize four risk indicators (obtained from Logistic regression, Poisson regression, XGBoost and Neural Network) in the *k*- shortest path algorithm. From our example, we demonstrate two major designed takeaways: (a) the shortest path may not always result in the lowest crash risk; and (b) a similarity in overall predictive performance may not always translate to similar outcomes from the prescriptive models. Based on the review and example, we highlight several avenues for future research.

1.2. Background: Hazmat Trucking Operations

According to the Pipeline and Hazardous Material Safety Administration (PHMSA) of the US Department of Transportation (USDOT), a hazmat is defined as any substance or material that is toxic, explosive, corrosive, combustible, poisonous, or radioactive that is capable of becoming a threat to the environment, properties and people's safety [1]. Hazardous materials are divided into the following nine categories: (a) explosives, (b) gases, (c) flammable liquids, (d) flammable solids, (e) oxidizers and organic peroxides, (f) toxic materials and infectious substances, (g) radioactive materials, (h) corrosive materials, and (i) miscellaneous dangerous goods [1].

The most important difference between hazmat and non-hazmat transportation is that moving hazmat raises an inherent risk for public safety and environment. A hazmat incident can occur in origin during loading, in transit, in transit storage, and in destination during unloading [2]. Even though hazmat incidents are not common, their occurrence leads to catastrophic consequences such as fatalities, severe injuries, and property/environmental damages. In 2018, 19,581 incidents including explosions, fires, and poisonous gas leakage were reported in the

U.S. These incidents caused 4 fatalities, 127 injuries, $80 million property damage and a huge effort of evacuating and restoring the affected areas [2]. Most of the fatalities and damages occurred on highways (approximately 90% of the reported incidents in 2018 [2]), emphasizing the importance of in-land hazmat transportation planning and routing. For this reason, most of the papers in the literature studied hazmat route planning on highways and roads; hereafter, we only consider such applications.

Hazmat transportation planning has traditionally received the attention of both carriers and regulators. Carriers tend to plan each shipment separately with the goal of minimizing travel time/cost, while complying with any regulations and risk management considerations. On the other hand, regulators consider all the shipments in the road network and work on promoting risk equity through various network design measures [3].

Hazardous materials (hazmat) routing problems can be categorized into two classes based on the different perspectives of the parties involved. The simplest type of the hazmat transportation routing problem deals with an origin and a destination (an O-D pair) and one type of hazmat to be shipped on a given road network. Thus, a single route will be chosen as the optimal solution for the problem with the objective of minimizing both the cost and risk. This class of the problems with a single O-D pair and single shipment is usually referred to as *local route planning*. In this type of problem, each shipment is planned separately, not taking onto account all other shipments. A more general version, involving several O-D pairs with several shipments can still be referred to as local as long as each is treated separately from the point of view of transportation risk analysis. On the other hand, it is often observed that such approach can lead to overloaded hazmat traffic on certain links of the network, leading to increase in incident probabilities and risk inequity. If multiple commodities are shipped through multiple routes with objective of minimizing cost and risk as well as promoting risk equity among all regions, then such problems are usually addressed as *global routing planning*. Some examples of problems modeled from the operational point of view (i.e. local route planning) can be found in: [4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15]. On the other hand for the network design perspective (i.e. global route planning), the reader is referred to the examples of: [16, 17, 18, 19, 20, 21, 22, 23].

From the above discussion, it should be clear that both problems have been extensively studied in the literature. Since our goal is examine how prescriptive hazmat transportation models can be applied to non-hazmat (i.e., more general) settings, the global route planning problem is not relevant for our application. Specifically, the primary reason to consider a risk equity criterion is related to considerable change in risk exposure of the communities due to relatively heavy hazmat traffic. This is not an issue for general non-hazmat traffic, so we will not consider global route planning approaches in this review. Furthermore, we will also not consider the policy-making literature discussing important decisions such as: (a) road segments closure [24], (b) toll-setting [25, 26, 27, 28], (c) locating waste treatment centers in safe sites [29, 30, 31, 32, 33], (d) locating hazmat emergency response teams [34, 35, 36], etc. The rationale behind not including these studies is that they are not informative to carriers who tend to focus on how to ship products and goods to meet agreed-upon delivery schedules at the least cost, while not violating any federal/state regulations.

1.3. Optimization Models for Minimizing Crash Risks/Costs

In this section, we review optimization models used for the prescriptive component of crash risk analysis. It must be noted that the vast majority of relevant literature originates in the area of hazardous materials (hazmat) transportation. Hazmat transportation, naturally, constitutes a significant portion of the crash risk modeling literature in general and prescriptive modeling aspect of it in particular. The potential for extremely impactful incidents means that risk consideration is a primary criterion in decision making for routing of such vehicles, which leads to a wide section of the literature dedicated to vehicle routing problems (VRPs) for hazmat transportation. Consequently, any analysis of general purpose safety-enabled routing has to rely on the extensive existing developments in hazmat literature. Therefore, our discussion in this section is divided into: (1) risk models in hazmat transportation, (2) classification of the relevant optimization papers according to model type, i.e. how they treat the underlying parameters, (3) classification according to basic optimization model elements (i.e. variables, objective function and constraints), and (4) a discussion of the type of algorithmic approaches used. It should be noted that hazmat-related problems often take into consideration aspects that are irrelevant to general-purpose applications. Hence, we also attempt to describe how these models can be reconciled with the general-purpose non-hazmat routing applications.

1.3.1 Risk models in hazmat transportation

In order to incorporate a stochastic parameter (e.g., traffic incidents) into a prescriptive model, it is not enough to determine the probability of an incident on each arc. One also needs to select a way to quantitatively measure and compare the risks associated with potential alternative decisions. In the case of hazmat transportation, [3] identified the following three important building blocks for risk measurement: (a) *incident probability*, (b) *exposed population*, and (c) *expected consequence*. Intuitively, the incident probability focuses on measuring the probability of an undesirable event, while the exposed population refers to the measure of potential effect. Either can be used in its own right, if the underlying understanding of the problem suggest is the most important factor. For example, if the incident probability is constant, then the exposed population can be employed as the primary way to differentiate between decisions [29, 9, 37]. Alternatively, if it is impossible to adequately estimate the potential effects, then incident probability can be used on its own [38]. However, when we can estimate both measures, combining both of them through the *expected consequence* measure allows for having a more complete picture. *Expected consequence* is defined as the expected value for the at-risk population taking into account the incident probability along the selected route. Note that other risk indicators have been proposed and used in the literature. These risk indicators present different penalization functions and focuses when compared to the traditional three measures. We present an overview of the indicators and the papers utilizing these approaches in hazmat settings in Table 1.1.

A number of factors must be taken into account when picking a specific risk indicator. First, there is not a model that is strictly superior to all others. Second, it can be seen from the formulations presented in Table 1.1 that these indicators have different objectives and assumptions. For example, the traditional *expected consequence* approach assumes a risk-neutral preference. On the other hand, the perceived risk, value at risk and conditional value at risk

Table 1.1: An overview of hazmat risk models, their indicators, formulations and application problems.

Model	**Risk indicator**	**Formula**	**Example application papers**
TR	Traditional risk	$\min_{l\in P} \sum_{(i,j)\in A^l} p_{ij}Cij$	[39, 40, 35, 41, 42, 43]
PE	Incident consequence	$\min_{l\in P} \sum_{(i,j)\in A^l} Cij$	[29, 9, 44, 37]
IP	Incident probability	$\min_{l\in P} \sum_{(i,j)\in A^l} p_{ij}$	[38]
PR	Perceived risk	$\min_{l\in P} \sum_{(i,j)\in A^l} p_{ij}(Cij)^k$	[45, 46]
MV	Mean-variance	$\min_{l\in P} \sum_{(i,j)\in A^l} (p_{ij}Cij + kp_{ij}(C_{ij})^2)$	[47]
DU	Disutility	$\min_{l\in P} \sum_{(i,j)\in A^l} (p_{ij}(\exp(kC_{ij}-1))$	[47]
MM	Maximum risk	$\min_{l\in P} \max_{(i,j)\in A^l} C_{ij}$	[47]
MM_2	MM (Uncertain probabilities)	$\min_{w} \max_{p} \sum_{(i,j)\in A^l} w_{ij}(p_{ij}C_{ij}+c_{ij})$	[48]
CR	Conditional probability	$\min_{l\in P} \frac{\sum_{(i,j)\in A^l} p_{ij}C_{ij}}{\sum_{(i,j)\in A^l} p_{ij}}$	[49, 50]
VaR	Value at risk (potential loss)	$\min_{\beta} P(R^l > \beta) \leq 1-\alpha$	[14, 20, 15]
$CVaR$	Conditional value at risk (Probability with large loss)	$minE\{R^l \| R^l \geq VaR_\alpha(R^l)\}$	[14, 51]

Notation: C_{ij} is the incident's consequences; P_{ij} is incident probability; k is risk preference parameter; α denotes the confidence interval; β is the risk level; A reflects the set of arcs and $i,\ j$ are used to represent each arc in A; P represents the set of different paths; and l denotes each path within P.

all introduce risk-averse decision making criteria. Specifically, the perceived risk model introduces a risk parameter k involved in higher-moment "perceived" loss evaluation [46, 45]. Since the concept of minimizing risk is not inherent to transportation problems, a detailed discussion of the properties of these methods can be obtained from the general stochastic optimization literature [see e.g., 47, 20, 15, 14, 51]. Third, in the case of non-hazmat problems, incidence consequence is typically not a major decision factor since the consequences are primarily related to speed and the number of vehicles involved in a crash. These consequences are typically hard to estimate beforehand and thus, the use of crash probabilities is often the preferred approach.

Most of the cited literature in Table 1.1 operates in a static fashion. Specifically, most papers assume a constant hazmat accident rate (usually between $10^{-8} - 10^{-6}$ per vehicle-mile), which is based on the work of [5]. However, crash risk is affected by weather/traffic among other conditions. These parameters tend to be time-variant and thus, a constant probability does not account for the findings in the crash risk prediction modeling domain. We recommend that the optimization literature should focus on more dynamic conditions to account for the time-varying factors affecting crash risk. It is important to note that most of the existing risk indicators, such as the ones shown in Table 1.1, can account for time-varying conditions. For example, [14] showed that CVaR-based models can be used for dynamic models, where the risk and cost are time-dependent. Hence, it can be used with the more advanced statistical models discussed in Section 5[52].

Based on the discussion in this subsection, one can see that hazmat risk models typically consider/emphasize the consequences/severity of a crash when it happens. For non-hazmat vehicles, the severity of a crash would depend on the number/type of vehicles involved, the type of collision, speed differential, etc. While these are also true in non-hazmat, the literature typically considers the "worst case outcome", where the probability of dispersion is utilized to capture the consequences of hazmat releases. Thus, in such cases, the effect on the involved vehicles is often ignored since it is assumed to be minor when compared to the health-outcomes and cleaning efforts that are associated with containing hazmat materials. On the other hand, the severity of non-hazmat crashes is dependent on: (a) the potential for injuries/fatalities; and (b) the traffic buildups seen by other commuters. Given that these two factors are relatively hard to predict/model for non-hazmat crashes, reducing the likelihood of a crash represents the important component of risk models for non-hazmat vehicles. Consequently, this component should be reflected in the choice of an appropriate risk model.

1.3.2 Classification based on model type

In this section, we classify the relevant transportation (hazmat) optimization papers based on the underlying parameters. Our classification combines the taxonomies presented in [53] and [42]. [53] differentiated hazmat transportation models based on whether the proposed solution will update in time according to new information. Their approach divided the literature into: (a) *a priori optimization*, where model updating is not permitted; (b) *adaptive-route selection*, if the result will be updated subject to the realization of certain data; and (c) *adaptive route selection in real-time*, if the updating considers real-time changes in the data. On the other hand, [42] divided the literature according to: (a) deterministic/static, and (b) stochastic/dynamic models. Thus, when combine both classifications, we have six different groups ($3 \times 2 = 6$). The definition of each group (G) and a sample of its literature are presented in Table 1.2.

Table 1.2: An updated taxonomy of (hazmat) trucking optimization methods that consider crash risk/probabilities.

	Semi-deterministic models	Stochastic models
Truly-static	**G1 Def.:** Risk only depends on the arc's length and the binary variable for each arc denoting path selection. All the parameters considered are **deterministic** and the optimal solution does **not update**. **Examples:** [54, 7, 50, 55, 44, 56, 37, 57]	**G2 Def.:** Risk only depends on the arc's length and the binary variable for each arc denoting path selection. Model has ≥ 1 **random parameter** and the optimal solution does **not update**. **Note:** This group cannot exist in practice since the inclusion of a random parameter will make the optimal solution changeable according to the conditions.
Semi-dynamic	**G3 Def.:** Risk only depends on the arc's length and the binary variable for each arc denoting path selection. All other parameters are fixed. The optimal solution is a **conditional decision**, which will be different according to the realization of parameters. **Examples:** [51, 20, 15]	**G4 Def.:** Risk only depends on the arc's length and the binary variable for each arc denoting path selection. Model has ≥ 1 **random parameter**. The optimal solution is a **conditional decision**, which will be different according to the realization of parameters and value of stochastic input(s). **Examples:** [9, 58, 40, 59, 35, 41, 46, 37, 60, 14, 42, 61, 43, 62]
Truly-dynamic	**G5 Def.:** Risk only depends on the arc's length and the binary variable for each arc denoting path selection. Other parameters are fixed. **The model has criteria to update the solution** (i.e. run the model based on querying the values of parameters) in real-time. **Examples:** None found.	**G6 Def.:** Risk only depends on the arc's length and the binary variable for each arc denoting path selection. Model has ≥ 1 **random parameter(s)**. **The model has criteria to update the solution** (i.e. run the model based on querying the values of parameters) in real-time. **Examples:** [63]

Based on Table 1.2, there are several observations to be made. First, we classified most of the papers that include some version of dynamic parameters as semi-dynamic (see e.g., Group 4). Our rationale for this classification is that these papers do not provide any discussion on updating the solution en-route. Second, the existence of semi-dynamic or truly-dynamic parameters does not mean that these papers should be considered as such in non-hazmat applications. For example, in [37], the dynamic parameters correspond to evaluation of incident consequences for hazmat transportation (e.g., real-time population within the affected area). While this allows us to classify them as semi-dynamic, these parameters are irrelevant for general transportation routing applications. Third, the limited research in Groups 5-6 shows that there is an opportunity to capitalize on the availability of real-time information of important inputs to improve the mathematical models' performances in practice (as shown in the results of [63]). Fourth, extending the models in Group 4 to truly dynamic (i.e. Group 6) models can be achieved with relative ease through providing (a) a procedure for periodic real-time update of the underlying parameters, and (b) well-defined criteria for periodic re-optimization. A case in point is the model presented in [15]. The problem there is solved with a two-stage solution procedure based on either Dijkstra's method or a heuristic. For a practical case with 90 intersections and 148 road segments the solution time does not exceed five seconds. Hence, with a clear criterion for updating the solution (e.g., every 10 minutes, or whenever significant change in risk estimation is observed) it can be efficiently adapted to a truly dynamic model.

One additional benefit from categorizing the optimization models based on the risk model is that it can help us better understand some of the inherent limitations/assumptions of the optimization model. For example, based on Part 1, *traffic* and *weather* conditions were found to be important risk factors in many models. Since these conditions can vary dramatically over the course of the drive, the truly-dynamic and stochastic optimization models would be a better choice in many trucking applications since they can capture the time-varying nature of the inputs.

1.3.3 Classification based on the types of decision variables, input parameters, objective function(s), and constraints

Type of decision variables

From an optimization perspective, decision variables constitute the optimized outputs obtained from the model's solutions. In many trucking safety problems, binary decision variables are used to define the type of decisions to be achieved by optimizing a particular model. In our view, the models can be divided based on whether the variables reflect decisions made on an arc or a path level. For example, in the context of a single O-D routing problem and an-arc based formulation, a value of 1 indicates that the driver should be routed through this arc, and 0 otherwise. More generally, if there are multiple trucks in the system, the decision can represent whether a certain truck should deliver a product for a given customer using a given arc. To illustrate this concept, let us consider the notation used in [60], where the binary variable x^{τ}_{ijv} is set to one, whenever truck v is leaving node i at specific time τ by using the link (i, j). On the other hand, one may define variables that are indexed over whole paths rather than separate arcs [see 51, for an example of such a formulation]. If such an approach is followed, practitioners are required to pre-compute a number of candidate paths between all O-D pairs in advance. This approach can be particularly useful when attempting real-time update of the solution, since it can significantly reduce the computational effort required. At the same time, it creates a separate problem of selecting a set of pre-computed paths, which, if done poorly, can limit the quality of the realized solutions. This means that there is a trade-off between both methods, and their pros and cons should be considered prior to model construction.

Types of input parameters

Depending on the assumptions of the model, availability of data, and application, the inputs to the prescriptive models can differ significantly. In the context of attempting to minimize crash risk, different types of parameters can correspond to different sources of risk, as well as different system components that can affect this risk. In addition, most of the problems also include various parameters generally associated with vehicle routing problems, e.g., time windows, vehicle parameters, etc. Based on our review, we identified 11 types of parameters used in the literature. Table 1.3 provides a brief description of each type along with citations for when each type was used. Note that these parameters are not mutually exclusive, and thus several of the papers can be found at different rows within the table. Additionally, for some of these types (e.g., traffic flows, road/weather conditions and/or exposed populations), it may be important to consider real-time updates. Models using those parameters can, in principle, capitalize on the advanced statistical models highlighted in the explanatory/predictive modeling section. Hereafter, we use the type ID (i.e. the number) to refer to a specific parameter type.

From Table 1.3, it should be apparent that most optimization models do not include parameters that relate to traffic, weather, and road geometric conditions. While this should not be a surprising observation based on the bibliometric analysis performed in Part 1, it is a potentially problematic observation since at least one of those factor sets was deemed important

Table 1.3: Type of input parameters included within trucking safety oriented optimization models

Type ID	Type of parameter	Example papers and applications
1	Risk parameters including probability of accident and/or expected consequence	These parameters are included in all safety-based routing optimization papers and thus, we will not highlight specific papers here
2	Parameters for the traditional vehicle routing problem (VRP)	[40, 35, 46, 41, 56, 60, 42, 43]
3	Parameters about the confidence interval of the probability of accident or the worst case	[59, 51, 14]
4	Parameters of travel time	[9, 40, 41, 46, 60, 14, 63]
5	Parameters about traffic condition	[59, 51, 61]
6	Parameters about weather condition	[54, 61, 63]
7	Parameters of dispersion model to calculate the concentration level	[54, 58, 60]
8	Parameters about road geometric condition	[61, 63]
9	Parameters about traveling cost	[56, 61]
10	Parameters about the threshold of accident probability or/and consequence	[50]
11	Parameters about equity constraint	[20]

by most of the explanatory/predictive modeling studies reviewed in Part 1. As a consequence, we estimate that crash risk would be underestimated by the optimization models in the case of adverse weather, traffic and road conditions. This is an important gap in the prescriptive modeling literature that needs to be further investigated.

Type of objective functions used in hazmat transportation

There are two main objectives in crash risk optimization models: economic savings and minimizing the total risk. Economic savings relates to improving travel time, distance and other corresponding costs. Total risk represents the economic or other type of loss associated with transportation incidents. Usually, the total risk is evaluated as a cumulative effect over the selected route. Furthermore, it is typical to assume that incident occurrence along each arc is independent, which in conjunction with very small incident probabilities leads to the standard assumption that the total probability along a route can be estimated through summing the probabilities on each arc. Note that the two objectives are not necessarily conflicting since it is not always the case that shorter routes are more risky.

There are two general ways to address multiple objectives in optimization models: (a) using a weighted sum method to get a single linear objective function [see e.g., 56, 60, 35, 40, 61], or (b) keep the multiple objectives and find a set of non-dominated solutions [as in 9, 42, 46, 41]. Sometimes, it may be possible to introduce a natural problem-specific way to combine the objectives. For example, in [61], the objective in the model is to minimize both travel cost and risk, but the authors present a way to integrate the direct freight cost as a component related to risk which is decided by the frequency and leakage probability. From a solution perspective, a key disadvantage of merging multiple objectives into one function (by using a generic weighed sum method) is that it is often difficult to find satisfactorily weights, and the result will be sensitive to the weight assigned. On the other hand, methods that aim at generating the full efficient frontier often require significant computational effort, especially if the underlying single-objective relaxation is hard to solve on its own.

In Table 1.4, we categorize the surveyed papers in this section according to the type of objective used (while integrating the information of parameters by applying the type ID from Table 1.3). From the table, one can observe the following: (a) most papers have focused on minimizing risk instead of a purely economic model, and (b) most papers attempt to optimize multiple objectives. In addition, with the exception of [61], the papers incorporated only two to three parameter types. In our view, the limited number of parameter types considered in the optimization model (despite the different objectives) reflects the divide between the crash risk prediction modeling and optimization literatures. For example, traffic conditions (PT-ID 5) and weather conditions (PT-ID 6) were considered twice and once, respectively. However, they are important crash risk predictors as shown in the references cited in the explanatory/predictive modeling section.

