Studying the Impact of a Distance Constraint and Inspection Points on Hazmat Transportation Risk

by

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Abstract

There has been much recent interest in controlling risk of hazmat transport via road bans and curfews and the use of tolls. The purpose of this thesis is to explore a new method of controlling hazmat transport risk by placement of inspection points. Our method strategically places inspection stations while requiring that each hazmat truck visit an inspection station after driving a given specific distance. A tradeoff is sought between total driving distance and risk. An exact solution is presented to the problem, followed by the development of a greedy heuristic solution that attempts to reduce the number of inspection stations and risk. This solution procedure is then applied to a real-world case study problem of Revenna (Italy). Computational results are discussed with a comparison of risk with the distance constraint and number of inspection stations.

Dedicated to my family and friends…

Chapter 1

Introduction and literature review

1.1 Hazardous material transportation and Motivation

Hazardous material or commonly known as hazmat are moved throughout the country by all modes of transport such as ships, pipelines, trucks and trains. United Nations sorts dangerous goods into nine classes according to their properties [2]. These classes are as in fig. 1.1 .

Even though the transport industry is highly deregulated, hazmat is an exception because of the public and environmental risk. There has been ongoing research with one of the main objectives being, providing appropriate answers to the safety management of dangerous goods shipments involved in the transportation process.

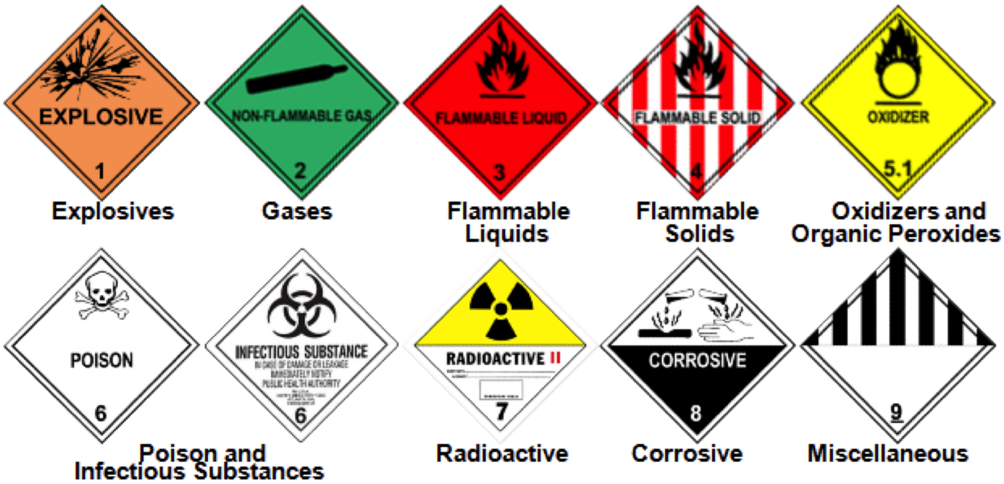

FIGURE 1.1: Hazmat Classes

In 2012 alone, hazmat shipments accounted for about 22.8% of the total freight shipped in the U.S on a tonnage basis (U.S Census Bureau 2012) out of which 69% was transported through trucks. Although there are multiple ways of transporting hazmat, major portions of the shipments of the hazmat materials are done via road. In the USA, in 2015, there were roughly 17,000 incidents related to hazmat transportation, and only 94 of them were classified as serious incidents with 12 fatalities (phmsa.dot.gov).

While the number is small compared to the overall number of accidents, the impact of hazmat accidents has shown a catastrophic impact in the past. An example is the November 2005 collision in Sinaloa, Mexico that involved an ammonia truck and caused 39 fatalities [2]. On October 6, 2012, a truck carrying liquefied gas crashed on a highway just before a tunnel and flipped over in Huaihai, Hunan province. The resulting explosion killed five people and injured two more, including three firefighters. In 2013, a truck carrying fireworks on the eve of the Chinese New Year celebrations exploded and destroyed part of an elevated highway in China's Henan Province, killing several people [3]. Hence the government's major concern lies in mitigating the risk. Reduction in risk of transporting hazardous materials (hazmat) can be achieved in many ways, some of them by practices such as proper driver training and regular vehicle maintenance. They have little connection to modeling and Operations Research (OR), whereas other methods present interesting challenges to OR. Research in hazmat transportation focuses on two main issues, risk assessment and hazmat shipment. Researchers assess the risk by modeling probability distribution over given areas and environmental conditions. Hazmat shipment planning involves two routing problems- local routing and global routing. Local routing deals with a selection of a route for a single shipment from origin and destination. When the central authority in charge of safeguarding the transportation security within its jurisdiction has the power to dictate and enforce one mandatory itinerary for each shipping, then the main issue is seeking a compromise between risk and equity: in so called local routing problems, the total risk related to multiple shipments between the same origin-destination pair should be minimized while equitably distributed over the whole region concerned [1] [4]. While the global routing deals with multiple trips among multiple origin- destination pairs to mitigate and equalize the social risk of the whole road network. In order to obtain a collaborative attitude by carriers, a cost must also be considered, often leading to multi-objective multi-commodity flow problems when modeling global routing problems, where shipments involve different origin-destination pairs [5] [6].