Structure of constraints in hazmat transportation

Similar to the previous subsections, the constraints that are widely used in optimization models can be grouped into two families: general vehicle routing constraints, and those related to

Table 1.4: Details about objective function(s) and parameter type ID (PT-ID) used in the literature

Objective	**Details about objective in model**	**Papers**	**PT-ID**
Minimize cumulative VaR for all hazmat routes	VaR is used to denote the maximum cutoff risk for each arc due to hazmat transportation	[20]	1, 3, 11
		[15]	1, 3
	VaR denotes the risk level, such that the risk for each selected arc exceeding a certain risk level is $\leq$ a pre-specified probability threshold	[51]	1, 3
Minimize CVaR	CvaR is coherent risk measure to avoid ignoring low-probability highly-consequential crashes	[51]	1, 3
		[14]	1, 3, 4
Minimize travel cost and/or risk	Population exposure and travel time	[9]	1, 4
	Travel cost and risk exposure costs such as: population exposure, facilities-related exposure and pavement-related exposure	[56]	1, 2, 9
	Traditional risk (the product of risk probability and the consequence) and travel time	[42]	1, 2
		[60]	1, 2, 4
		[35]	1, 2
		[40]	1, 2, 4
	Perceived risk (PR) and travel time	[46]	1, 2, 4
	Direct travel cost and the risk cost depends on frequency of risk and leakage probability	[61]	1, 5, 6, 8, 9
	Total risk, which is defined in this application as the total expected concentration level of gas or aerosols when accident happens	[54]	1, 7
	Population Exposure model (including travelers)	[37]	1, 5
	Conditional expectation of the consequence given an accident happens (at the same time the probability of accident for the path can not exceed a certain number and also the consequence should lower than or equal to a threshold)	[50]	1, 10
	Total number of vehicles, scheduling time, and the traditional risk (TR)	[41]	1, 2, 4

evaluation of risk. The general VRP constraints are well-understood in the literature, and are enforced to make sure that the proposed transportation plan is feasible, i.e., loading capacity is not exceeded, the demand is satisfied, delivery time windows are observed, etc. [35, 60]. Risk-specific constraints, on the other hand, are closely related to the objectives; it is often possible to consider a risk term as an objective or a constraint depending on whether the decision maker is interested in achieving a minimal risk, or satisfying a risk threshold. Some model-specific constraints can also be used; for example in [20], the authors consider a model based on risk-equity constraints, while minimizing a global Value-at-Risk function.

1.3.4 Types of algorithms (computational methods) used

From a computational perspective, most of the considered models solve either a shortest path or a vehicle routing problem (VRP). A pure shortest path problem is usually trivial to solve with Dijkstra's, label-setting or label-correcting algorithms and therefore, we will not discuss those in much detail. On the other hand, VRPs are often very computationally demanding, and hence often require a heuristic algorithm to solve.

As discussed earlier, multi-objective problems are usually represented as series of single-objective [40, 35, 46] or using several bi-objective problems [57]. Another general approach that has been used in several papers considers a two-stage framework; the inner subproblem solves for a shortest path exactly, while the outer master problem iterates VRP solutions [15, 51, 14]. It is also common to integrate exact and heuristic algorithms. For example, using an exact algorithm to find the shortest path, then people apply a heuristic algorithm to find non-dominant solutions satisfying the objectives efficiently [46, 35, 40, 60, 41]. From a conceptual perspective, the papers can also be divided into whether they focus on: (a) model development for a specific problem (authors compare different models for bench-marking), or (b) improving existent algorithms for obtaining solutions (bench-marking is achieved in terms of comparing the speed and whether an optimal solution is achieved). We present a tabulated summary of the algorithms used in the literature in Table 1.5.

Based on the optimization models described throughout this section, one can see that they can be easily extended to non-hazmat scenarios once an appropriate risk model is used. In the following section, we provide an example for how risk can be computed for non-hazmat scenarios and demonstrate how the predictive and prescriptive components can be better integrated.

Table 1.5: Algorithms used in the mathematical/optimization models accounting for crash risk.

Type	Description of the Algorithm	Example papers
Exact	Branch-and-Bound	[64, 50]
	Brand-and-Bound with a relaxing risk equity constraint as the penalty parameter in the objective function	[20]
	Two-stage solution: Inner stage is to the solve shortest path problem using Dijkstra's algorithm; Outer loop is an algorithm to select a solution to minimize VaR and CVaR	[51, 15]
	Two-stage solution: Sub-problem uses a back-labeling algorithm to solve the dynamic shortest path problem; Main problem is a CVaR minimization problem by the proposed algorithm	[14]
	An approach using STDLT(DD), STDLT(SD) and EV algorithms	[9]
Heuristic	An insertion heuristic algorithm is used to determine non-dominated scheduled route-paths; then a newly proposed label setting algorithm is used to identify the entire set of k-shortest scheduled route-paths	[46]
	Based on the shortest path algorithm, the bi-objective VRP is decomposed to single objective problems, then solved using an insertion heuristic algorithm to approximate a set of non-dominated solutions	[40, 35]
	Multiple objectives are converted to a bi-objective problem using a decomposition method; then a proposed constrained parametric method is applied to solve the shortest path problem and transfer the bi-objective problem to two single objectives	[57]
	A labeling algorithm is applied to find the shortest path between customers and the depot, then a MOACS-based algorithm is used to find a set of non-dominant solutions for the VRPTW	[42]
	An algorithm based on heuristic GA is applied to solve HVRPTW	[56]
	A route-building heuristic algorithm based on label-setting algorithm is used to solve the single objective time-dependent shortest path problem	[60]
	Meta-heuristic algorithm based on ACS is supported by labeling algorithm for HVRPTW	[41]

Acronyms: STDLT: Stochastic, Time-Dependent Least Time; DD: Deterministic Dominance; SD: Stochastic Dominance; EV: Expected Value; VRP: Vehicle Routing Problem; MOACS: Multiple Objectives Ant Colony System; VRPTW: Vehicle Routing Problem with Time Windows; GA: Genetic Algorithm; HVRPTW: Hazmat Vehicle Routing Problem with Time Windows; ACS: Ant Colony System.

1.4. Case Study

In this section, we will use a simulated example to illustrate how different statistical/machine-learning risk models can impact the outcomes obtained from the prescriptive optimization models. The procedure for this example is comprised of three sequential steps. First, we use the Poisson distribution to simulate the number of crashes (Y_y) observed during a trip. The rate of crashes is set to be a function of both precipitation, and road traffic conditions whose distribution is assumed to be known. The advantage of using a simulated procedure is it allows us to know/compute the "true risk" associated with a trip. Then, in the second step, we use four popular predictive models (logistic regression, Poisson regression, neural networks and XGBoost) to predict the probability of a crash or the number of crashes as a function of the aforementioned predictors. In the third step, we use the *k-shortest path* algorithm to identify the shortest routes ranked by the distance between two nodes [65]. Then, we conclude the third step by comparing the risk obtained as a result of the k-shortest path algorithm using each of the four crash risk predictive models.

1.4.1 Data generating process

The process of modeling crash-risk in road networks is quite complex and involved. Given that our purpose is to highlight the effect of model choice on the optimization performance, we chose to simulate a road network since that allows us to know the "true" risk. In this simulated example, we have assumed that number of crashes, Y_i, can be generated from the following Poisson process:

$$\begin{aligned} Y_i &\sim \text{Poisson}(d_i \cdot \lambda_i) \\ \log(\lambda_i) &= \beta_0 + \beta_1 x_{1i} + \beta_2 x_{2i} + \varepsilon_i \\ \varepsilon_i &\sim \text{Normal}(0, 2^2), \end{aligned} \tag{1.1}$$

where d_i, x_1, and x_2 represent the i-th trip's distance, precipitation, and road traffic conditions, respectively. Note that: (a) we have added a normally distributed random error as a noise term; and (b) the distance of each path d_i is considered as the offset term in the Poisson distribution.

Furthermore, we have arbitrarily set the following data distributions:

$$\begin{aligned}
&\beta_0 = -3,\ \beta_1 = 0.5,\ \beta_2 = 0.9, \\
&d \sim \text{Poisson}(1000), \\
&x_1 \sim \text{Bernoulli}(0.15), \\
&x_2 \sim \text{Beta}(2,2).
\end{aligned} \tag{1.2}$$

These parameters have been chosen to make the number of crashes Y_i in all the simulated trips fall in a somewhat sensible range of 0 to 5. We have simulated 10,000 trips with various lengths under random precipitation and traffic condition in order to assess the performance of the four different predictive-prescriptive model combinations. The reader should note that the "true" risk is computed via the data generating process defined in Equation 1.1. To allow readers to replicate our analysis, we provide all the Python code used to simulate the data sets in the provided link in the *Supplementary Materials*.

1.4.2 Predictive modeling

As an illustrative example, we have applied two traditional statistical models (logistic regression and Poisson regression) and two machine learning models (neural networks and XGBoost) to model crash risk in the simulated 10,000 trips. In the case of the Poisson regression approach, the outcome variable corresponds to the number of crashes (or more generally safety critical events such as hard brakes) in the path. On the other hand, the outcome variable for the other three models is binary, which indicates whether at least one event/crash has occurred. Thus, they can be considered as a simplification of the Poisson model implementation, where a practitioner would be interested in modeling the number of unsafe events instead of whether or not they occur. Since the four models are predicting different outcomes, we have used the predicted rank of risk in each model to compare the concordance of prediction among the four models.

Figure 1.1 presents the concordance results with the logistic regression model used as a benchmark. The results show a higher concordance of prediction among the statistical models as well as among the machine learning models. There is less concordance across the statistical and machine learning models: for example, the highest risk paths (4-14, 1-12, and 5-6) predicted by statistical models are predicted to rank between 10 and 15 for the machine learning models.

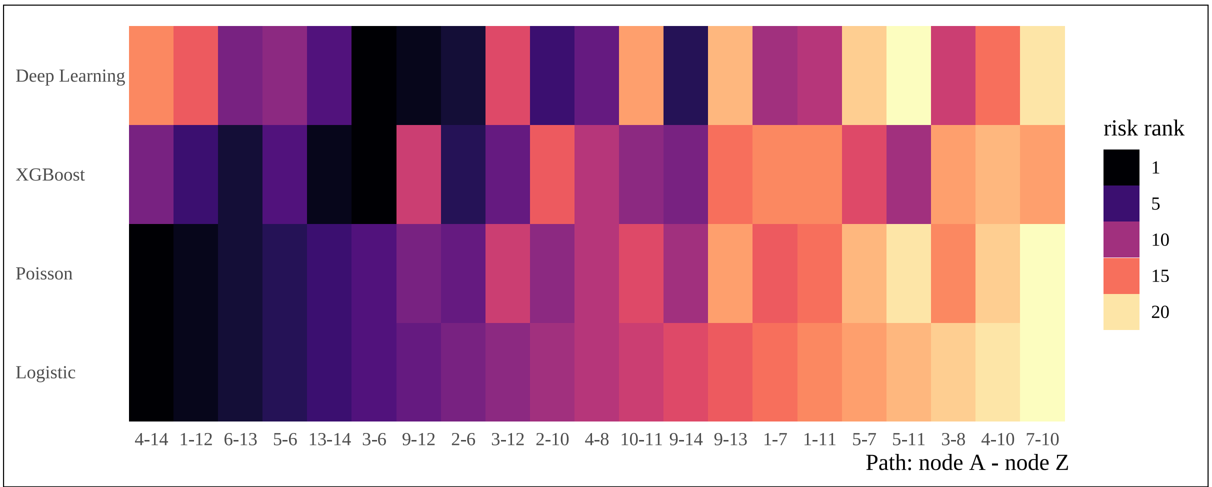


Figure 1.1: Concordance of four models for evaluating the risk of crash. Darker color indicates higher rank of crash risk. The highest rank is 1 and the lowest is 21.

Table 1.6 presents the model performance metrics for the four models. The difference of area under curve (AUC) between training and test set indicates that machine learning models have a minor issue of overfitting, which is commonly seen among machine learning models and requires state-of-art hyperparameter tuning and regularization. Neural networks in this case has very similar performance as logistic regression regarding accuracy and MSE (Mean Square Error), but the AUC of test set is not as good as that of training set. Although the Poisson regression has the highest MSE, it does not indicate the Poisson regression has worse prediction than the other three models since the outcome variable is different. Among the three binary prediction models, logistic regression seems to have the best performance given the balance of performance between training and test set, as well as high AUC, accuracy, and low MSE. The reader should note that the four models were trained and measured using the `h2o` package in Python [66], and the concordance plot was generated using `ggplot2` in **R** [67].

1.4.3 Prescriptive modeling using the *k*- shortest path routing algorithm

Here, we consider a road network including 14 nodes and 21 arches. Similarly, the weather and traffic conditions have been simulated using the same data generating process showed in Equation 1.2. With the help of $k = 4$ shortest path algorithm, we find the four shortest paths

Table 1.6: Performance metrics for the four predictive models.

Model performance metrics	Logistic	Poisson	XGBoost	Neural Networks
train AUC [1]	0.5596	—	0.6024	0.5743
test AUC [1]	0.5639	—	0.5456	0.5327
train accuracy	0.8936	—	0.8933	0.8936
test accuracy	0.8941	—	0.8941	0.8941
train MSE [2]	0.0948	0.1647	0.2353	0.0949
test MSE [2]	0.0938	0.1717	0.2352	0.0954

[1] AUC (Area Under Curve) ranges between 0.5 and 1. Higher values suggest better models.

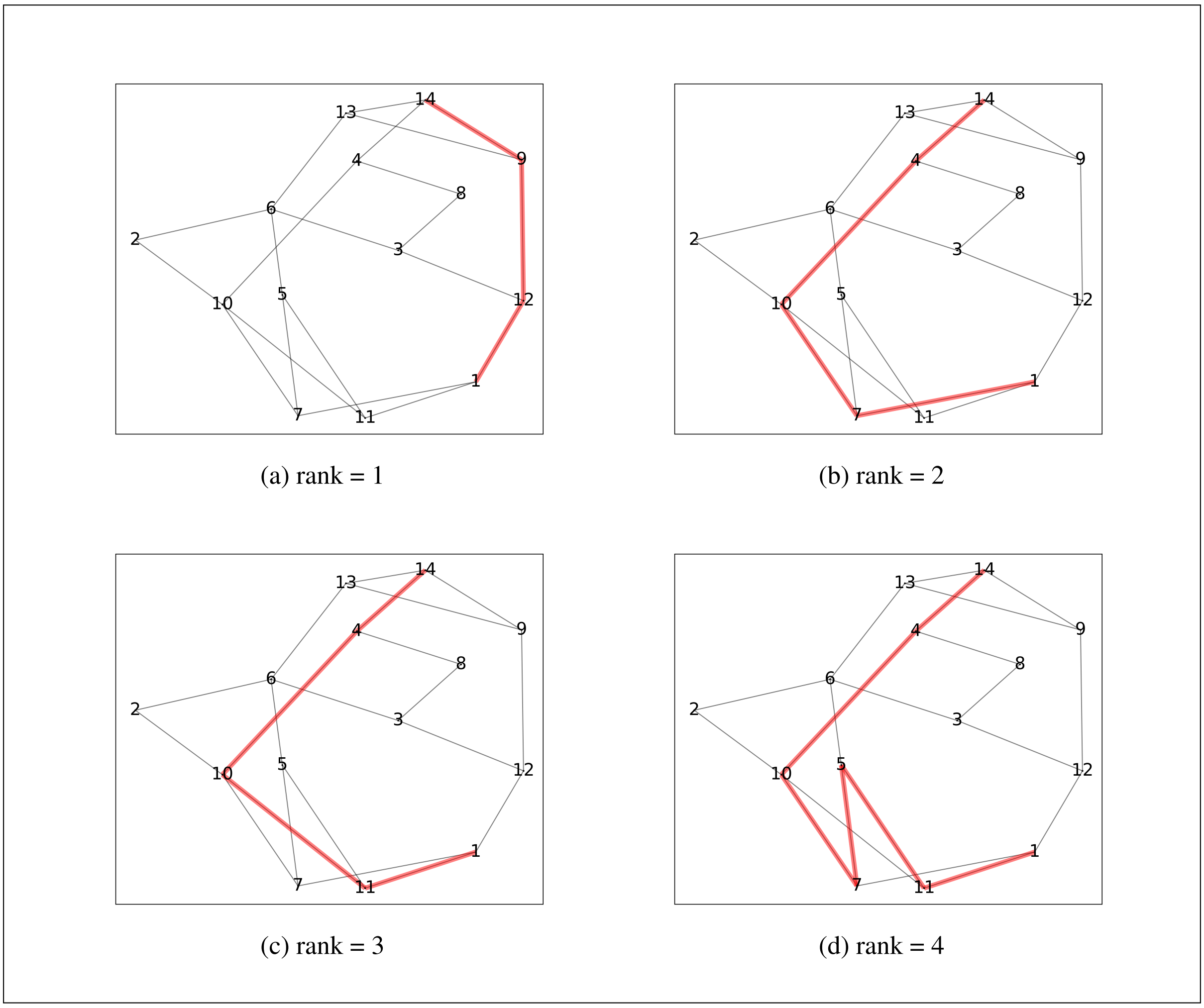
[2] MSE (Mean Square Error) is a positive number. Smaller values suggest better models.

from node 1 to node 14 and rank them by the corresponding distance. Figure 1.2 shows the selected path from rank 1 to 4. Furthermore, the rank of risk for each of those four paths using the four predictive models is provided in Table 1.7.

Table 1.7: Risk ranking for the $k = 4$ shortest paths using the four predictive models.

Path	**Rank by Distance**	**Rank by Logistic Regression**	**Rank by Poisson Regression**	**Rank by XGBoost**	**Rank by Neural Networks**
$1 \longrightarrow 12 \longrightarrow 9 \longrightarrow 14$	1	1	1	1	4
$1 \longrightarrow 7 \longrightarrow 10 \longrightarrow 4 \longrightarrow 14$	2	2	2	2	3
$1 \longrightarrow 11 \longrightarrow 10 \longrightarrow 4 \longrightarrow 14$	3	3	3	3	2
$1 \longrightarrow 11 \longrightarrow 5 \longrightarrow 7 \longrightarrow 10 \longrightarrow 4 \longrightarrow 14$	4	4	4	4	1

From Table 1.7, there are two observations that can be made. First, with the exception of neural networks, the rank of risk corresponds to the distance traveled. This indicates that the logistic regression, Poisson regression and XGBoost models indicate that the shorter the route, the less likely one is involved in a crash. This is similar to the general assumption made by the majority of the optimization literature, where the crash probability is assumed to be a constant value of the distance traveled. On the other hand, the neural network shows an inverse relationship where for this simulated dataset, there may be some “safety” benefits from selecting longer routes. If one were to deploy the neural network model, in such a case, practitioners would need to balance the “cost” between risk and distance travelled. Second,



(a) rank = 1

(b) rank = 2

(c) rank = 3

(d) rank = 4

Figure 1.2: The results of the *k*- shortest path algorithm

the differences in crash risk ranking between the binary prediction models that have relatively similar performance predictive performances and the same selected features indicates that it is important to consider the effect of deploying these models on prescriptive models for decision-making. One can easily assume that, if the overall performance of the models is similar, the choice of implementing a given model would be similar. However, as this example clearly shows that a closer examination/diagnosis of the predictive performance of these models are needed. For example, can we characterize what instances is each model accurate. Note that, due to the simulated nature of this example, we do not discuss this issue further. The interested reader is referred to our *Supplementary Materials* for further analysis.

1.5. Result

Most of the reviewed research efforts can be viewed as contributing to the progress towards development of practical dynamic decision-making tools for improving driving safety of either commuter traffic or commercial trucking operations. Such tools necessarily have to rely on a combination of data collection, descriptive analytics, predictive/explanatory modeling and optimization methods. At the same time, there have been tremendous advancements in availability and sophistication level of both data and models. Hence, the development of a mature engine incorporating all of these stages "from scratch" is probably beyond the scope or ability of any single researcher. This is especially true since there is not a conscious effort in pulling all of these areas together with the goal of informing practical decision-making. The most significant gap that we have identified, is in the translation of outcomes/insights from the predictive/explanatory models (which aim to help us better understand and quantify crash risk) into prescriptive optimization models (which aim to inform route/path selection and rest-break scheduling to minimize the quantified risk). Thus, there is a limited work done in the area of truly-dynamic optimization modeling. Perhaps, an underlying reason can be attributed to the variety of necessary data sources and data processing tools within each category, which makes considering other domains in the literature more daunting.

It is also worth noting that in addition to the gaps identified above, another piece sometimes missing from the literature is a thorough discussion of the value proposition of such techniques. While intuitively it is clear that a reduction in traffic crash risks would be extremely beneficial to drivers, companies and the society in general, the existing literature (outside of hazmat applications) does not necessarily adequately measure the potential improvement or discuss the trade-off between safety and delivery efficiency. In the case of hazmat transportation, it is clear that ignoring crash risks can lead to catastrophic consequences, and the *exposed population* represents a key decision-making parameter. This parameter is relatively easy to measure, and consequently translate it into the operators' liability. This then leads to clear advantages associated with using intelligent routing and scheduling. On the contrary, in non-hazmat cases, while it is possible to demonstrate statistically significant increase in crash risks associated with different conditions, this effect is not always large. For example, it is well demonstrated that texting while driving leads to a drastic increase in accident risk, leading to widespread adoption of corresponding laws and regulations. At the same time, there are not sufficient studies convincingly establishing that, for example, a dynamic routing policy that avoids severe weather conditions, reliably leads to a measurable improvement in driving safety. Partially, this is due to lack of practical implementations of safety-conscious routing in regular (non-hazmat) operations that takes advantage of the most recent developments in statistical crash prediction literature. At the same time, we cannot expect to see practical implementations until the value of such techniques is established more clearly.

From our perspective, there exists a distinct opportunity for the development of advanced analytical methods for safety-enabled routing. The following areas represent the main avenues for progress:

(A) We have repeatedly observed the disconnect between the predictive and prescriptive models used in the literature. In our view, this is the most important gap in the literature. Before a practical implementation of safety-enabled dynamic routing for mainstream transportation can be achieved, a considerable effort in establishing best practices and guidelines is required. These efforts should primarily originate in the operations research community and should take advantage of the best ideas from the point above.

(B) In the absence of advanced dynamic routing models, it is difficult to adequately evaluate potential benefits of such systems. At the same time, the uncertainty in such an evaluation is a significant factor discouraging efforts in this area. We believe that a thorough analysis of the extent of potential risk-reduction with intelligent routing represents a primary research goal for the near future.

(C) The integration of risk prediction models with intelligent and dynamic routing models should be done with due diligence. As we showed in our simple simulation, an overall similarity in predictive performance does not necessarily lead to agreement on crash risk for a given path/route under certain conditions. Thus, researchers and practitioners should also attempt to diagnose/understand cases when the crash risk prediction models are performing poorly. While this is more of a research-to-practice issue, we highlight this here to emphasize the possible dangers from deploying predictive models when their performance is not fully understood/analyzed.

To sum up, the literature is mature enough to produce a general-purpose safety-conscious routing engine for commuters. Such an engine should be based on: (a) real-time feeds of weather and traffic data and forecasts, (b) pre-trained statistical models that evaluate driving conditions ahead, and (c) a collection of dynamic routing algorithms prescribing changes in the route as the conditions change. Using this information, the engine should automatically address the efficiency-risk trade-off.

Chapter 2

Dynamic model in scheduling the rest stops for truck drivers

2.1. Introduction

In the previous chapter, we have introduced the gap between the predictive modeling and prescriptive models in the area of motor vehicle safety. To bridge the gap, we decided to apply dynamic programming to incorporate the statistical risk model into the optimization model. There are two reasons for us to produce a Markov Decision Processes (MDP) model here. The first one is that many factors that impact the crash risk are real-time data. For example, most of the features related to weather and traffic that have significant effects on the road accident can vary over time. By applying dynamic programming, we find the optimal solution for each subproblem and also the final solution for the entire process. Further, when the driving condition has been updated in the real time, the MDP model allows us to adjust the solution only for the unfinished process. The other reason is that the structure of MDP model makes it convenient to replace the objective since it is separated from the other components of the model. In this chapter, we will discuss those features firstly, which is followed by the details of the mathematical model. In the end, a case study is demonstrated to show how this model works in integrating thees two research areas by using the data from a truck company.

2.2. Background of predictive modeling and decision making related to Motor vehicle safety

The motor vehicle fatalities are for the most part preventable. However, the fact is that the worldwide death rate has been increasing both in magnitude and in relation to other causes of death despite the advances in motor vehicle safety technologies. According to the World Health Organization (WHO), an estimated 1.35 million people die annually due to injuries sustained from motor vehicle crashes. Also, traffic incidents are the 9th leading cause of death in the world and it is projected to be the 5th by 2030, unless prompt and consistent action to change is taken [68]. Furthermore, the economic cost and societal impacts caused by the car accidents can not be ignored. It is estimated that traffic incidents cost 3% of gross domestic product (GDP) in most countries [69], with the annual estimated cost of car accidents at $242 billion[70]. These are further exacerbated by property damage, indicating that transportation safety is one of the most urgent problems in the world.

The advances brought by computing and sensing technologies have led to the ability to collect near real-time data on important contributors to motor vehicle safety (weather, traffic conditions, and behavioral/driver-related factors). With respect to the application of sensors in traffic control, it could help people examine the driving conditions in order to manage the traffic and also collect the data related to the weather and traffic for the purpose of analyzing the risk on the road[71]. Further, the development of in-vehicle sensor technology makes it possible for us to gather the information concerning the driver behavior. For instance, the use of in-vehicle sensors can track the real-time position of the vehicle based on Global Positioning System (GPS). Even a smartphone in the vehicle can observe the speed, acceleration, deceleration, etc [72]. However, all this data can not be useful without corresponding advances in decision-making and data analytics.

From the perspective of building decision-making models, there are two major groups of research efforts relating to the transportation safety that are relevant for this discussion: statistical modeling (focusing on determining the relationship between risk factors and road safety) and prescriptive approaches (aimed at efficient routing, scheduling, assignments, etc). The former can be classified as descriptive, since they are emphasizing extracting data, and then interpreting it by applying statistical tools. In general, these models can be classified into two major groups: crash frequency and real-time crash predictions models. The first one focuses on identifying the risk factors that affect the crash likelihood, while the second one aims to predict the crash likelihood based on the most important risk factors. These models can then generate continuous output describing incident probability, discrete output depicting the number of accidents [73], or a binary output characterizing whether an incident is predicted to occur

[74, 75, 76]. One particular area of interest is the exploration of relevant features (risk factors), which usually relate to weather condition (e.g., precipitation), the traffic situation (e.g., velocity variability), geometric road characteristics (e.g., changes in the number of lanes), driver characteristics (e.g., cumulative driving time, or distractions). Note that most of these factors (other than road geometry) are time-dependent and, in fact, can change in real-time, which then means that the corresponding prescriptive models that take these factors into account also need to be capable of real-time updates.

The second group of literature relevant for our purposes consists of optimization models aimed at making better decisions, which can be referred to as prescriptive models. It can be observed that, in fact, most of the papers, specifically built as optimization approaches (e.g., routing, scheduling, etc) with explicit safety criteria, come from the field of hazardous material (hazmat) transportation. It is not surprising that safety objectives are often considered in hazmat transportation, since it is characterized by potential for high consequence of any incident, hence placing safety as a particularly important consideration. Further, hazmat transportation is heavily regulated, which means that all agents (shippers as well as regulators) often have to apply advanced optimization techniques to determine the best compliance strategies.

These two research directions and their interaction have been extensively reviewed in [52] and [77]. Both highlight the existence of a gap between the two groups of efforts. Specifically, while intuitively, the prescriptive approaches should explicitly rely on the outputs of the descriptive models (i.e., optimization methods should directly employ statistical models as objectives or constraints), most do not. At the same time, as evidenced by the review of the literature, there is a lack of synergy between the two approaches. While the most recent statistical research suggests that significant factors, such as weather, traffic and driver fatigue, are dynamically changing in real-time, most optimization research does not account for this. For example, it is not uncommon for vehicle routing problems to assign a constant crash probability (e.g., 10^{-8}) per mile driven. Hence, the purpose of the current paper is to outline one way that this can be bridged by proposing a dynamic programming framework for real-time decision-making for traffic safety.

In addition, we proposed a way to compare human driving and autonomous driving in this paper. By reviewing the papers related to the risk for autonomous vehicle, we found out that most of the studies are focused on avoiding collision by taking the correct action under different driving conditions like the experts in the real life [78, 79, 80, 81]. However, the author in [82] suggests the risk for autonomous vehicles can not be ignored the impact of weather and traffic. In this paper, we assumed both driving models will be effected by weather and traffic, but the driver is another significant factor in terms of human driving. Hence, we utilized one indicator in the optimization model to represent the effect caused by human driving in this model.

The goal of this chapter is to outline a way to construct an optimization framework explicitly based on the dynamic nature of risk factors. The model is based on natural assumptions supported by the existing statistical literature. It must be emphasized, though, that in the current form the approach does not rely on a specific statistical model. Instead, we propose a well-structured framework and study some of its properties. The remainder of this chapter is organized as follows. In section 2, we give the literature review in terms of the descriptive models and prescriptive models related to the transportation safety. Then the mathematical model will be presented in section 3, followed by case studies of human driving and autonomous driving. In the end, we will discuss the conclusion and future study.

2.2.1 Important factors in motor vehicle crash risk

As observed in systematic review [75] variables related to traffic safety can be grouped into five categories: driver-related factors including fatigue, distractions and impairment; traffic condition such as traffic flow, volume, speed and others; weather conditions; geometric characteristics of the road; and the condition of the vehicle. Some existing approaches only focus on evaluating the risk caused by one of the sources, while others attempt to integrate many factors in a single model [83, 84, 85]. Here we focus on reviewing the factors that exhibit dynamic behavior such as weather, traffic and driver conditions for three reasons. Firstly, part of the optimization models being evaluated are limited to shortest-path models. In this case, the road geometry will be fixed. Also, if you are comparing more than two paths then you will need to account for some dynamic features except for the distance. Secondly, for vehicle routing and scheduling problem, the objective is usually to minimize the travel time/cost which could be affected by the weather and traffic. However, not all the decision models have included these important features. For instance, the paper[77] has grouped the optimization models into different types. We can see that most of the models who have random risk are because of weather and traffic[59, 51, 61, 63]. Lastly, those non-dynamic variables do not interact with the dynamic ones, but the dynamic variables could interact with different choices from the decision models. For example, weather and traffic could change as time and locations and any decision related to the vehicle routing may lead the driver to various driving conditions. In other words, the risk and the travel time could be significantly affected by these dynamic variables.

Weather conditions It is natural to expect that adverse weather conditions, such as precipitation or low visibility, can have significant effect on the traffic incidents. Indeed, multiple studies analyzing various type of data have observed this relationship going as far back as 1967, see for example, [86, 87, 88, 89, 90, 91]. At the same time, it must be emphasized that different studies often find different factors to be significant, which include precipitation [88, 89, 92, 93, 94, 76], winter weather [95, 96], fog [97], snow [95, 98, 88], wind gusts [99], daylight duration [100] and even temperature [101, 102]. Furthermore, different aspects of each of these feature have been shown to contribute to traffic incidents, for example, [90] concluded that the duration of precipitation is more important compared to the intensity. Furthermore, the author in [103] compared the Poisson model, the uncorrelated random effect model and the random effect model under two scenarios including the seasonal model and single/multiple vehicles crashes models. The result indicates that the weather and speed are the most significant variables in single vehicle model while the variables related to the traffic have more significant effects in multiple vehicle model. Another example in [104] illustrates the traffic flow variables play different roles for those models under various levels of severity. More specifically, it is more likely to have property-damage-only crashes when encountering congested traffic condition. However, the lower variable speed and lane changes increase the probability of fatal/incapacitating injury crashes and non-incapacitating/possible injury crashes.

We can then conclude that while the significance of weather factors is well-established, a wide variety of particular aspects of these factors may be relevant, and the exact relationship between them is less clear. This, of course, significantly complicates the decision-making step of the analysis, since it is not always clear which aspects must be included in the decision-making process.

Traffic condition Most models consider the term “traffic flow”as a factor in incident risk prediction (among others, [105, 106, 107]). At the same time, sometimes the traffic flow indicates aggregated traffic volume in a unit time [105], while it can also be used as the speed/volume measure [108, 106, 109]. The elements of traffic condition that have been shown to be significant can be classified into three groups: traffic volume, density/occupancy and speed [76]. Most of the statistical analysis use more than one group of traffic characteristics in order to predict the crash risk more accurately [108, 110, 106, 109]. For instance, the author in the paper [110] illustrates a predictive model can be more reliable if the traffic density and V/C(volume to capacity) ratio can be included as well as traffic volume. Hence, traffic conditions features are similar to the weather conditions, in that, while both are firmly established as significant, the precise definition of what is significant differs depending on the author.

Driver-related factors Driver-related factors usually refers to distraction, fatigue and impairment. While distracted driving is widely accepted as a significantly important factor in traffic incidents, (see for example, [111, 112]) we must note that it is not particularly relevant for the routing/scheduling aspect of the decision-making, and hence we do not discuss it in any detail. Similarly, driver impairment, is not relevant for optimization problems.

On the other hand, fatigue-related issues can be expected to be mitigated with intelligent routing and/or scheduling. The factors leading to fatigue can be categorized into driving environments, economic pressure and carrier support [113]. Their result shows that 12 out of 25 indicators of driving environments have significant effect on fatigue and crash rates. However, it does not provide details of how to precisely measure the fatigue score. Similarly, other author [114] admits that fatigue is a key factor for crash risks among lots of researches, but the indicator of the fatigue haven’t been clearly observed from self-assessment and temporal vehicle separation. Instead, they often conduct the statistical analysis by taking into account the possible factors concerning the fatigue. For example, the authors of [85] apply a logistic regression model to understand the impacts of human factors (age, driving skill, etc.), vehicle factors, road geometric and environment conditions for the fatigue-related accidents. By contrast, the author in [115] tried to predict the number of hard break by incorporating a biomathematical model to evaluate the driver's fatigue and performance based on the sleep and sleep loss [116]. In contrast, the fatigue model in some papers uses the the effects of sleep/awake pattern and work/rest schedules [115].

2.2.2 Optimization literature

As discussed above, the majority of prescriptive models that explicitly consider safety criteria are concerned with hazmat transportation. While some aspects of such models are irrelevant for general transportation (e.g., affected population measures), others are not hazmat specific, hence we still review these models here.

Of the three factor groups discussed above, driver fatigue has been the only one widely used in decision making. One effective way to mitigate the driver's fatigue is to find the optimal schedule for those drivers [113, 117, 62]. In some models, the fatigue risk isn't part of objectives, but it has been employed as a constraint in the model. For example, the researchers built an optimization model to minimize the total routing duration while the minimum alertness level for any given segment is above the threshold [62]. Furthermore, although the effect of rest stops during the route hasn't been quantified yet, some researches in this area have showed the rest stop can bring benefit in reducing the crash risk. Specifically, [118] mentioned the crash risk may be reduced by the driver if they can use rest stops in the highway. In addition, the analysis in [117] considered the effect brought by the driving break by adding a categorical variable representing one, two, three or more stops during the route and each break is at least 15 minutes. The result shows there is a reduction in crash odds at 32% when the driver takes two breaks during 11 hours driving.

On the other hand, very limited literature exists, that incorporates the statistical models based on weather or traffic factors. The author in [77] found most of optimization model haven't taken those parameters related to weather and traffic into consideration. Even though we could observe some features in some optimization models, they are not the inputs for the statistical risk analysis. Specifically, [59] applied the expected exposed population on-line along each arch to represent the consequence of an hazmat accident. Another example could be found in [61] that used the product of the expected frequency, the road length and the vehicle number of each road as the frequency of an accident for each road section. In addition, the expected frequency is calculated from the road geometrical condition and the traffic flow. The author decided to take this way to evaluate the risk of accident since it was mentioned in [119] as an effective way to evaluate the accident frequency. Moreover, the risk distribution for the road network in [63] has been grouped into different levels which also takes weather condition into account. However, the risk is not generated by studying the relationship of the features and risk from the perspective of statistics. Comparing with those methods of estimating the risk in optimization models, the prediction models incorporate the analytic tools could be more accurate and realistic. As discussed above, while both of these factors are widely accepted as significant, there is no consensus on which aspects of these factors are most important, and how they should be used in decision making.

2.2.3 Risk factors data availability

As we know, from the view of prescriptive and descriptive models, the quality of the data is critical in building a robust model. Many years ago, the data collection related to the road accident is very time-consuming and the accuracy of the data is not always ensured [120]. Now with the help of modern technology, it is possible to collect both traffic and weather information on a massive scale and much more effectively. Collecting traffic data is not limited to the manual counts, and instead utilizes either specially designed technology (pneumatic tubes, inductive loops, weigh-in-motion sensors, micromillimeter wave Radar detectors) or IT solutions [121]. Furthermore, this data is more readily accessible to practitioners and researchers (see [52]). Besides that, the government also collects and documents the traffic data that is open to the public. As a case in point, the website of National Highway Traffic Safety Administration (NHTSA) can be used to gather the historical crash information. Similarly, the weather conditions data comes from different resources which increase the accuracy and cover more areas. For example, the U.S. has approximate 2,000 Automated Surface Observation System, more than 250,000 Personal Weather Stations and also over 26,000 weather stations [122]. Moreover, the prediction of the weather has enlarged from 2-days to 5-days compared with 20 years ago owning to the advanced technologies [123]. For the researchers, the historical weather data becomes easier to be obtained and most of these data has been well-structured. For example, National Weather Service (NWS) or Climate Data Online (CDO) provide free source to the people who are looking for historical weather data in the USA. Also, some websites provide more accurate data to meet different requirements. For instance, the Dark Sky API allows the researchers to get the weather data aggregated by hour, day and month.

More importantly, with the development of data management tools, all these data can be merged and applied to achieve different goals. From the perspective of optimization, the optimal solution could be more reliable if the action is determined by taking those important factors into account. In terms of the safety for the driver, a better decision should be based at least on the traffic and weather conditions. Our aim then is to provide a theoretical model designed to minimize the total travel time and the cumulative risk integrating recent research result of crash risk. Besides that, a driver-related factor named as the performance degradation, which is the reduction quality of driving based on driving history, speed and driving conditions, will be employed in our model to evaluate the risk. In this way, our model could be easy to transfer between diver-related driving and unmanned driving.

2.3. Mathematical model

2.3.1 Proposed framework to address the gap

In this section, we produced a framework to connect the predictive and prescriptive models. Generally speaking, there are three stages for the entire process of improving driver's safety, as shown in figure 2.1. The first stage is ETL(Extraction, transformation and loading) process for the purpose of preparing data sets in the next two stages. With respect to the predictive model, it usually starts with the question of how to define the risk. It could be the mile-driven or time-driven probability of a crash or safety critical events. Also, it could be the risk cost such as the traditional risk in hazmat transportation which is the product of probability of accident and the expected consequence [37]. Later, the researchers should perform the model selection to determine the best model. When it comes to the machine learning methods, it is very common to apply cross-validation to select the best model with the appropriate parameters. The way to decide whether we have a good prediction is to evaluate the model based on the testing data. If we satisfy with the result from the evaluating step, then a prediction tool has been built to serve in the optimization model. From the view of optimization, the major problem is what we should do to prevent the crash and how could we do when taking into account the risk prediction from the second stage. After we get all the answers, we need to decide the methodology to develop an optimization model, followed by formulating the mathematical model in terms of each component. Most time, the basic optimization model should clearly define the objective function, decision variable, parameters and constraints. By checking those significant factors in the risk predictive models, we can group them into controlled or uncontrolled variables. Further, those controllable variables will be our decision variables while those uncontrolled ones will be the parameters that could vary as the decision variables. The next step in this stage is to select the appropriate algorithm to find the optimal solution. Finally, we need to find a way to verify the result. In this paper, we compared different policies with the optimal one and also did the sensitivity analysis on the parameters.

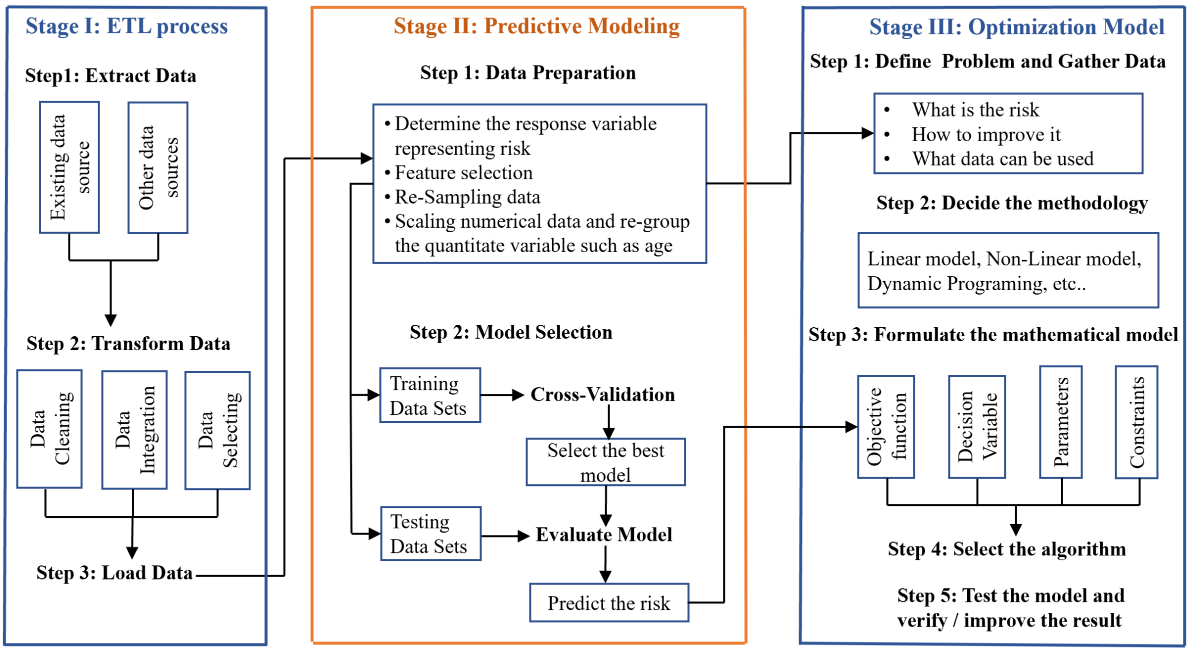


Figure 2.1: The framework to address the gap

2.3.2 Model

In this section, we introduce a dynamic decision-making model aimed at addressing the gap described above. Note that, as suggested by most of the reviewed traffic incident prediction literature, driver fatigue and corresponding degradation in performance represent a key factor in crashes. Further, dynamically changing external conditions (weather and traffic) significantly contribute to risk estimates. Finally, interaction between the two is also important. Hence, the model adopts Markov Decision Process (MDP) framework with the following key concepts.