Carriers and government have different objectives with regards to hazmat regulations, as can be seen from fig. 1.2. From the carriers viewpoint, a hazmat

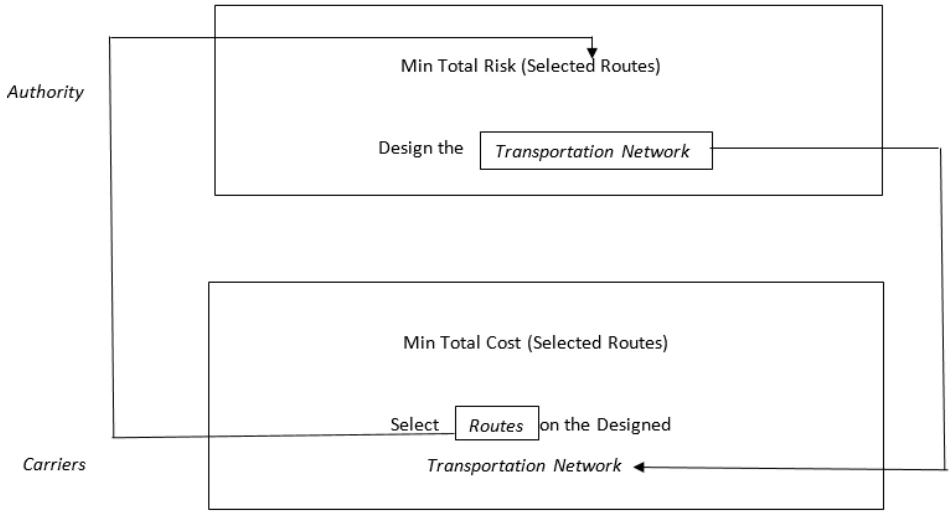

FIGURE 1.2: The hazmat transportation design problem

shipment is a means to make profits by abiding the regulations, securing public and environmental safety so as to stay in business. On the other hand, government and environmentalists are generally interested in minimizing the overall risk of the network. Another major difference is the scope of the problem. Given the amount and type to be shipped, the problem of a carrier boils down to identifying the most appropriate route between the origin and destination. A government agency has to deal with all the hazmat shipments in its jurisdiction. Although the main concern of the government is the public risk, it is reasonable to assume that they would somewhat be concerned about the financial cost imposed on the carrier.

1.2 Focus of Thesis

This work is focused on reducing the overall risk in hazmat transportation with the consideration of cost for carriers. Our proposed method aims to set up inspection stations at selected locations in the transportation network, with the additional stipulation that every carrier passes through an inspection station after driving prescribed distance limit (Let say K miles) on every trip between an origin-destination pair of nodes. Having explained the overall idea of our proposed hazmat transportation model and justification for the same, we now give an overview of our overall solution approach. Given our stipulation with the prescribed distance limit, we can design the optimal route that any hazmat carrier would consider for any given origin-destination pair of nodes since their sole objective is to minimize costs by choosing any feasible path that contains an inspection station for any segment of this shortest path that is of the same length as the prescribed distance limit. The major features that affect the type of solution for the problem are:

1. The number of inspection stations
2. Placement of the inspection stations and
3. The distance after which every inspection stations needs to be visited

To implement this method, we assume that there would be a cost associated with setting up the inspection station and that every destination is an inspection station. We further assume that a severe penalty can be imposed if the carrier fails to check in at the inspection station after every K miles. Given the following factors, the carrier would try to maximize the profit of the shipment by going through the most economical path for the carrier, not considering the risk of the path, but respecting the constraint of visiting an inspections station after having driven K miles.