1. performance degradation index. As evidenced by the literature, there are multiple factors that affect driving outcomes, some of which are external (traffic, weather, etc.) and some internal (fatigue, time since the last rest, distractions, etc.). Here, we propose to group all internal factors into a single state parameter, we will refer to as *Performance degradation*. Note that we prefer a single cumulative parameter for two reasons. First, since the internal factors are directly influenced by driver's decisions, having a multidimensional set of factors would significantly complicate the state space. Secondly, as noted in the literature review, different authors come to somewhat different conclusions when describing relative effects of different factors. Hence, we suggest that a simpler model with single factor can be easier to quantify. We will denote performance degradation index as g.

2. Driving conditions vector. Unlike internal factors, the set of external factors does not necessarily need to be simplified to a single index, since these can be treated as exogenous parameters for our model, that do not depend on the decisions made. Hence, we will define a multidimensional vector w, corresponding to driving conditions. In the case study below we will consider two factors, that we will refer to as adverse weather conditions, and adverse traffic conditions. In this case we can characterize as $w_{nk} = W(w^1_{nk}, w^2_{nk})$, the two factors for road segment k during stage n. Two interpretations are possible. We can assume that these are deterministic, i.e., accurate forecast for both weather and traffic is available for the duration of the planning horizon. Alternatively, these can be treated as random, indicating the uncertainty in the forecasts.

3. Markov Decision Process (MDP). The specific problem under consideration is assumed to be formulated as an MDP, where the decision maker is looking to determine an optimal policy for minimizing traffic risk when completing a specific task. In the case study we assume that the problem is a simple driving task from point A to point B and the risk can be reduced by scheduling rest stops. The same framework can be used for more complicated problems, such as route selection, multiple-vehicle dispatching, etc. As usual, an MDP consists of state and action spaces, objective function and transition laws.

The MDP components are constructed as follows.

1. States. S and $s_n \in S$. The state variable is two-dimensional (x_n, g_n) indicating the vehicle location (x_n) and the performance degradation (g_n).

2. Actions. A and $a_n \in A$. The action is a categorical variable representing the different levels of speed on the highway.

3. Time interval. Δt. In order to model the decision making problem as a Markov decision process, we split the time horizon T into discrete pieces of duration Δt. Δt on hand should be short enough that dynamically changing conditions can be assumed to be constant, yet long enough as to not be prohibitively challenging from the computational perspective.

4. Risk function. $c_{n+1} = \phi(g_n, a_n, w_{n+1,k})$. Driving risk is one of the factors determining the quality of a candidate solution. We assume that when transitioning from stage n to $n+1$, the risk depends on the performance degradation parameter at the end of the current stage (g_n), the action (a_n) and the driving condition for the next stage ($w_{n+1,k}$).

5. Performance degradation evolution. $g_{n+1} = G(g_n, a_n, w_{n+1,k})$. If the decision is to take a rest, the performance degradation gets a refresh to some degree; otherwise, the performance degradation deteriorates based on the speed and the degree of the adverse driving condition.

6. Transition function in MDP.

$$(x_{n+1}, g_{n+1}) = \begin{cases} x_{n+1} = F(x_n, a_n) & x_{n+1} \geq x_n \\ \\ g_{n+1} = G(g_n, a_n, w_{n+1,k}) \end{cases}$$

where function F determines the change in location given decision a_n.

7. Cost structure. We assume that the objective consists of two conflicting factors: minimizing the traffic risk, and maximizing some form of an economic characteristic of trip, e.g., arrival time. We can then write it as $p \sum_n c_n + qT$, where T is the arrival time and p, q are relative weight factors.

Nomenclature

Notation

Δt	Time interval between two consecutively stages.
$\bar{r}_n$	Expected risk incurring during stage n.
$\overline{w}^1_{nk}$	Expected weather condition of segment k at stage n.
$\overline{w}^2_{nk}$	Expected traffic condition of segment k at stage n.
$\overline{w}_{nk}$	Expected driving condition of segment k at stage n.
a_n	Speed chosen at the end of stage n.
c_n	Cost including risk and time during stage n.
g_n	Driver performance at stage n.
k	Segment number.
N	Total number of stages.
n	Stage number.
p	Weight of risk.
q	Weight of travel time.
r_n	Risk incurring during stage n.
t_n	Travel time during stage n.

w_{nk}^1 Weather condition of segment k at stage n.

w_{nk}^2 Traffic condition of segment k at stage n.

w_{nk} Driving condition of segment k at stage n.

x_n Distance from the origin to current location at stage n.

MDP

Horizon: N.

States: S, $s_n = (x_n, g_n)$ and $s_n \in S$.

Actions: A and $a_n \in A$.

Transition function:

$$(x_{n+1}, \overline{g}_{n+1}) = \begin{cases} x_{n+1} = F(x_n, a_n) & x_{n+1} \geq x_n \\ \overline{g}_{n+1} = G(g_n, a_n, \overline{w}_{n+1,k}) & \end{cases}$$

Cost: $c_n(x_n, g_n) = p\bar{r}_n + qt_n$.

Objective: Min $\sum_{n=1}^{N} c_n$.

2.4. Case Study

As an illustration of the proposed methodology, we will use the model in a randomly generated case study, with two cases: driver-operated and driverless modes. By design, the main factor in the way that the model evaluates risk is the performance degradation parameter (g) and the way the changes to it accumulate. In the driverless case, the performance degradation does not change, since the AI does not fatigue or rest, hence, our model can account for that case by considering a fixed performance degradation parameter. Next, we will first illustrate the general behavior of the model and then compare the two modes. In practice, the decision-making model described above needs to be calibrated against practical data using appropriate statistical methods. In the absence of extensive statistical analysis, in this section we explore the general behavior of a model with hypothetical parameters. Specifically, we focus on verifying that the proposed model performs according to our expectations and evaluate how sensitive it is to the changes in the parameters. The data set used in the case study is randomly generated, which includes weather and traffic condition for the whole route in the next 24 hours. The total length between the origin and destination is 400 miles, and it has been divided into 16 segments with equal distance. Besides that, the driving condition within one segment will remain unchanged for every half hour.

2.4.1 Driver-operated model

A deterministic dynamic model is used for illustration purpose in this section to better observe how the optimal policy changes under different conditions. We compare the solution due to the proposed model with two heuristic policies: no-stop and no-risk. No-stop policy disregards the risk component of the objective, and hence prescribes continuous driving for 8 hours at maximum speed, arriving at the destination before 4 pm if the driver starts at 8 am. On the other end of the spectrum, no-risk prescribes stopping whenever both weather and traffic are adverse, hence avoiding as much risk as possible. Note that we limit the maximum number of stages for the optimal policy to 16 (i.e., 8 hours of either driving or stopping), while not restricting the no-risk policy. We make the following additional assumptions on the specifics of the decision-making model.

1. According to the literature, both weather and traffic conditions have significant impact in crash risk, yet there is no single agreed upon model for evaluating relative importance of these factors. For the illustrative case study presented here we adopt a simple linear regression relationship between adverse weather and traffic variables (binary) and the cumulative driving conditions.

   $$w_{nk} = \alpha_0 + \alpha_1 w_{nk}^1 + \alpha_2 w_{nk}^2$$

   Here, w_{nk}^1 and w_{nk}^2 are indicators of adverse weather and traffic, respectively.

2. Performance degradation evolution $g_{n+1} = G(g_n, a_n, w_{n+1,k})$ and

$$G(g_n, a_n, w_{n+1,k}) = \begin{cases} g_n + \beta_0 \Delta t + \beta_1 a_n + \beta_2 w_{n+1,k} & a_n > 0 \\ g_n - \beta_3 \Delta t & a_n = 0 \end{cases}$$

A similar approach has been considered in, for example, [115] where the authors estimated hard break events based on the performance degradation and traffic density by building a generalized linear model. We assume that performance degradation is additive, i.e., $g_{n+1} = g_n + \ldots$, and that it deteriorates at base rate β_0 when driving and recovers at base rate β_3. Note that performance degradation recovery is in accordance with, for example, [117], where the authors have found that stops of at least 15 minutes can have positive effect on reducing crash odds. The parametric form can also be seen as a discretized version of the crash risk model presented in [124], where the authors built a Bayesian Hierarchical Jump Power Law Process(JPLP) to take into account the effect of rests on the risk by modeling the intensity function of safety critical events(SCEs). In this context, performance degradation index plays the role of the variable intensity in the JPLP. Specifically, the results in [124] show that rest stops can decrease the likelihood of collision mitigation critical events that is a strongly correlated with actual crashes [125].

3. Risk probability:

$$p_n = 1 - e^{-(\gamma_0 + \gamma_1 g_n + \gamma_2 w_{n+1,k}) * \delta_n}$$

$$\delta_n = \begin{cases} 0 & a_n = 0 \\ 1 & a_n > 0 \end{cases}$$

We adopt the risk model proposed in [124], where crashes (or safety critical events) are modeled as a Poisson process with variable intensity. Consequently, the probability of no crashes is described through a Poisson random variable distribution.

4. Risk cost function:

$$c_n = \phi(g_n, a_n, w_{n+1,k}) = (\gamma_0 + \gamma_1 g_n + \gamma_2 w_{n+1,k}) * \delta_n$$

Prove:

$$\begin{aligned}
&\text{maximize} && \prod_{n=1}^{N}(1-p_n) \\
&\text{maximize} && \sum_{n=1}^{N} \ln(1-p_n) \\
&\text{minimize} && \sum_{n=1}^{N} \text{-}\ln(1-p_n) \\
&\text{minimize} && \sum_{n=1}^{N} (\gamma_0 + \gamma_1 g_n + \gamma_2 w_{n+1,k}) * \delta_n \\
&\text{Let} && c_n = (\gamma_0 + \gamma_1 g_n + \gamma_2 w_{n+1,k}) * \delta_n \\
& && \text{for n = 1, ..., N} \\
&\text{minimize} && \sum_{n=1}^{N} c_n
\end{aligned}$$

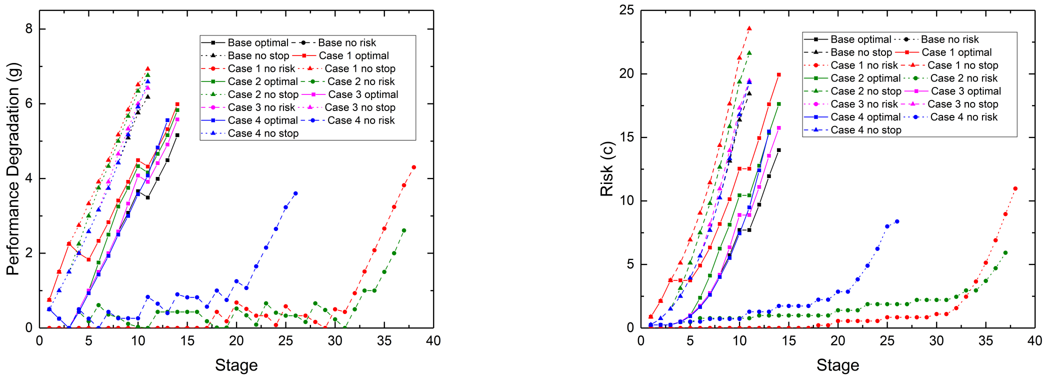
As we mentioned in the previous section, the entire route will be divided into a few stages and each one is a half hour duration. Here, the objective function in the dynamic model is to maximize the probability that no stage incurs any SCE. Based on our proof, it works the same as to minimize the c_n for each stage. Finally, the cost for each stage in our model will be be written as c_n.

5. $\Delta t = 0.5$ hour. Half-hour interval is selected as a reflection of typical time scale for weather and traffic changes and forecasts, as well as government regulation requiring 30 minutes of rest for every 8 consecutive hours of driving.

6. $A_n = [0, 55, 75]$. Generally speaking, the highest speed limit in USA could be 70 mph on the west coast and the inland eastern states while it could be $75 - 80$ mph for inland western states [126]. As a simplified model for action space we consider three choices for highway driving: maximum allowed speed (75 mph), reduced speed (55 mph) or a rest stop.

In order to obtain the unknown coefficients in the dynamic model, we studied on the same data from a commercial truck company in paper[124]. The data describes the weather, traffic and other information for all the trips for various drivers. More importantly, a binary variable is the outcome for each trip, representing whether there happens any SCE. Firstly, we set $\alpha_0, \alpha_1, \alpha_2$ as $0, 0.7, 0.3$ respectively to find the driving condition. By extension, w^1_{nk} is decided by the level of the visibility and precipitation intensity. Further, the traffic condition is determined by whether the travel time is during the peak time. Then we build a non-linear model in Excel to find the parameters for the performance degradation evolution and the risk cost simultaneously by minimizing the sum of the absolute value between the probability of risk and the binary variable of the true SCE. By evaluating the result from the non-linear model on the testing data, the performance in terms of Receiver Operating Characteristic(ROC), sensitivity and specificity is not very good. Similarity, the result for the same data in [124] does prove that there exists a positive association between different type of SCEs and the real crash while the indicators are not very strong for some types of SCEs such as head-ways and hard-breaks. Also, when we built a logistics regression model by using more features than those in the non-linear model based on the same data, the model still has not been proved significantly. Consequently, we believe the parameters we select are good enough from the perspective of data analyzing. Further, the point of our paper is to show the necessity to integrate two branches of researchers, so we choose to use the most interpretable parameters to demonstrate our model. In that way, β_0, β_1, β_2 and β_3 are equal as 0.25. Moreover, γ_0, γ_1 and γ_2 are 0, 0.5 and 0.5 respectively. Based on these parameters, ROC, sensitivity and specificity are 0.55, 0.67 and 0.43.

The first experiment is aimed at investigating how performance degradation changes under different driving conditions. We generated a random data set (available in the appendix) which consists of the simulated forecast for adverse weather and traffic conditions for every location along the intended path (segments 1–16) over the planning horizon (0–8 hours). Assuming a fully rested driver, the initial performance degradation g_0 is set to 0 and the weights for the risk and time are assumed to be equal. In order to illustrate the behavior of the model, we then introduce additional adverse conditions for specific road segments. It is noted that the adverse conditions here indicate weather and traffic are both unfavorable. Specifically, four cases are generated with adverse driving conditions for the next 8 hours in road segments 1–4, 5–8, 9–12 and 13–16 respectively. Note that in the no-risk policy, the driver is not restricted by the 8-hour time limit, and hence can wait as long as necessary to avoid adverse conditions.



(a) performance degradation (b) risk

Figure 2.2: The changes of performance degradation and risk for different policies under different cases. Please note the result of the base, case 3 and case 4 under the no-risk policy overlap most of time.

Figure 2.2 summarizes the results. Since the adverse conditions are prolonged and the model planning horizon is restricted to 8 hours, the optimal policy can not avoid driving in adverse conditions. Hence, the model produces a driving schedule that balances time and risk objectives. On Figure 2.2 we can observe that both performance degradation and risk corresponding to the scenario that have the adverse condition earlier will end up with higher performance degradation and risk. As an illustration, the base case has the lowest performance degradation and cost while the case 1 has the highest ones no matter under which policy, followed by the case 2, case 3 and case 4. Note also that by the end of the planning horizon, in three of the cases the system arrives to very similar states (exactly the same performance degradation and almost the same cumulative risk), corresponding to the idea that the optimal policy can, to an extent, mitigate adverse conditions no matter when they occur.

As naturally expected, the optimal policy presents a compromise between the no-stop and no-risk policies in terms of risk and time trade-off: not taking conditions into account results in dramatic accumulation of performance degradation parameter and corresponding risk, while fully avoiding adverse conditions is prohibitively time-consuming. Similarly, if reward function weights are adjusted, the optimal policy can be moved closer to either of these two extremes (subject to total driving hours restrictions). Figure 2.3 illustrates optimal policy behavior as the coefficient ratio between the time and risk cost changes from 0.01 (largely favoring time) to 10 (largely favoring risk).

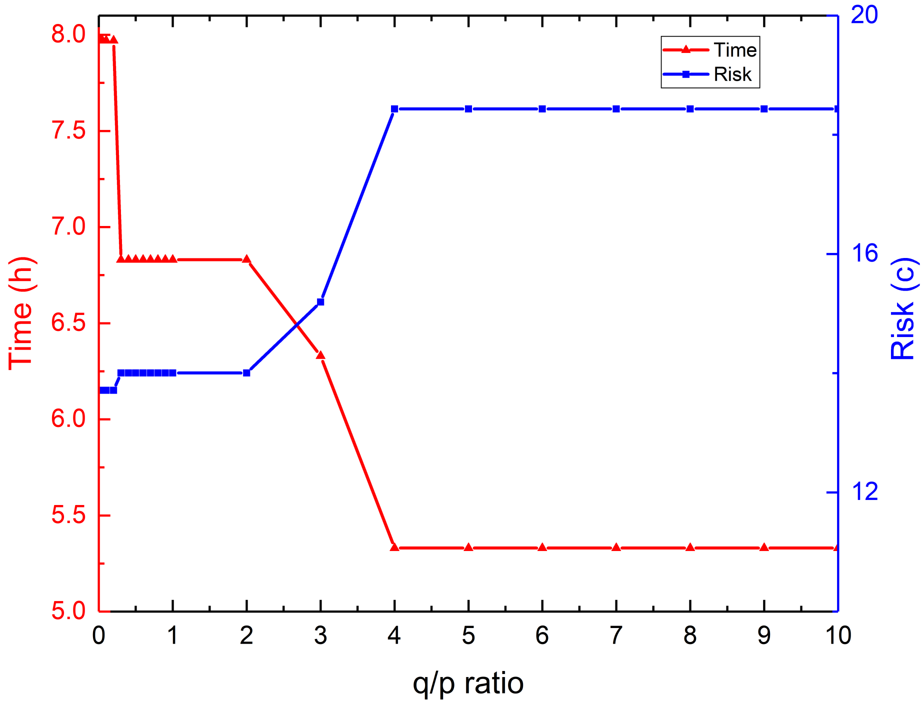


Figure 2.3: Time & Risk of the optimal policy under different ratios

The behavior of the model can also be sensitive to two important parameters: initial performance degradation (g_0) and the degree of decreasing (β_3), i.e., recovery rate due to rest. Figures 2.4 depict the change in performance degradation under optimal policies for a range of these parameter values. Naturally, larger initial g_0 always results in worse cumulative performance (sometimes corresponding to shorter driving time). Similarly, if recovery rate is relatively low ($\beta_3 = 0.25$), it may not be worthwhile for the model to schedule rest stops in most cases, resulting in higher overall risk, compared to the high recovery rate $\beta_3 = 1$, where it is possible to fully recover ($g = 0$) on a regular basis. At the same time, the particular details of each policy are not trivial, hence highlighting the need for the optimization problem.

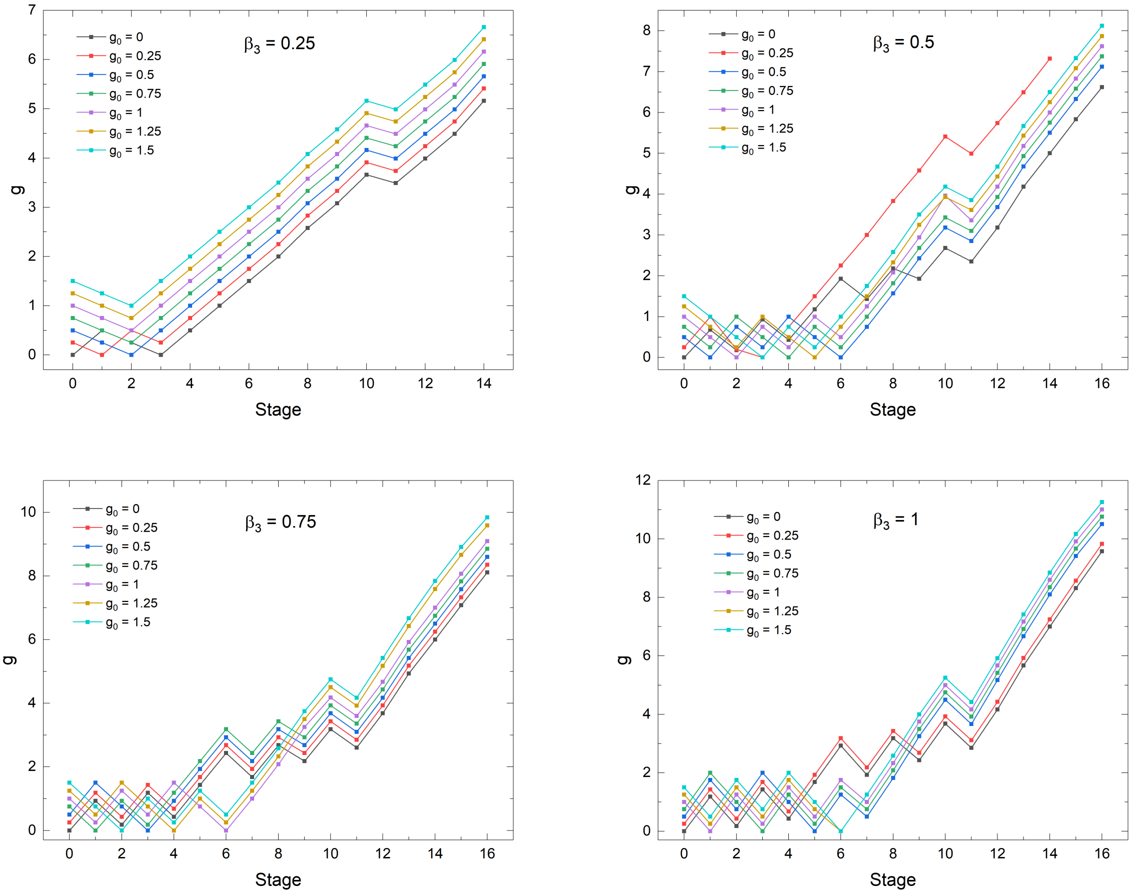


Figure 2.4: Sensitivity analyses of initial performance degradation(g_0) and the degree of decreasing (β_3) on performance degradation (g)

2.4.2 Autonomous vehicle model

According to our research, current study of risk estimation in the discipline of autonomous vehicles are focused on avoiding the collision on the road [127]. The data in paper [128] concludes that the failure probability for autonomous vehicles caused by weather and road conditions is less than 1%, while the failure probability of autonomous vehicular components is the larger reason of risk. It is nature to have this kind of statistical result, since the autonomous vehicles is not mature enough as the human-drive vehicles. However, it suggests the risk estimation of intelligent cars should consider incorporating the real-time crash prediction model and take into the weather and traffic condition into account [82].

As a way to demonstrate the use of the proposed model for analysis, we consider a comparison between human driver and autonomous use cases. Specifically, we are interested in investigating the way that the optimal policy behaves in two cases. As described above, the autonomous case, corresponds to a constant performance degradation ($g = g_c$), i.e., there is no accumulation of "fatigue". Intuitively, in the case of human driver, in addition to the immediate effect of the increased risk, adverse conditions also contribute to the "future" risk through accumulating performance degradation parameter. Hence, there is a significantly larger incentive for avoiding adverse conditions, especially early on. Conversely, in the autonomous case, there is no difference in when the vehicle is subjected to elevated risk, hence, the only consideration in scheduling breaks is the goal of avoiding immediate risky conditions.

Note that while "tiredness" is not present in the case of autonomous driving, such mode is not immune to errors leading to traffic incidents, and these error rates can be compounded by driving conditions (e.g., reduced visibility due to heavy rain). In [128], the authors group the risk present in autonomous driving into vehicle components and infrastructure factors. Vehicle component issues can be related to Lidar failure, radar failure, etc. Similarly, we assume the risk function here is a linear combination of the features such as the driving time, the integration between the speed and weather condition and the interaction between the speed and fix performance degradation. Consequently, the cost in the linear case can be modeled as

$$c_n = \phi(g_c, a_n, w_{n+1,k}) = (\gamma_0 + \gamma_1 g_c + \gamma_2 w_{n+1,k}) * \delta_n$$

First, observe that the parameter g_c essentially plays the role of the scaling factor for the total risk (and total cost) for the optimal policy. Hence, while its choice is important for determining relative performance of the policy, its value does not have an effect on the optimal decisions themselves.

Figure 2.5, depicts the cost (risk and total driving time) associated with the autonomous vehicle model for the same cases as above. We also vary the value of g_c to evaluate its effect. Observe that as the value of parameter g_c increases, the optimal solution inserts rest stops. Specifically, as g_c increases to 0.5, one rest in stage 14 could be found. After that, anther rest stop is recommended at stage 15 when g_c is 0.75 and 1. This behavior is expected, since a large value of g_c corresponds to higher sensitivity to adverse driving conditions, i.e., the model prescribes to stop to avoid the worst conditions, regardless of when en route it appears.

When comparing the driver-based against the driver-less model, the result significantly depends on the value of g_c. Figure 2.6 presents the results of this comparison for a number of test cases. When g_c is small, the cost of autonomous vehicle performance is always lower than for manned driving. As before, given accurate estimates for the model parameters, it can then be used for a comparative study.

2.5. Conclusion

The goal of this study is to address the gaps mentioned in chapter 1. The first gap is addressed by developing a structure for the researcher to integrate the predicted risk indicator from the data analysis and optimization models. Concerning the second gap within the optimization model that rarely finds the truly dynamic model, we introduced the dynamic model to incorporate the statistical models in decision-making to schedule the speed and rest stops, which can easily update the optimal solution for the unfinished route. The outcome shows that the model can help the driver balance the risk and time by adjusting the speed and rest stops. Besides that, we proposed a way to evaluate the driver's performance degradation caused by cumulative driving under various driving conditions followed a similar idea from [124]. Because of performance degradation, we find a way to compare human driving and autonomous driving in which the performance degradation will not be affected by the long-time driving. The

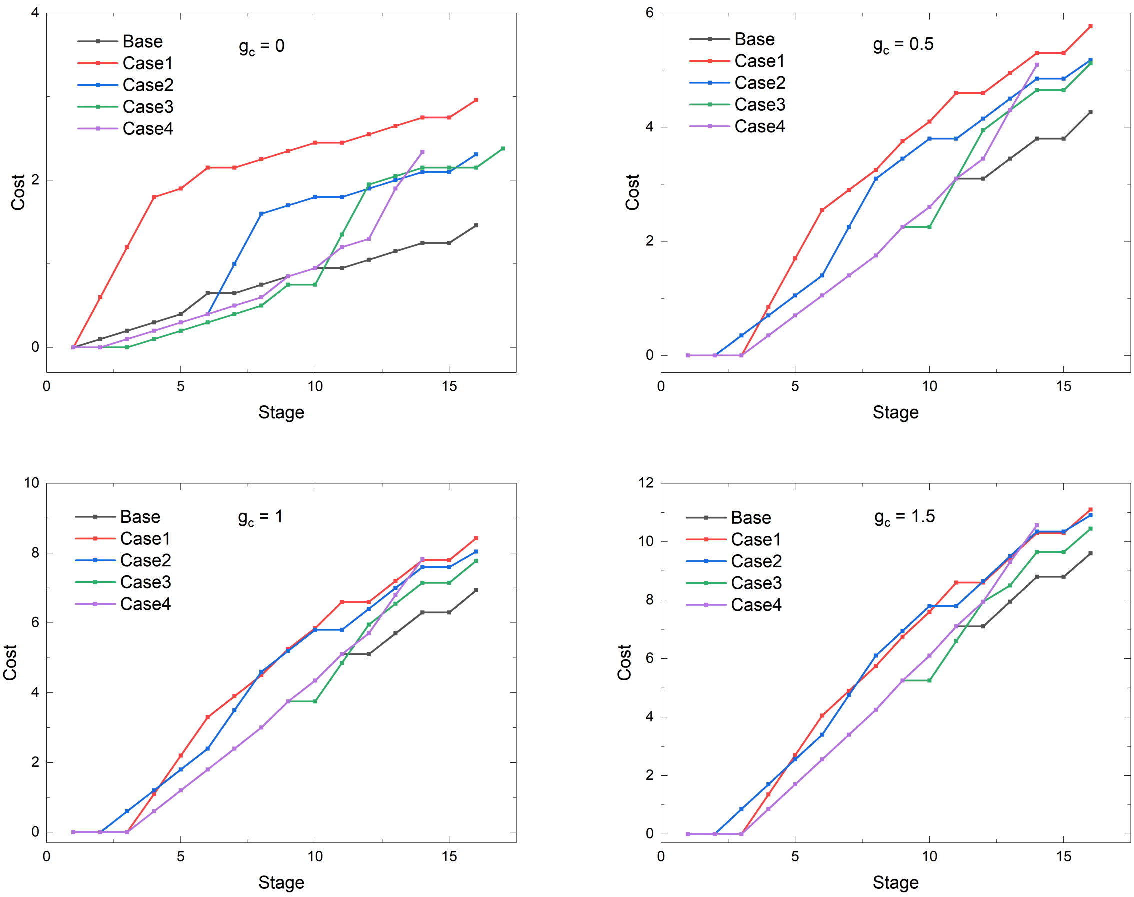


Figure 2.5: Autonomous driving under different cases with various performance degradation(g_c).

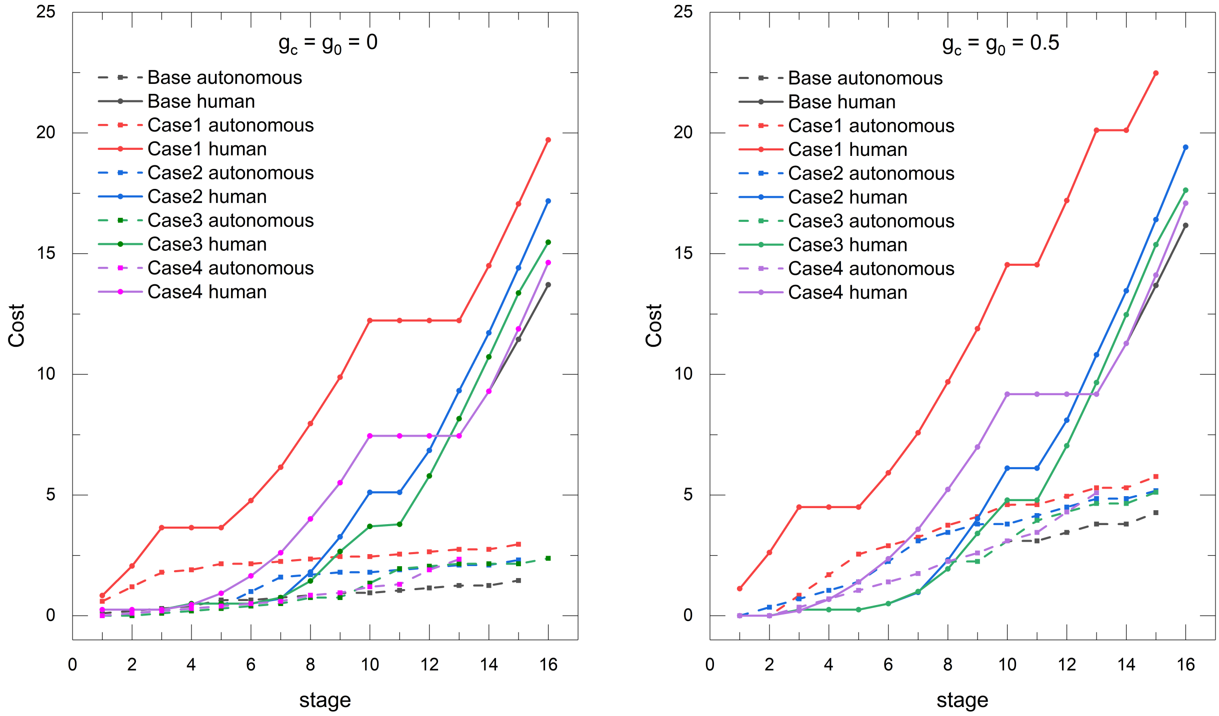


Figure 2.6: Comparison between autonomous and human driving for different cases. The left one is when the fixed performance degradation(g_c) and initial performance degradation(g_0) are 0; the right one is when the fixed performance degradation(g_c) and initial performance degradation(g_0) are 0.5.

results show that human driving always avoids high performance degradation initially, while autonomous driving aims to avoid the immediate adverse driving condition ahead. In the future, we can input any alternative risk indicator in our model to observe how they change the driver's decision. The limitation of this research is that it is only applicable after we decide the optimal route. The following section will focus on making the optimal decision related to route selection to overcome this limitation.

Chapter 3

Bi-objective k-shortest paths incorporating machine learning methods

3.1. Introduction

In [52, 77] we have previously discussed the apparent disconnect between predictive models connecting the driving risk and relevant risk factors on one hand, and prescriptive models addressing how to minimize this risk on the other. Specifically, while the predictive models are generally explicitly constructed to allow for uncertain and/or dynamically changing factors (such as weather and traffic conditions), it is common in vehicle routing problems to assume constant incident probability per mile driven. Naturally, allowing for such factors requires a significant change in the structure of the prescriptive models and the corresponding algorithms. As argued in [77], the apparent gap can be attributed to both this modeling challenge on the prescriptive side, as well as lack of predictive models constructed with prescriptive applications in mind.

In another previous research effort [129] we have established that machine learning methods can adequately predict the risk from safety critical events (SCEs) for medium-scale time intervals (dozens of minutes) assuming accurate weather and traffic forecasts are available. Note though that the methods exhibiting the best performance (XGBoost, neural network, random forest) all are explicitly nonlinear in the input variables. This implies that many standard vehicle routing problem formulations, which rely on either (linear) integer programming or (linear) Markov decision processes, cannot naturally incorporate such an approach. Consequently, in this paper, we consider the problem of constructing a risk-aware routing selection model. Specifically, we approach the task from two perspectives. On one hand, we consider the specific machine learning approach presented in [129] and demonstrate how it can be used in a risk-aware shortest path problem formulation. Simultaneously, we also propose a more general framework that is applicable in similar cases.

Significantly, we focus on data driven approaches for both predictive and prescriptive modeling, specifically in trucking applications. It must be emphasized that trucking companies routinely collect significant amounts of data that can be relevant to the problems of interest. Specifically, we assume that the following types of data are available.

1. Periodical records of the location and speed of the trucks, i.e., information from an on-board GPS tracker. We will refer to these records as *pings dataset*, and it can naturally be used for inferring underlying network structure, average and distribution of driving speed, etc.
2. Some form of either driving incident records or appropriate surrogate. Note that throughout this paper we will concentrate on safety critical events (SCEs) used as surrogates for actual traffic incidents. SCEs are defined as surrogates for crashes and are associated with the road accidents[130]. While these are intuitively related to the actual incidents, it is not necessarily clear whether their use as incident surrogate is always justified. [130] has established that, at least for the four particular kinds used in study (the same data set was used in [129]) are positively correlated with both traffic incidents and injuries. Note that SCEs are regularly recorded by many trucking companies as part of regular operation.
3. Records for relevant risk factors, which usually include, weather conditions (visibility, precipitation, etc), traffic conditions and driver-related factors (e.g., time on shift, quality of rest, etc). [52] discusses in detail some relevant aspects of data collection issues related to these factors.

Consequently, taken together, these datasets can naturally be combined to generate a version of predictive risk model (i.e., connecting risk factors with the outcome), which then should feed into the prescriptive framework.

The contribution of the paper is twofold. First, we demonstrate how a particular machine learning-based predictive model connecting traffic incident risk with relevant risk factors can be incorporated into a routing problem. We formulate a risk-averse shortest path problem and discuss a solution approach. A case study illustrates the performance of the model. Simultaneously, we also discuss a more general setting and outline framework for constructing prescriptive approaches for risk-aware routing and assignment problems in trucking applications.

The rest of the manuscript is organized as follows. A literature review will be demonstrated in the next section, which is followed by the illustration of methodology. After that, we will use the case study to show the application of our model. In the end, we will provide the conclusion and discuss the future study.

3.2. Review of relevant literature

A gap in the existing literature between the predictive models that focus on forecasting traffic-related risk on one hand and prescriptive models dealing with routing, driver assignment and similar problem, has been discussed in detail in recent reviews in [52] and [77]. Specifically, the former focuses on the predictive literature and demonstrates that most approaches identify a number of dynamically changing factors as significant (e.g., weather conditions, traffic situation, etc). On the other hand, as discussed in the latter, few prescriptive models employ these findings. In fact, traditional vehicle routing problems do not consider driving risk, with the exception of models related to hazardous material transportation. Even then, the dynamic nature of driving risk is usually ignored, and, for example, constant incident risk (e.g., $10^{-}8$ per mile driven) is assumed.

A routing problem concerned with traffic incident risk naturally allows for multi-objective modelling perspective. Traditionally, vehicle routing problems are concerned with objectives related to economic outcomes (operational cost, travel time, etc.). In Table 3.1 we review a few examples of multi-objective routing problems, including all cases that we were able to find that incorporate risk as one of the objective. Note that risk, is only considered in hazmat problems. Note that while some lessons learned from hazmat modeling can be applied to general transportation, it must be emphasized that a significant portion of relevant research focuses on ways to estimate hazmat-specific risks, usually measured as some form of measure of expected consequence, which combines the hazmat incident probability and a measure of exposed population. Naturally, this stream of research is not relevant for non-hazmat applications. Further, in the absence of explicit accounting of the dynamic nature of risk factors, i.e., if incident probability is assumed to be constant, driving risk objective is directly proportional to driving distance, and hence the problems should not be treated as multi-objective.

As mentioned above, a detailed review of different risk prediction models for driving applications is given in [52]. Note that we explicitly concentrate driver/vehicle based predictive approaches (as opposed to ones that consider road segment) and on medium timescale ahead (more than a few minutes but less than a day). Other approaches can be required for different kinds of applications, e.g., automatic breaking or road-network planning. For the purposes of this study, we specifically focus on the machine learning approach presented in [129]. The authors, who use the same data set as the one used here, propose a collection of forecasting tools, that take weather conditions, driver characteristics, predicted speed profile (as a surrogate of traffic conditions) and driver's recent incident history as input and return either the probability or the number of SCEs predicted to occur in the next 30 minutes of driving. The best model (XGBoost) is reported to achieve 0.765 AUC (area under the curve), 70% accuracy with consistent sensitivity and specificity.

3.3. Methodology

The purpose of this paper is to provide a systematic method for constructing data driven risk-aware optimal routing. The main prescriptive component naturally allows for Pareto ranking of the candidate solutions (with trip duration and estimated risk as the two objectives). We assume that the decision maker can start with either ping-type data for both machine learning and network construction, or can rely on pre-trained or pre-constructed models and networks. The overall framework then allows for mixing of different modeling approaches. Figure 3.1 presents the overall framework diagram. We next briefly outline each component, and then discuss them in more detail in separate sections.

ETL sequence consists of usual data preparation, cleaning and aggregation steps. Naturally, its specifics significantly depend on the particular kind of datasets used. *Machine learning* here refers specifically to models for SCE risk estimation. For our purposes, we employ the

Table 3.1: A review to investigate the interaction between the application of data analytics and multi-objective vehicle routing optimization models.

Paper	Methods	Objectives	Included risk	Applied data analytics
[131]	Clustering Method and Linear Goal Programming	Minimize Travel Time and Customer Waiting Time	No	N/A
[132]	Multi-objective GA	Minimize Risk, cost and Population Affected	Yes	No
[133]	GA based Pareto Ranking	Minimize Travel Cost and Length of The Longest Path	No	N/A
[60]	Weighted-Sum Method	Minimize Travel Time and Risk	Yes	No
[134]	Population-based Algorithm Based on Scatter Search	Minimize Distance and Time-Balance of Route	No	N/A
[135]	ε-constraint Method	Minimize Max Risk and Transportation Cost	Yes	No
[136]	GA based Pareto Ranking	Minimize Transportation Cost and Time	No	N/A
[137]	Neighborhood Dominance-based Algorithm	Minimize Transportation Cost and Risk	Yes	No
[138]	Simulated Annealing Algorithm	Minimize Combination of Cost, Fuel Consumption, Gas Emissions and Max Reliability of Alternative Paths	No	N/A
[139]	Meta-heuristic Evolutionary Algorithm	Minimize Operational cost and the sum of Max Earliness and Tardiness	No	N/A
[140]	Hybrid Evolutionary Algorithm	Minimize Number of Vehicles and Risk	Yes	No

Notation:GA in the table represents Genetic Algorithm.

methodology proposed in [129]. Note that the method proposed there can be adapted for general applications. Alternatively, at this step another approach could be considered. The routing problem naturally relies on the underlying *network construction* model, which can be either extracted from existing map databases (e.g., OpenStreetMap), or relevant roadways and junctions

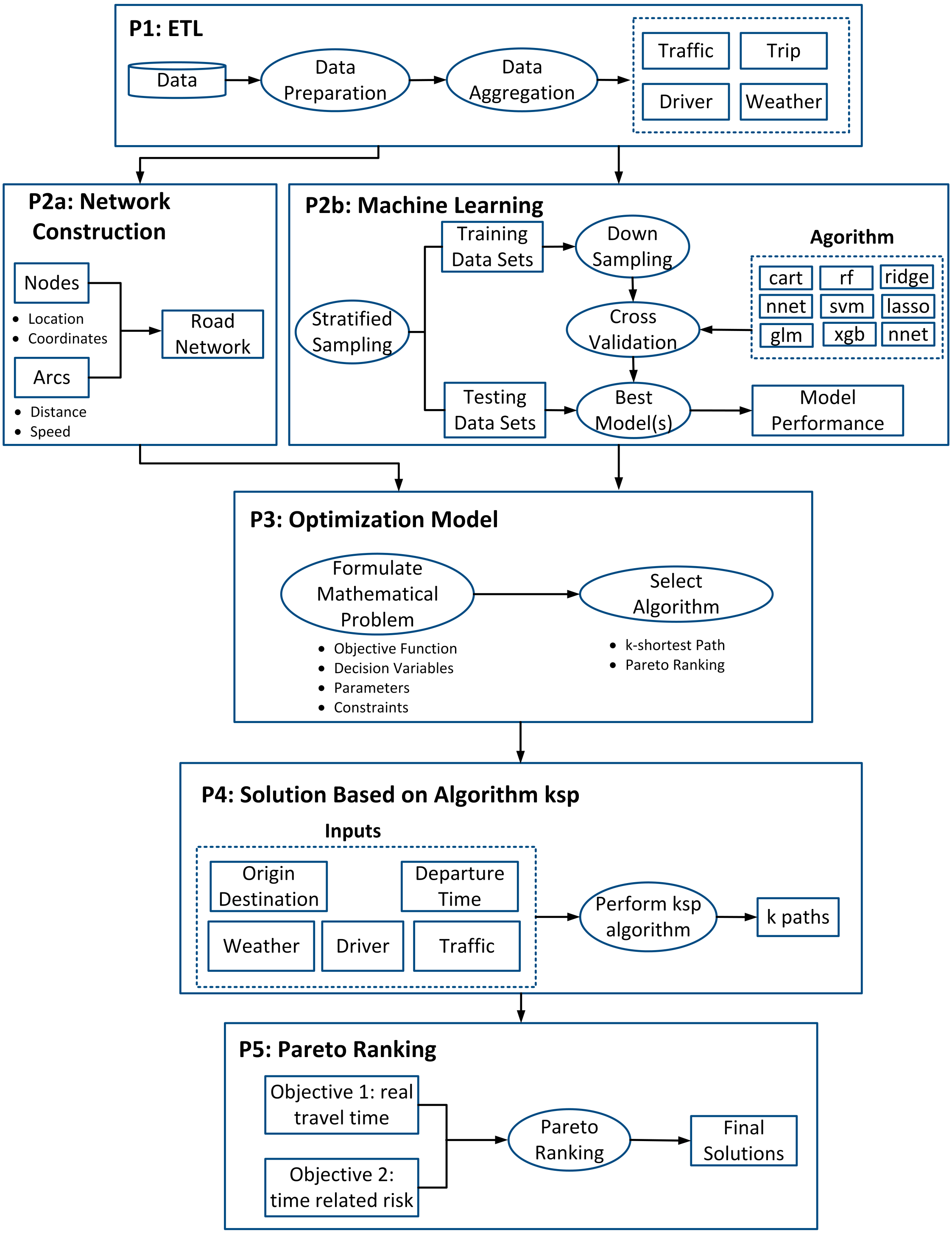
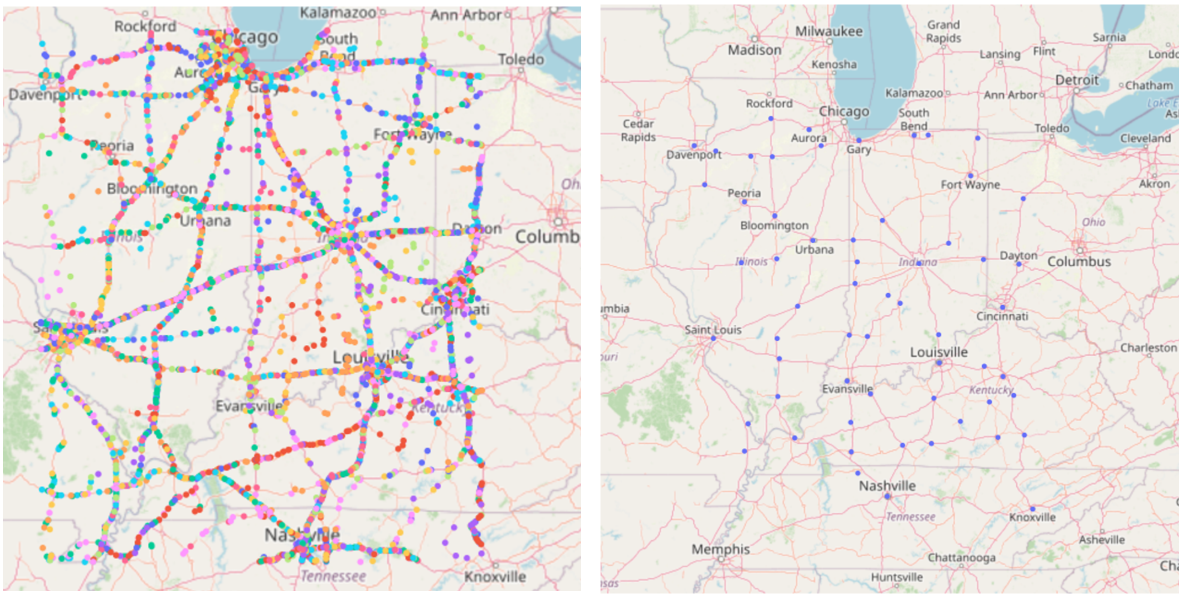


Figure 3.1: Working Process

can be generated in a data-driven way based on the ping data. The proposed framework is relatively flexible to the particular kind of *routing problem* considered. In the simplest case, we can consider a single vehicle with one origin-destination pair of locations. The resulting optimization problem then is a bi-objective shortest path problem. On the other hand, it can naturally be extended to more advanced vehicle routing tasks, e.g., travelling salesman-type problems (multiple destinations for a single vehicle), multiple vehicles, time windows, etc. In each case, the specific formulation may change, but the overall framework and the need for construction of Pareto ranking remains the same. *Inputs* refers to the selected relevant risk factors that are fed to the risk prediction tool. *Solution algorithm* gives a way to solve the underlying two-objective problem. In the case of single origin-destination problem, i.e., bi-objective shortest path problem, we consider an approach based on k-shortest path method for ranking candidate solutions. Finally, *model validation* step serves to verify the quality of the obtained solutions.

3.3.1 Network Construction

Naturally, the decision-making problem depends on the underlying network model, consisting of a set of nodes representing important junctions and a set of arcs connecting them. Such a model for a relevant area can be obtained from any of the GIS services available (e.g., OpenStreetMap). Note that in some cases, a particular application may restrict the set of arcs (e.g., if certain streets are inaccessible to trucks or are otherwise preferable). In this case, it may be preferable to extract the network model from the historical ping data. The following process, illustrated with the particular example, can be considered (see Figure 3.2b). First, select a relevant area. For the case of a trip from Nashville, TN to Gary, IN, used in the case study, the relevant region can be naturally selected based on coordinates. Specifically, we select the latitude from 36 to 42.1 and the longitude from -90.65 to -84.12. Then, all pings within the region can be selected and depicted, as in Figure 3.2a, next to the important nodes. Finally, arcs are drawn to connect all crucial nodes. We manually found those key nodes from the map concerning the important nodes, which consists of a few steps. Firstly, all the possible routes used by those truck drivers can be observed based on the figure 3.2a. After that, we labeled the nodes shared by more than one segment. The next step is to check whether there exists only one path between two connected segments. If so, we do not need to add extra nodes between those two positions. Otherwise, we need to add an extra node to specify the segment included in our network.



(a) All the points within Nashville, TN and Gary, IN

(b) Extract Road Network from Trip Data

3.3.2 Predictive model

As discussed in Section 3.1, the approach presented here is based on a machine learning predictive approach. A detailed description of the methodology, dataset used and testing performance can be found in [129]. Here we briefly describe the most significant aspects that are relevant for the remainder of the discussion.

The goal of the machine learning model is to predict the likelihood of an SCE for a truck during a period of 30 minutes in the immediate future. The approach is based on a large dataset which includes SCE information, ping data as well a weather-related characteristics. Table 3.2 provides a brief explanation of the predictors that have been used in the prediction models. Note that speed mean and standard deviation were used as proxies for traffic turbulence due to the lack of publicly available traffic data.

We used five-fold cross-validation to tune the hyperparameters and choose the best model for each algorithm on the training set. Further, following the suggestions by [129, 141, 142], the random search method was used to tune and optimize hyperparameters during the cross-validation step. Furthermore, due to the nature of crash/SCE data which are extremely rare (less than 1% in our data), we used down-sampling approach to train the models.

Table 3.2: Definition of the predictors of the ML models.

Name	Definition	Type
	Block 1: trip related	
dayOfWeek	day of the week	categorical
holiday	whether or not the trip is within a holiday	binary
hourDayCat	time of the day's category (rush1, mid day, rush2, night)	categorical
starting point	GPS location of the starting point of the trip	continuous
ending point	GPS location of the ending point of the trip	continuous
distance	the distance between the starting and ending points	continuous
weekend	whether or not the trip is on weekend	binary
	Block 2: driver related	
age	driver's age	continuous
gender	driver's gender	binary
SCELag7	number of SCEs recorded for a given driver in the past 7 days divided by their total hours driven during that period	continuous
	Block 3: traffic related	
speedMean	average speed during the trip	continuous
speedSD	average standard deviation of speed during the trip	continuous
	Block 4: weather related	
prepInten	average precipitation intensity during each trip	continuous
visibility	average visibility during each trip	continuous
windSpeed	average wind speed during each trip	continuous

Based on the detailed description of the results of the experiments in [129], XGBoost model had the best performance by achieving AUC equals 0.765, accuracy of 0.803, sensitivity of 0.684 and specificity of 0.805. However, it is worth noting that the other models also achieved similar (slightly worse) performance. The analysis of variable importance indicated that driver-related predictors and, specifically, SCELag7 are the most important risk factors in the occurrence of an SCE. This finding implies the importance of a driver-based risk-aware routing framework in trucking applications.

3.3.3 Mathematical model

As discussed above, here a variety of underlying decision-making models could be considered as the basis for decision-making. To illustrate the construction, consider a simple shortest path formulation with single origin and destination. Suppose a graph $\mathscr{G}$ is constructed with set of nodes $\mathscr{N}$ and set of arcs $\mathscr{A}$. Without loss of generality, assume that the origin is designated as node 0 and the destination as node n. The standard shortest path problem is well-studied and is generally easy to solve. On the other hand, the presence of incident risk variable, dependent on dynamically changing risk factors, can pose a significant modeling challenge. Specifically, we can consider the following formulation.

Sets

$N = 0, 1, 2, ..., n$	set of nodes
$S = N \setminus n$	set of nodes except destination node n
A	set of arcs
T	set of time

Parameters

$v_{ij}^{d_i}$	speed for arc(i,j) when arrival time at node i is d_i
$rv_{ij}^{d_i}$	speed variation for arc(i,j) when arrival time at node i is d_i
l_{ij}	length for arc(i,j)
$w_{ij}^{d_i}$	weather condition in arc(i,j) at time d_i
e	parameters related to driver's characteristics such age and ratio

Function

R	the function to get the risk

Variables

x_{ij}	whether the driver will travel on arc (i,j)
t_{ij}	driving time for arc(i,j)
r_{ij}	risk when driving on arc(i,j)
d_i	arrival time at node i

Objective

$$\min \quad (Z_1, Z_2) \tag{3.1}$$

$$\sum_{i \in N} x_{is} = 1 \qquad s \in S \tag{3.2}$$

$$\sum_{j \in N} x_{ij} = \sum_{j \in N} x_{ji} \qquad i \in S \setminus 0 \tag{3.3}$$

$$\sum_{j \in N} x_{0j} = 1 \tag{3.4}$$

$$\sum_{i \in S} x_{in} = 1 \tag{3.5}$$

$$v_{ij}^{d_i} t_{ij} = l_{ij} \qquad \forall (i,j) \in A \tag{3.6}$$

$$d_j = \sum_{i \in S} \Big(x_{ij}(d_i + t_{ij}) \Big) \qquad \forall (i,j) \in A, j \in N \tag{3.7}$$

$$r_{ij} = R\Big(w_{ij}^{d_i}, v_{ij}^{d_i}, rv_{ij}^{d_i}, l_{ij}, e \Big) \qquad (i,j) \in A, i \in S, j \in N \tag{3.8}$$

$$Z_1 = \sum_{i \in S} \sum_{j \in N} t_{ij} x_{ij} \qquad \forall (i,j) \in A \tag{3.9}$$

$$Z_2 = \sum_{i \in S} \sum_{j \in N} r_{ij} x_{ij} \qquad \forall (i,j) \in A \tag{3.10}$$

$$N = 1, 2, 3, ..., n \tag{3.11}$$

$$S = N \setminus n \tag{3.12}$$

$$r_{ij} \geq 0 \qquad \forall (i,j) \in A \tag{3.13}$$

$$x_{ij} = 0 \text{ or } 1 \qquad \forall (i,j) \in A \tag{3.14}$$

$$t_{ij} \geq 0 \qquad \forall (i,j) \in A \tag{3.15}$$

$$d_i \geq 0 \qquad i \in S \tag{3.16}$$

$$Z_1, Z_2 \geq 0 \tag{3.17}$$

The model is constructed as a bi-objective optimization problem, with the objectives corresponding to arrival time (Z_1) and total risk along the route (Z_2). Equations 3.2 and 3.3 are standard flow balancing constraints used to encode a solution to the shortest path problem, where the variable x_{ij} provides whether arc (i, j) is included into the candidate path. The only complication can be related to the evaluation of the time-based objective, if the arc traversal time is assumed to be dynamically changing, i.e., depends on the driving conditions at the time of traversal. In this case, we define additional variables t_{ij} and d_j corresponding to arc traversal duration and the arrival time on each node. Equations 3.6 and 3.7 define these variables, which then allows for evaluation of the objective function Z_1 in equation 3.9.

In order to evaluate objective Z_2 a relationship between the routing decisions and the resulting traffic risk on an arc needs to be established. Note that this can take various forms depending on the risk prediction model employed. As discussed earlier, here we assume that a machine learning model for predicting the number of SCEs along a driving period is used as a surrogate for risk. Equation 3.8 expresses this dependency. Note that the risk function (R) in general is nonlinear (e.g., neural network predictor) and its arguments depend on the time-related variable d_j. Assuming that the risk measure in the number of predicted SCEs, the risk objective can then naturally be expressed as the total predicted number of SCEs along the selected route as in equation 3.10.

Observe that while the original underlying shortest path problem is simple to solve, introduction of dynamic traversal time and risk significantly complicates the mathematical programming approach. Specifically, equations (3.6) and (3.8) are explicitly nonlinear. In general, such problems may be solved with a Dynamic Programming framework, similarly to dynamic shortest path formulations, e.g., in [143, 144]. Here, for the problem under consideration, we propose an alternative approach based on the k-shortest path algorithm.

3.3.4 k-Shortest path algorithm for bi-objective shortest path problem

Solution to the two-objective problem defined above is a finite set of Pareto optimal solutions. Note that the two objectives, while not fully alighted, are significantly correlated. Intuitively, a shorter route has an inherent advantage against a longer one in terms of risk, as a longer drive naturally allows for more opportunities for incidents, and the Pareto optimal solutions can be expected to only include relatively short paths. Further, depending on the predictive scheme used, it may be possible to a priory estimate the maximum path that can still be non-dominated, which implies that the following procedure can be guaranteed to return the full Pareto optimal set of solutions.

1. Find the shortest path from origin to destination. Denote its length as Z_1^*. Naturally, it is a non-dominated solution.
2. Evaluate the risk associated with the shortest path (Z_2^*).
3. Find *MaxDistance*, which given the shortest path length and risk, gives the value of maximum path length, which (under most favorable conditions) can result in risk lass than or equal to Z_2^*.
4. Find the maximum k such that kth shortest path length is less than Z_1^*.
5. Find k the shortest paths and evaluate their length and risk.
6. Select non-dominated paths among the k shortest paths.

In this model, ksp algorithm is employed as the first step to reduce the number of potential candidates in Pareto Ranking since it is unnecessary to perform the Pareto Ranking for all the paths. However, there still has a low probability to eliminate the safest path too early to pass over the non-dominated solution. Further, after ordering k paths and labeling them with the rank, the non-dominated set may include the safest route with intolerant travel time. Also, as the cumulative driving time goes up, it may result in more SCE on the road. The author in [145] points out long driving time on a highway is a significant factor for fatigue-related crashes. Thus, it is not reasonable to select the route with the least risk, which takes an extremely longer driving time on the road. By investigating the machine learning models, we discover a way to obtain the lower bound of risk per mile to improve our model. More specifically, we can utilize the result by dividing the total number of SCEs of the shortest path by the lower bound of risk per mile as the maximum acceptable difference for the driver to use an alternative route with a longer distance. It is noted here the shortest path from ksp is based on the mean travel time. The equation 3.18 demonstrates the way to find out the maximum tolerable driving distance when taking into account the risk.

$$\underbrace{MaxDistance}_{\text{max acceptable distance.}} = \underbrace{ShortestDistance}_{\text{distance for the shortest path}} + \frac{\text{Number of SCEs in Shortest Path}}{\text{Lower Bound of Risk}} \tag{3.18}$$

Based on the prediction from the machine learning methods, we calculated the ratio between the prediction and distance for all the trips with SCE among all the models. Accordingly, we found the lower bound of risk(θ) is 0.025 per mile from all the predicted models. In the algorithm 1, once the shortest path has been identified from the ksp algorithm, the associated the shortest distance(l_{min}) and the number of SCE(Z_2) on that routes can also be obtained. By applying the equation 3.18, we can find the $MaxDistance$.

Algorithm 1: Main

Data: N, A, l_{ij}, t_0, v_{ij}^T, $\bar{v_{ij}}$, R, w_{ij}^T, k, θ // t_0 is the departure time, $\bar{v_{ij}}$ is the mean speed for each arch, θ is the lower bound of risk

Result: Non-dominated solutions among k-shortest paths

Set: Origin node, Destination node

Procedure

1 Create road network by inputting N, A, l_{ij}

2 Compute the mean travel time($\bar{t_{ij}}$) by using $\bar{v_{ij}}$ and l_{ij}

3 Demonstrate ksp algorithm to find k paths based on $\bar{t_{ij}}$

4 Summarize l_{ij} for all the arcs in the shortest path to obtain l_{min}

5 Find t_{ij} and di in each path with starting time as t_0 at origin node

6 Calculate Z_1 for each path

7 Calculate Z_2 by applying $R(w_{ij}^{d_i}, v_{ij}^{d_i}, rv_{ij}^{d_i}, l_{ij}, e)$ for each path

8 $MaxDistance = l_{min} + \frac{Z_2^*}{\theta}$ // Z_2^* is the number of SCEs for the shortest path

9 **if** *the longest distance in k paths is less than MaxDistance* **then**
    Increase k and go to step 3
  else
    Go to next step
  end

10 Perform Pareto Ranking algorithm to sort k paths according to Z_1, Z_2 for each path to find the non-dominated paths

---

Algorithm 2: Pareto Ranking

Data: Z_1, Z_2 for all paths

Result: k paths with rank status

Procedure

```
for each path do
    paretoStatus = 0; dominatesCount = 0; dominatingSet = [ ]
end
for every pair of paths among k candidates: do
    if path m denominates path n then
        n.dominatesCount += 1
        m.dominatingSet.append(n)
    end
end
for each path m do
    if dominatesCount = 0 then
        currentLevelSet.append(m)
    end
end
nextLevelSet = [ ]; currentLevel = 1
while CurrentLevelSet is not empty do
    for path i in CurrentLevelSet do
        for dominatedPath j in i.dominatingSet do
            j.dominatesCount -= 1
            if j.dominatesCount = 0 then
                nextLevelSet.append(j)
                j.paretoStatus = currentLevel
            end
        end
    end
    currentLevel += 1
    currentLevelSet = nextLevelSet
end
```

3.3.5 Risk-shortest path problem

We arbitrarily select three pairs of origin and destination to evaluate the behavior of the model: Nashville, TN to Gary, IN, Springfield, IL to Lexington, KY, and Cincinnati, OH to Gary, IN.

The assumed departure time is 8 am on Oct. 1, 2020 for the purposes of querying the weather conditions. We adopt the XGBoost predictive model as described in Section 3.1.

Risk, distance and $MaxDistance$ were evaluated for each origin-destination pair and the results are given in Table 3.3. Importantly, note that in the first case the shortest path is predicted to have zero SCEs, which naturally implies that it is the only Pareto non-dominated solution. On the other hand, in the second case, 4 SCEs are predicted for the shortest path, meaning that the Pareto optimal set can be expected to contain at least 5 paths (paths that are shortest with 0 to 4 SCEs). Note that while not required to find strictly non-dominated solutions, we still set $k = 10$ for both Cases 1 and 3 to investigate variability among some of the dominated solutions.

Table 3.3: The result of ksp for three cases, and the distance listed here is in miles.

Origin → Destination	$ShortestDistance$	Number of SCE for shortest path	$MaxDistance$	k	The Longest Distance among k paths
Nashville, TN→ Gary, IN	464	0	464	10	526
Springfield, IL → Lexington, KY	414	4	574	150	585
Cincinnati, OH → Gary, IN	268	1	308	10	376

Table 3.4 presents the non-dominated solutions found for the three test cases. As discussed above, despite the bi-objective nature of the model, only one non-dominated solution is found for Case 1. As could be expected, in Case 3, two non-dominated solutions are possible, corresponding to zero and one predicted SCE. On the other hand, as is observed, four non-dominated solutions for Case 2 are identified, as no paths with zero SCEs are possible. We also report average and real driving time corresponding to the paths. Also, the mean travel time and real travel time have been demonstrated in table 3.4. The real travel time is calculated based on the time dependent speed, while the mean travel time didn't take into account that the speed during rush hour is lower than the others. For Case 1, the mean travel time and the mean time are 7.73 and 7.79 hours, respectively. Concerning the mean travel time for Case 2, the least time is 6.99 hours. However, if the preference here is to have a relative smaller number of SCE, the time

can increase to 8.13 hours. Similarly, the true travel time rises from 6.88 to 8.13 in hours as the decrease of the SCE. In terms of Case 3, when there only one SCE, the real travel time is 4.53 hours. However, it takes 5.62 hours if we choose the route without any SCE.

Note that naturally, as discussed earlier, it is not preferable to only find a single optimal solution for the purposes of many routing applications. Consequently, in addition to the non-dominated solutions, it may be preferable to also report ranked dominated paths. Recall that rank 1 are paths that are non-dominated. Rank n are paths that are non-dominated if all paths with ranks $1,\ldots,n-1$ are excluded. Figures 3.3, 3.4 and 3.5 depict the first three ranks of Pareto optimal solutions for the three cases respectively.

3.4. Concluding remarks

The paper is aimed at addressing a gap that is present in data analytics-based approaches to the problem of driving risk (particularly as applied to trucking operations) between predictive and prescriptive methodologies. Particularly, while it is well-established that various stochastic and dynamically changing factors are relevant in evaluating incident risk from the point of view of predicting adverse effect, most prescriptive models do not account for these results. Given that modern predictive models are usually constructed as advanced statistical or machine learning methods, they can be challenging to incorporate into typical vehicle routing problems as usually considered in the operations research community.

We begin with a particular machine learning risk forecasting model that takes into account dynamic weather, traffic and shift history factors for predicting safety-critical events (SCEs), which are used as surrogates for traffic incidents. We then demonstrate how this tool can be incorporated into routing decision-making by considering the risk-aware shortest path problem. We also establish a more general framework for combining predictive and prescriptive models in a data-driven way. In the case of the shortest path problem we also discuss the solution algorithm and propose a version based on k-shortest approach, which, given some assumptions on the predictive model, can produce the full Pareto optimal set of solutions.

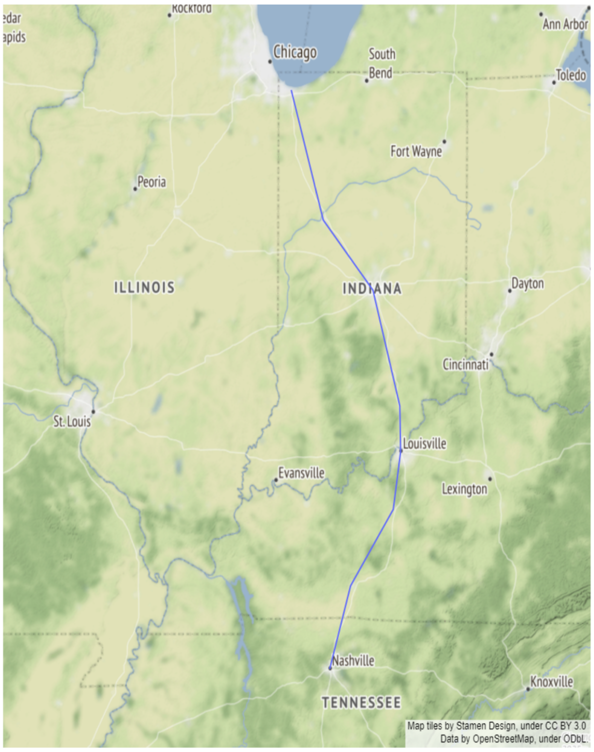
We demonstrate how this approach can be employed with a case study based on real-life data provided by our industry partner. We consider a specific area in the Midwest of the

Table 3.4: Non-dominated solutions for three cases.

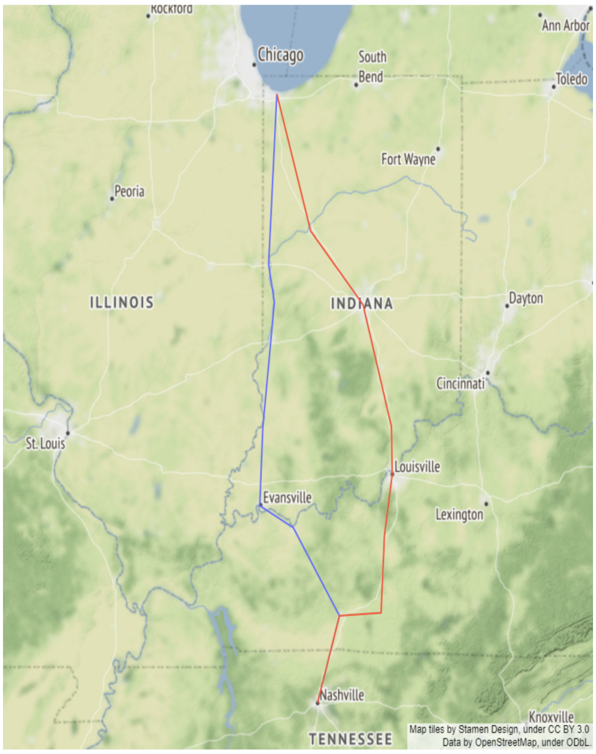
Case 1: Nashville (TN)→Gary (IN)				
Path	Distance	Mean Time	Real Time	SCEs
Nashville (TN) → Bowling Green (KY) → Elizabethtown (KY) → Louisville (KY) Scottsburg (IN) → Indianapolis (IN)→ Lafayette (IN) → Gary (IN)	463.54	7.73	7.79	0
Case 2: Springfield (IL)→ Lexington (KY)				
Path	Distance	Mean Time	Real Time	SCEs
Springfield (IL) → Decatur (IL) → Champaign (IL) → Covington (IN) → Indianapolis (IN) → Cincinnati (OH) → Lexington(KY)	413.34	6.88	6.99	4
Springfield (IL) → Decatur (IL) → Champaign (IL)→ Covington (KY) → Indianapolis (IN) → Scottsburg (IN)→ Louisville (KY)→ Frankfort (KY) → Lexington (KY)	413.15	7.30	7.41	3
Springfield (IL) → Decatur (IL) → Champaign (IL) → Montezuma (IN) → Terre Haute (IN) → Indianapolis (IN) → Cincinnati (OH) → Lexington (KY)	456.58	7.71	7.85	2
Springfield (IL) → Decatur (IL) → Champaign (IL) → Montezuma (IN) → Terre Haute (IN) → Indianapolis (IN) → Scottsburg (IN) → Louisville (KY) → Frankfort (KY) → Lexington (KY)	456.40	8.13	8.30	1
Case 3: Cincinnati (OH) → Gary (IN)				
Path	Distance	Mean Time	Real Time	SCEs
Cincinnati (OH) → Indianapolis (IN) → Lafayette (IN) → Gary (IN)	267.81	4.40	4.53	1
Cincinnati (OH) → Indianapolis (IN) → South Bend (IN) → Gary (IN)	317.52	5.43	5.62	0

Notation: the distance is in miles and the time is in hours. Mean travel time is the average travel time and real-time is the time-related travel time due to the variation of speed.

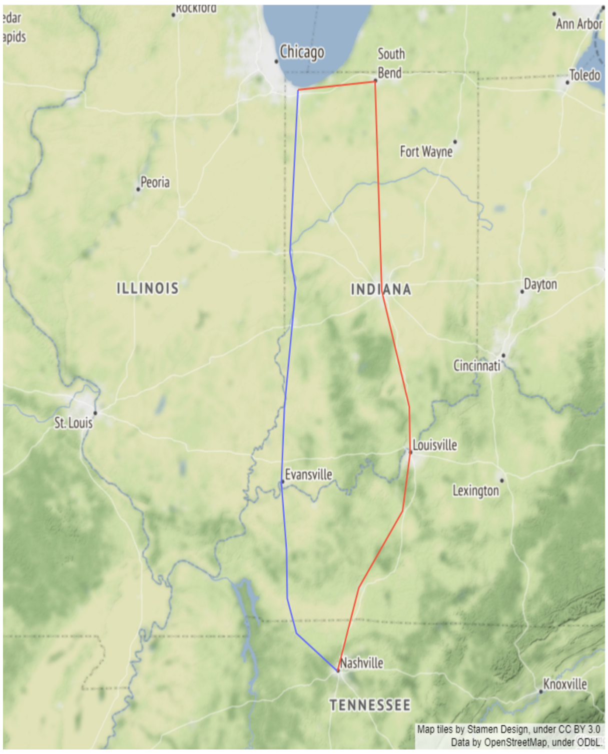
Figure 3.3: This image shows the paths with ranks 1 - 3 from for the first case between Nashville, TN, and Gary, IN. If the rank is 1, it indicates this is the optimal solution.



(a) Rank = 1



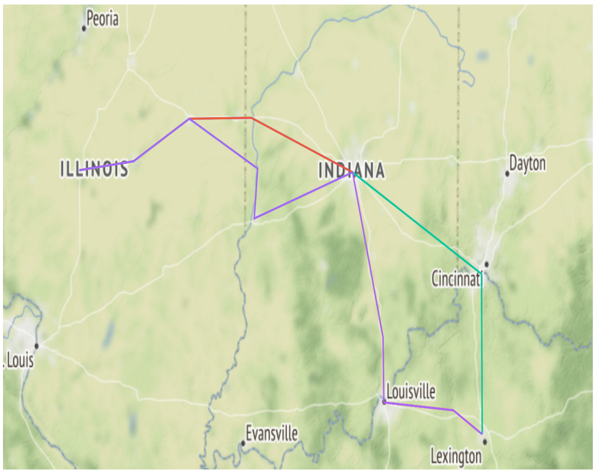
(b) Rank = 2



(c) Rank = 3

USA and apply the risk-aware route selection algorithm for a few origin-destination pairs. An interesting property of the problem, is that unlike usual multi-objective programs, here

Figure 3.4: This image shows the paths with ranks 1 - 3 for the second case between Springfield, IL, and Lexington, KY. If the rank is 1, it indicates this is the optimal solution.



(a) Rank = 1 (4 paths)

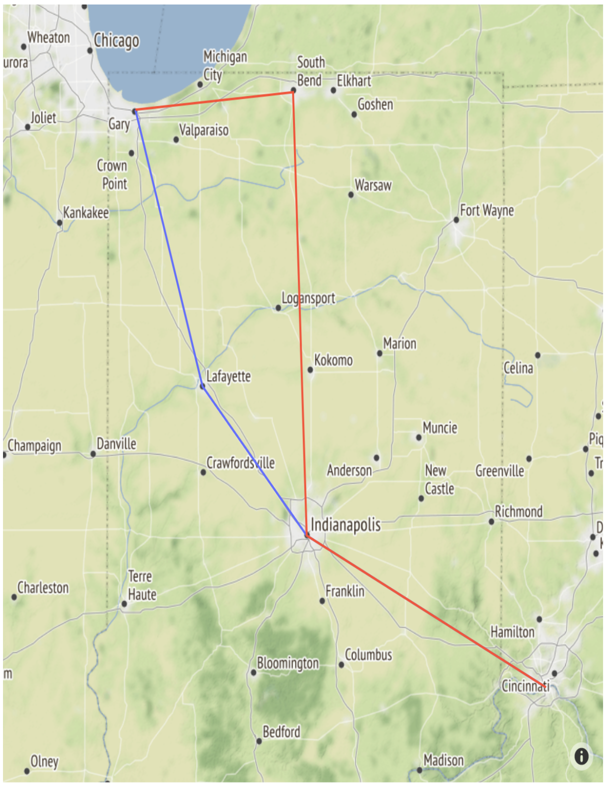
(b) Rank = 2 (4 paths)

(c) Rank = 3 (3 paths)

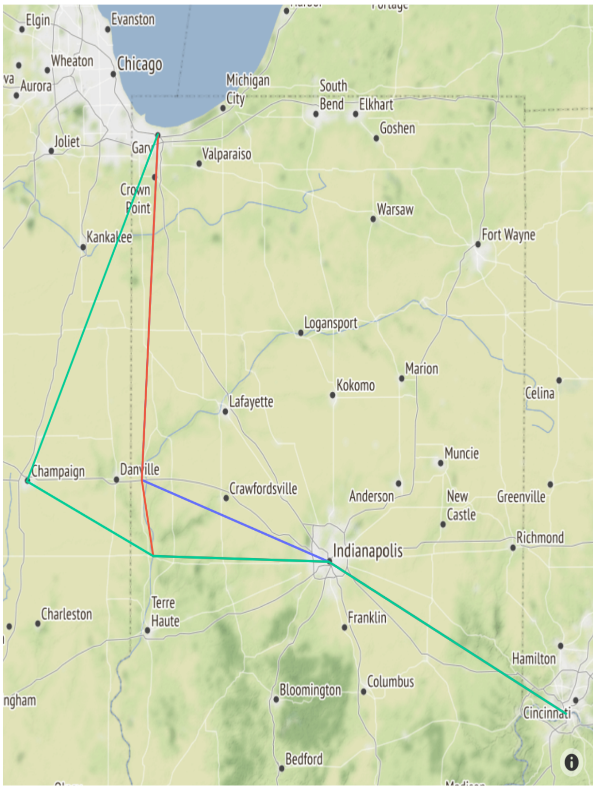
the two objectives are significantly correlated. While usually objectives are conflicting (e.g., expected return on investment vs risk of the investment), in this case longer routes tend to also involve higher risk, thought the correlation is certainly not perfect. This results in a very restricted Pareto optimal set, which is one of the objectives is discrete (in our case, the number of predicted SCEs), may mean that only a handful of non-dominated solutions are present.

In future work, we will explore more algorithms by using the same process in 3.1 to help the driver make optimal solution in selecting the route. Comparing with the accurate algorithm, the heuristics methods are more favorable choices in ksp problem, which is due to that the computational time increases dramatically as the problem size. In the last few decades, there are many heuristics methods that have been widely used in vehicle routing problem, such as

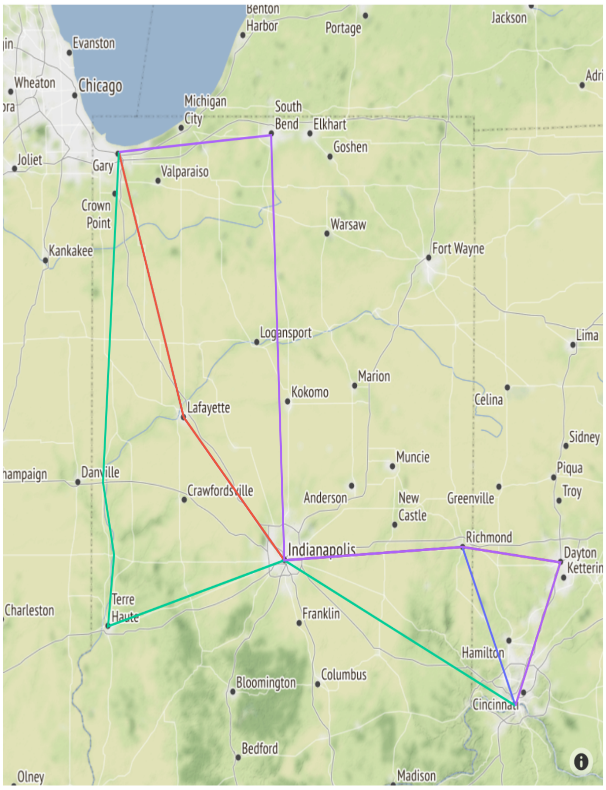
Figure 3.5: This image shows the paths with ranks 1 - 3 for the third case between Cincinnati, OH and Gary, IN. If the rank is 1, it indicates this is the optimal solution.



(a) Rank = 1 (2 paths)



(b) Rank = 2 (3 paths)



(c) Rank = 3 (4 paths)

the genetics algorithm. Our next step is to applied other algorithms under the same structure to explore more benefits for the trucking drivers. Further, the truck drivers may need to consider the order of the customers along the route if the customers have a specific requirement of delivery time windows. As a result, we need to extend our model to the area of vehicle routing and scheduling with time windows.

Chapter 4

Inverse Reinforcement Learning in transportation safety

4.1. Introduction

In the previous two chapters, the risk indicators are generated using separately constructed predictive tools, either a statistical model in Chapter 2 or machine learning method in Chapter 3. Recall that in the former the driver could schedule the speed on the road by taking into account the risk estimations based on the driving condition. Alternatively, the latter approach allows for guiding the driver to select the optimal route by considering the real-time speed and risk. In this chapter, we would like to analyze the extensive data set from the perspective of decision-making directly, i.e., attempt to learn the information about risk that is directly applicable in a decision making setting. In other words, we are interested in finding a policy for how the driver selects the optimal decision under various conditions. Then we can have a better understanding of making decisions given the driving conditions. This research aims to train the agent to make the optimal decisions in a way emulating expert behavior from the data available. Naturally, the reward in this model is associated with the number of safety-critical events, and higher rewards indicate less risk on the road. For instance, reward-SCE relationship can be decoded as follows. If the driver has no critical event during the trip, the reward is set to 1. One safety-critical event results in one unit penalty in the reward, so -3 represents three critical events during the trip.

Our purpose in this chapter is to learn from the data to better understand the expert's decision-making. More specifically, it is hypothesized that divers with no or few SCEs may be following better decision-making policies, and hence the goal is to adjust the reward structure in such a way as to emulate this decision-making, i.e., such that optimal policies result in no SCEs, while those who experienced the safety-critical events, those follow sub-optimal policies. Comparing with the statistical analysis in transportation safety that focuses on learning the effects of factors in risk, our approach in this chapter emphasizes the decision-making application, rather than focusing on explicitly evaluating risk.

The methodology used in this chapter is inverse reinforcement learning (IRL) algorithm proposed in [146]. The strategy is to build the reward function based on the features and historical data on outcomes. The objective is to find the weights for the feature variables in the reward function to make the optimal policy have a higher or equal value than any other policies[146]. A specific approach for implementing this idea was proposed in [147] who extract the reward function by matching the feature counts between the demonstration and the learner's behavior. However, the challenge here is that the coexistence of many policies in the data can also result in the same feature counts as the demonstration. To overcome this challenge, the authors in [148] attempt to relate the feature frequency with the rewards. In other words, assuming there is a distribution of all possible actions given each state, higher reward is incurred when the specific actions are preferred based on data. To achieve it, the authors utilized a gradient descent method by splitting the gradient into two parts: the one measures the difference between the expected state counts in the data set and the expected frequency of state visitation from the learner; the other one represents the gradient of the reward concerning the weights acquired from the neural network. The disadvantage is that the final weights from the neural network can not be used to interpret the relationship between the features and the reward directly, since the final weights are for the nodes in the last hidden layer. To understand how the expert makes the decision under the reward structure, we decide to use IRL to find the optimal policy using Q-learning methods. In the next section, we will discuss the methods regarding IRL and provide more information related to the recent development of IRL. After that, we will have a further discussion of the MDP model and algorithms in our project. In the end, we will demonstrate the results and discuss the limitation of this project.

4.2. A brief overview of inverse reinforcement learning

The inverse reinforcement learning has been first proposed in [146] which aims to recover a reward function from the historical reference data. The reward function is usually constructed as a linear combination of the features in the state vector, i.e., the problem is to find a collection of weights. Recall that each state is represented by a vector of features and a trajectory consists of a sequence of state variables. Consequently, total reward for a trajectory is evaluated as the summation of the rewards in each state as in (4.1) and (4.2).

$$f_\zeta = \sum_{s_j \in \zeta} f_{s_j} \tag{4.1}$$

$$r(f_\zeta) = \theta^\top f_\zeta = \sum_{s_j \in \zeta} \theta^\top f_{s_j} \tag{4.2}$$

The goal of IRL then is to find weight vector to maximize the value for the trajectory under the optimal policy (π^*) given the initial state(s_0), as shown in equation (4.3).

$$V^{\pi^*}(s_0) \geq V^{\pi_i}(s_0),\ i = 1, 2, \ldots, k \tag{4.3}$$

However, an efficient method for how to find the optimal weight is not defined in the original paper [146]. Although the authors of paper[147] proposed an approach where feature expectations are matched between the observed data and the learner's policy. Alternatively, the authors of [149] applied the theory of maximum entropy. More specifically, it assumes that there is a distribution for all possible behaviors, but only the best distribution can demonstrate the preference shown in the data, which can match the feature expectations between the demonstration and the learner's behavior. The purpose of max entropy then is to find the distribution that exhibits the preference of the action for each state based on the rewards acquired by taking that action under the specific state. As a result, when the feature count is higher, the reward will be larger. Therefore, the probability of choosing that action will be greater.

$$P(\zeta|\theta) = \frac{1}{Z(\theta)} e^{\theta^\top f_\zeta} = \frac{1}{Z(\theta)} e^{\sum_{s_j \in \zeta} \theta^\top f_{s_j}} \tag{4.4}$$

Equation (4.4) implies that the higher reward is associated with higher probability for each state-action pair. Besides that, the probability is related to the reward function based on the features and corresponding weights. The objective here is to obtain higher rewards for the optimal policy by finding the appropriate weights vector. Then, the probability for the action under the optimal policy will be higher than the actions from any other sub-optimal policies. For any finite horizon problem, or an infinite horizon with discounted factor, the reward weight will be convergent in the end [149].

For a non-deterministic model given the current state, the next state is random within the state space conditioned to the transition function and the action as shown in equation (4.6). Here, T is the outcome for each action and o is an outcome sample. Only when the path is compatible with the sample outcome, $I_{\zeta \in o} = 0$; otherwise it is set to 0.

$$P(\zeta|\theta,T) = \sum_{o \in \tau} P_T(o) \frac{e^{\theta^\top f_\zeta}}{Z(\theta,o)} I_{\zeta \in o} \tag{4.5}$$

$$\approx \frac{e^{\theta^\top f_\zeta}}{Z(\theta,T)} \prod_{s_{t+1},a_t,s_t \in \zeta} P_T(s_{t+1}|s_t,a_t) \tag{4.6}$$

Further, since this is a stochastic model, the probability of an action given the state is exponentially related to the expected reward of all the paths beginning with that action[149].

$$P(action\,a|\theta,T) \propto \sum_{\zeta : a \in \zeta_{t=0}} P(\zeta|\theta,T) \tag{4.7}$$

When working on trajectory data, the objective is to maximize the likelihood of the observed data under the assumed distribution. The probability of each demonstration is related to the total rewards obtained from each state-action pair along the path. In addition, the reward is defined as the product of weights and feature variables. The purpose here is to find the optimal weights which can maximize the likelihood between the observed data under the distribution generated by the reward function (4.8). In order to achieve this objective, the authors applied gradient-based methods to update the weights by calculating the gradient of loss between the expected feature counts from the observations and the expected feature visitation frequency from the learning process, as shown in equation (4.9). The expected feature counts for the learner are conditioned on the reward structure based on the weights.

$$\theta^* = \underset{\theta}{\operatorname{argmax}} L(\theta) = \underset{\theta}{\operatorname{argmax}} \sum_{examples} log\, P(\tilde{\zeta}|\theta, T) \tag{4.8}$$

$$\nabla L(\theta) = \tilde{f} - \sum_{\zeta} P(\zeta|\theta, T) f_{\zeta} = \tilde{f} - \sum_{s_i} D_{s_i} f_{s_i} \tag{4.9}$$

In conclusion, the max entropy method proposed in [149] gives us a way to include the sub-optimal policies in the data set by relating the distribution of all possible paths with the reward obtained from the entire trajectory. We want to enforce the trajectory with higher rewards to acquire a higher probability distribution by altering the feature weights.

A number of potential challenges to applying IRL to real life data remain. Firstly, the number of states increases exponentially with the number features. Further, the data may not include the information for all the states, which means that some states may never be visited in the data. Secondly, the relationship between the features and reward is very complex in many real applications. Consequently, a linear reward function is not a proper way to depict the relation. As a result, by using linear regression to evaluate the features and reward [146, 149] can not characterize the actual relationship.

Hence, we need to find a better way to express the reward based on the features explicitly. If we find the reward based on the features, even without complete information of all the states, we can approximate the reward for those unvisited states from the relationship recovered from those visited states. To deal with the non-linear relationship in IRL, the author in [150] proposed to use Gaussian Processes (GP) to model the relationship between the features and the reward, but the computational work is burdensome when the size of the problem increases. At the same time, the neural network became a popular machine learning algorithm due to the efficiency to solve significant size problems by adding only a few layers and nodes at desired accuracy [151]. In [148], the authors utilized the neural network in searching the gradient descent methods to maximize the likelihood of observing expert demonstrations D given the reward r and the weight θ.

$$L(\theta) = log\,P(D, \theta|r) = \overbrace{log\,P(D|r)}^{L_D} + \overbrace{log\,P(\theta)}^{L_\theta} \tag{4.10}$$

As shown in equation (4.10), the authors of [148] tried to maximize the likelihood of the posterior distribution of the observation from the data given weight and reward. The likelihood function can be rewritten as a joint likelihood of L_D and L_θ. More importantly, by taking L_D and L_θ concerning θ, the total gradient becomes the sum of two parts in equation (4.11). The first part indicates the regularization of weight θ, and the second part is the same as equation (4.9) which is the gradient between the demonstrations from the data with respect to the weights of the reward function. In [149], the weights are used to evaluate the linear relationship between the rewards and features. As we mentioned, the reward in many practical instances are more likely to have a non-linear relationship, so the authors in [148] proposed to rewrite the likelihood of L_D for the weights by relating the likelihood of the observation from the data to the reward and the likelihood of reward to the weight (4.12). Consequently, by applying a neural network, the gradient of reward with respect to the weights can be evaluated in the step of back propagation. Moreover, based on the same idea in equation (4.9), the gradient of L_D for the reward is the difference between the feature counts from the observed trajectories (μ_D) and the expected frequencies of state visitation from the learned policy ($E[\mu]$).

$$\frac{\partial L}{\partial \theta} = \frac{\partial L_D}{\partial \theta} + \frac{\partial L_\theta}{\partial \theta} \tag{4.11}$$

$$\frac{\partial L_D}{\partial \theta} = \frac{\partial L_D}{\partial r} \frac{\partial r}{\partial \theta} \tag{4.12}$$

$$= (\mu_D - E[\mu]) \frac{\partial r}{\partial \theta} \tag{4.13}$$

4.3. Methodology

4.3.1 Data

This section will discuss the data used in this research and then introduce how it fits into the MDP for IRL. The data in this section is the same as the one for machine learning methods in Chapter 3. More specifically, we randomly sampled 500 drivers from the regional drivers from our data set. In order to check the driver's behavior within a similar time scale, we applied one hour as the time interval to divide the entire shift into trips. Then we chose to use only historical data for shifts that have 8 trips. The reason for us to use one hour instead of half-hour is that in paper [152] shows there has no significant effect between a half-hour and one hour as the interval time in terms of predictive accuracy. Our purpose is to learn from those observations, which perform a similar schedule for each day. Also, we abandoned those shifts with limited traveling time on the road. In the end, we have 1214 shifts, and each shift is divided into eight trips. The cumulative driving time for each shift is from 7.5 hours to 8 hours.

Moreover, since most of the features are continuous variables we further use k-means discretization transformation on the selected features. Concerning the feature selection in IRL, multiple factors need to be considered. Firstly, because the calculation complexity increases exponentially as the number and the dimension of features, only those predictors impacting the SCE will be considered in the MDP model. Further, although some features indeed play essential roles in predicting the risk, they will not be under consideration if only trivial changes happen on those features during the trips. The reason is that the purpose of this research is to train the model to make an optimal decision by learning from the existing data. If the feature does not change as the result of driver's decision, it indicates that the feature is irrelevant in differentiating the optimal and sub-optimal policies. Note also that according to a large amount of research related to transportation safety, we know that precipitation and visibility are significant factors in estimating the risk. As a result, we chose to construct the reward function based on the mean of speed, precipitation intensity, and visibility.

4.3.2 MDP model

Based on variables considered, we choose to define the action as the average driving mean. Recall that the state variables should be selected in such a way as to allow for observation of all features in each stage. In other words, the change of the state variable should be reflect by the selection of the decision variable (and potential random events) only.

In order to balance the need to account for driving history and the need for discretization, we introduce three additional variables, reflecting the number of stages with high, medium or low speed during the current shift. This allows for on one hand, accounting for potential driver performance deterioration on one hand, and not explode the size of the state space. With precipitation intensity and visibility as two important risk factors, this allows for defining state space as a five-dimensional vector.

Consequently, the state variable is a multidimensional variable, which we will denote as $(x_1, x_2, x_3, x_4, x_5)$. Here, x_1 is the visibility during the trip, x_2 indicates the precipitation intensity and x_3, x_4, x_5 represent the total number of segments with low, medium and high speed, respectively, during the current shift. For x_1 and x_2 are binary, while x_3, x_4 and x_5 take integer values. By design, whenever $x_3 + x_4 + x_5$ is equal to the maximum number of segments, the corresponding state is declared as absorbing.

As a way to train the IRL model, we define observed reward structure based on realized SCEs. Specifically, we award reward of 1 to a trip segment without an SCE, while trips with an SCE earn negative reward proportional to the number of SCEs. Finally, if the driver arrives at the absorbing state, an additional reward of two is earned. Note that the pre-defined reward is only used to initialize the algorithm and is then updated with IRL, that is, to find the reward structure that maximizes the likelihood of the distribution of the observation given the reward function based on the features.

As a summary, the MDP components are constructed as follows:

1. <u>States.</u> S and $s_n \in S$. The state variable is five dimensional $(x_1^n, x_2^n, x_3^n, x_4^n, x_5^n)$. x_1^n and x_2^n are binary variables indicating the precipitation intensity and visibility at each stage. x_1^n as 0 represents bad visibility while 1 shows the good visibility for driving. In terms of x_2^n, 0 suggests no rain while 1 means it has rain. For the other three variables, they are

demonstrating the cumulative number of stages at different levels of speed mean, such as low, medium and high.

2. Actions. A and $a_n \in A$. The action is a categorical variable representing the mean of speed for each stage. $a_n = 1,2,3$. The value of action variable indicates the choice of speed. More specifically, as the value increases, the average speed goes up. For instance, 3 represents the high speed mean.

3. Horizon. N is the total number of stages. $n \in N$ and $N = 8$.

4. Time interval. Δt. In this model, we split the driving time by using the interval time as 60 minutes. The reason is that there is no significant difference between 30 minutes and 60 minutes when choosing the interval time to divide the shift into trips[153].

5. Feature variable. f is the feature variable based on the state variable(s_n) and action variable(a_n).

6. Reward structure. $r = g(f,\theta)$. The reward function is based on features and weights.

7. Transition function in MDP. T is the transition function, and it can be divided into two parts: the deterministic and the stochastic processes. The change regarding the cumulative stages of speed mean is fully depended on the action variable, while the transition for the weather condition will follow the pre-defined matrix.

$$(x_3^{n+1}, x_4^{n+1}, x_5^{n+1}) = \begin{cases} (x_3^n + 1, x_4^n, x_5^n) & a_n = 1 \\ (x_3^n, x_4^n + 1, x_5^n) & a_n = 2 \\ (x_3^n, x_4^n, x_5^n + 1) & a_n = 3 \end{cases}$$

$$\mathbf{x_1} = \begin{array}{c c} & \begin{array}{cc} 0 & 1 \end{array} \\ \begin{array}{c} 0 \\ 1 \end{array} & \begin{pmatrix} .838 & 0.162 \\ .086 & 0.914 \end{pmatrix} \end{array}$$

$$
\mathbf{x_2} = \begin{array}{c c} & \begin{array}{cc} 0 & \quad 1 \end{array} \\ \begin{array}{c} 0 \\ 1 \end{array} & \begin{pmatrix} .974 & 0.026 \\ .155 & 0.845 \end{pmatrix} \end{array}
$$

4.3.3 Algorithm

In this paper, we followed the algorithm presented in [148]. It consists of three major steps in each iteration. First, the value iteration finds the optimal policy given the rewards structure at the beginning of each iteration. Then the expected visiting frequencies for each state can be determined based on the current optimal policy and rewards. After that, the maximum entropy loss and gradients can be examined by finding the difference between the expert frequencies from the data and the expected frequencies according to the rewards. Next, the loss and gradients will be applied to the back propagation in the Neural Network to generate the network gradients, which help us update the weights and rewards at the end of each iteration. Finally, the updated weights and rewards will be used for the next run.

Algorithm 1: Deep Inverse Reinforcement Learning

Data: $\mu_D^a, A, S, T, \gamma,$ `// ` μ_D^a `is the state frequencies under action` a`;` γ `is the discount rate.`

Result: the optimal rewards

Procedure

Initialized the weights

for n = *1: N* **do**

Reward from Forward Neural Network by applying the current weights

Approximate the value iteraton by using current reward

Find the optimal policy(π^n) based on the values from the last step

Caculate the expected frequencies($E[\mu^n]$) for each state given the reward under the current optimal policy

Decide the Max Entropy gradient of loss with respect to reward $(\frac{\partial L_D^n}{\partial r^n} = \mu_D - E[\mu^n])$

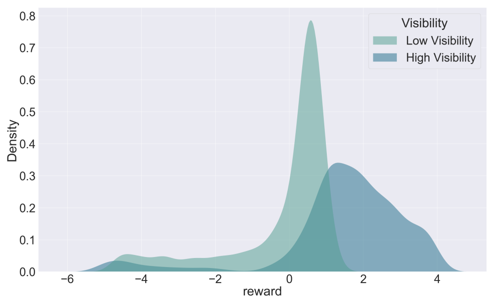
Measure the network gradients from back proporgation in Neural Network $(\frac{\partial L_D^n}{\partial \theta^n} = nn\_backprop(f, \theta^n, \frac{\partial L_D^n}{\partial r^n}))$

Update the rewards

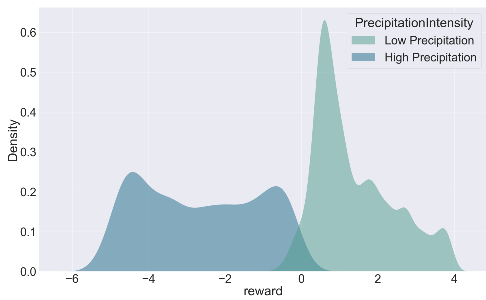
end

4.4. Result

After running the algorithm in section 4.3.3, the reward for each state-action pair has been obtained. In other words, the optimal policy is able to acquire according to this reward structure. In order to further understand the reward function, there are two types of analysis. The one is to examine the relationship between the reward value and the feature variables. The other one is to check the availability of the reward in deciding by applying the Q-learning method. The figure 4.1 demonstrates how the variables related to weather affect the reward values. Here, we plot the kernel density estimate for the reward under visibility (x_1) and precipitation intensity (x_2). As we mentioned in section 4.3, both variables are binary. Recall that when the visibility is 1, it represents favorable conditions, while bad visibility is represented with value 0. By contrast, x_2 is decoded as presence of precipitation, i.e., 1 refers to rains and 0 to no rain.



(a) KDE of rewards under visibility(x_1)



(b) KDE of rewards under precipitation intensity(x_2)

Figure 4.1: The kernel density estimate(KDE) of rewards under weather variables

The visibility and precipitation have an impact on the reward as presented in Figure 4.1, both indicating generally expected trend: lower visibility or presence of precipitation tend to reduce the accumulated reward. Comparing with visibility, the precipitation is more significant in affecting the reward. By extension, in Figure 4.1b, the KDE associating with 1 for precipitation intensity has been shifted dramatically to the left. Hence, for those states with an adverse driving condition related to the rain, the reward is relatively lower regardless of the action. In other words, if the driver arrives at any state under the rainy situation, the reward mostly will not be larger than those states without any rain. Along the same lines, the KDE distribution of the rewards when x_1 is 1, spreads heavily on the right side, which results in a larger reward. The analysis between the other three features concerning the cumulative stages of the average speed at three levels is not easy to capture due to the structure of the state variable (co-dependence in the last three variables). Moreover, we also tried to interpret the reward from the perspective of the action variable, which means the speed means for the next stage. The result has been illustrated in figure 4.2. A similar problem we have here is that although the action variable can be the same, the state can significantly differ.

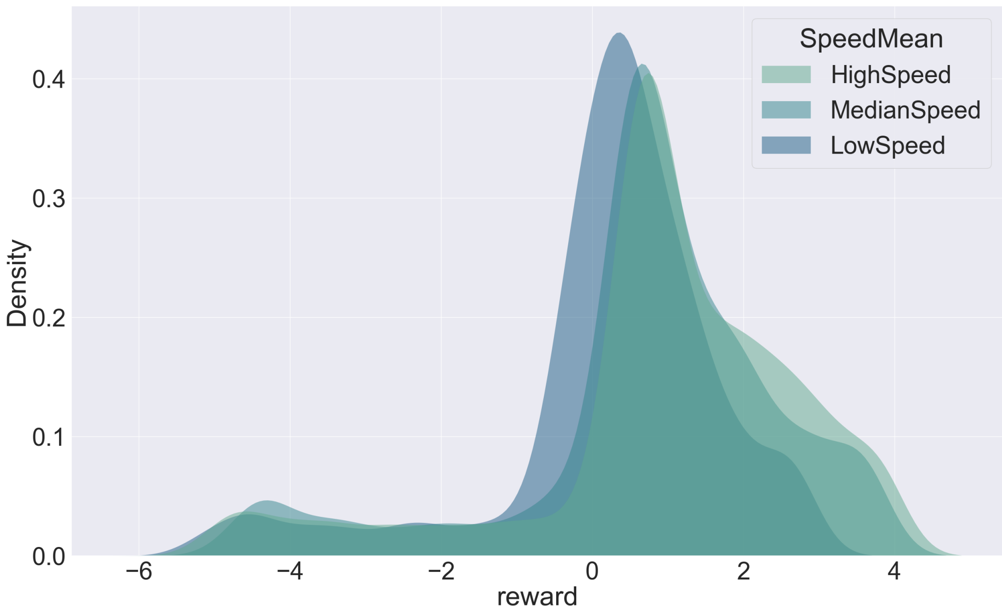


Figure 4.2: KDE for reward under the action variable(a_n)

We applied the final rewards obtained from the inverse reinforcement learning to figure out the optimal policy to demonstrate how those drivers organize the traveling for the eight one-hour trips. Here, we used the Q-learning method, since it can train the agent to make an optimal decision given the state-action rewards[154]. By figuring out the optimal decision for each state, we can examine how the expert decides the optimal policy given various conditions. Table 4.1 illustrates the optimal decision sequence for four scenarios (4 initial states). Scenario 1 represents low visibility but no precipitation, scenario 2 corresponds to high visibility and no precipitation, etc. The agent's behavior in the four scenarios is generally consistent with intuitive expectation. Specifically, presence of precipitation results in low speed suggestion (scenarios 3 and 4). Absence of precipitation and high visibility allows for high speed for most of the trip duration, while low visibility results in lower initial speed.

Table 4.1: The best action under various initial states for different scenarios.

Scenario	s_0	a_1	a_2	a_3	a_4	a_5	a_6	a_7	a_8
1	(LowVisibility, LowPrecipitation, 0, 0, 0)	Medium	Medium	Medium	High	High	High	High	Medium
2	(HighVisibility, LowPrecipitation, 0, 0, 0)	High	High	High	Medium	Medium	Medium	High	High
3	(LowVisibility, HighPrecipitation, 0, 0, 0)	Low	Low	Low	Low	Low	Low	Low	Low
4	(HighVisibility, HighPrecipitation, 0, 0, 0)	Low	Low	Low	Low	Low	Low	Low	Low

Notation: Low, Medium and High represent the decision of speed leverl.

4.5. Limitation and Future Study

In conclusion, our result shows that IRL can help us better understand the expert's actions from decision-making differently from the statistical analysis. The direct outcome from IRL is the reward for each state-action pair. After applying the rewards in Q-learning, we can observe the optimal policy. Consequently, the optimal action under each state is revealed, which gives us a chance to perceive the expert's decision. Further, studying the expert's behaviors based on the MDP, especially the reward structure, enables us to evaluate the relationship between feature variables and the reward. However, the limitation is that the effect brought by the speed is not straightforward like the precipitation intensity and visibility in our model. The main reason is explained in section 4.4 that there exist iterations among the three features regrading the level of speed and also the action variable. Also, our model has not investigated all the features that are used in machine learning methods discussed in chapter 3 such as the driver's characteristics because of insignificant changes during the trip. Additionally, the reward is primarily replied on the feature structure. Hence, the explanation is also limited to the chosen features. In the future, it is necessary to study the expert's behavior by taking into account more features. For instance, according to the characteristics related to the drivers, we can run multiple MDP models, then compare how the optimal policy varies for each driver. Lastly, we can also discover a way to compare our results with the statistical analysis in our future work.

Chapter 5

Conclusion

During the Ph.D. training, our research starts with the literature review on transportation safety from the perspective of predictive and prescriptive analyses in chapter 1. According to our study, the outcome shows two research gaps need to be addressed. First, the interaction between the predictive modeling and optimization models is not very obvious. Consequently, we proposed a framework to bridge the gap between these two research areas. Secondly, the optimization models related to transportation safety rarely consider building a truly dynamic model which allows the optimal solution to change in real-time. In order to develop a truly dynamic model, we created a dynamic model which enables the researchers to quickly build in risk indicators to improve the safety for the drivers in chapter 2. Due to the limitation of the dynamic model that can only be applied after the route has been decided, a bi-objective k-shortest path model is built to help the driver select the optimal route. In chapter 3, we demonstrate a complete process of work to further combine predictive analytics and decision-making by integrating the machine learning methods into the optimization models. More specifically, we chose the best risk indicators among nine various machine learning algorithms as part of the objectives in the optimization model. Besides that, we also consider other factors such as mean travel time and time-related speed, impacting the actual travel time. The last topic in chapter 4 aims to examine the data from the viewpoint of decision-making, other than relying on using data analytics tools. The ultimate goal of optimizing transportation safety is to reduce the risk for the driver by taking the optimal actions. The action in chapter 2 is to schedule the speed and the rest stop for the driver on the road, while the decision in chapter 3 is to decide the optimal route. In addition, the relationship between the risk and the features can indeed be studied from our studies, but it is still not straightforward for us to understand how experts eliminate the occurrences of SCE by making the best decisions. In order to learn the optimal action under different conditions, we decided to apply inverse reinforcement learning in chapter 4 to figure out the expert's decision from the data. More importantly, the application of inverse reinforcement learning provides an opportunity for us to investigate the relationship between the features variables and the rewards. The outcome shows that the expert arranges the mean speed to mitigate the risk given various weather conditions by learning the optimal policy. The limitation of this work is that some features that have insignificant influences provoked by the action variable. To amend the limitation, we can build separate models according to those features.

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