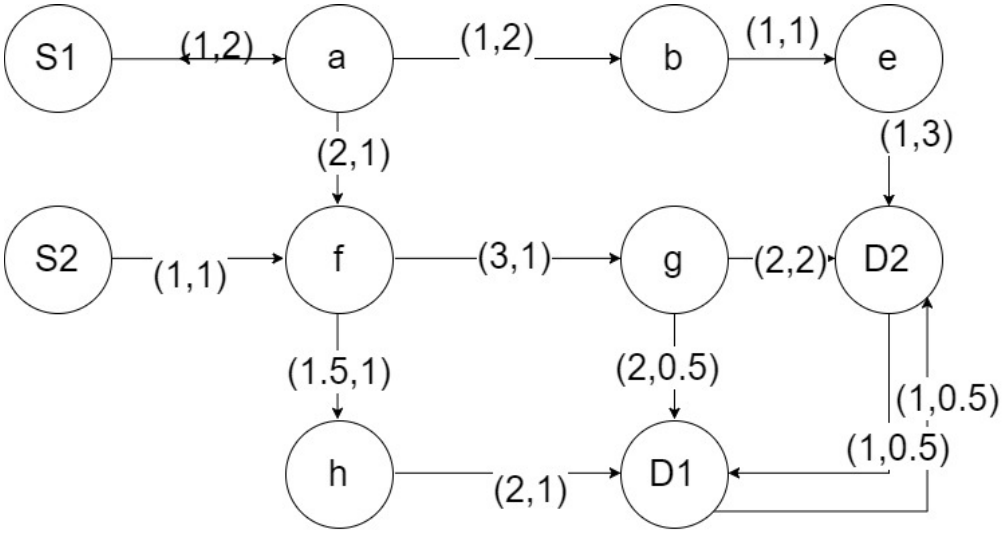

FIGURE 1.3: Hazmat transportation network

Let's take a directed network graph as shown in figure 1.3, involving two carriers from S1 and S2 and their respective destinations to be D1 and D2. On each arc (i,j), the couple (c_{ij},p_{ij}) is reported where c_{ij} is the cost for that link and the p_{ij} is the risk for that link. If there are no regulations to the carriers, the carriers would choose the least cost path i.e, for carrier 1, would choose S1-a-b-e–D2-D1 and carrier 2 would choose S2-f-h-D1-D2. But as the authority would try to minimize the risk on the path, authorities would want the carriers to take the path S1-a-f-g-D1 and S2-f-g-D1-D2. In our method as we propose inspection stations at nodes f and g along with D1 and D2. By placing the inspection stations at the proposed nodes and putting the value of K as 3 units, then the carriers would be forced to take the path S1-a-f-g-D1 and S2-f-g-D1-D2. But, if we increase the distance constraint, i.e the value of K to 3.5, the carriers will then take the path S1-a-f-h-D1 and S2-f-h-D1-D2 which is slightly riskier but still safer route compared to the shortest distance. Hence, the route that the carrier takes depends upon the placement of the inspection stations and the value of K. With this the authority will have the power to place the inspection stations, but it would be reasonable to assume that authority would consider carriers objective while placement of the inspection stations. Later, we'll see how the risk is affected with change in number of inspection stations and the distance constraint. In further sections of this chapter, we discuss the literature review of the existing methods.

1.3 Literature Review

Transportation of hazardous materials (hazmat) is necessary for an industrial economy to exist. Hazmat transportation is possible via all transportation modes (air, highway, railway, water and pipeline). Mainly hazmats are transported by road and most of the incidents caused by vehicles carrying hazmat results in fatalities, injuries and environmental damage. If an accident causes hazmat release from the vehicle, then these accidents are called as incidents. Table 1.1 shows the number of incidents and fatalities by transportation mode in the USA between the years 2007-2016. Hazmat transportation is very important with respect to economic concerns. Incidents caused by hazmat transportation only in the USA caused approximately $82.2 Million dollars damage over the last ten years. The damage amounts of the last seven years in the USA can be found in table 1.2. Since the amount of damage to the number of accidents is too high, it becomes an important topic of research in the field of transportation.

Researchers have studied hazmat transportation and how to force the transportation to follow the route which decreases the risk or which route is best for hazmat

Mode of Transportation	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	Grand Total
AIR	8	7	10	2	7	20	12	15	20	7	108
Highway	160	153	153	152	130	147	142	134	157	143	1471
Railway	57	63	38	13	20	18	15	14	213	17	468
Water	3	0	0	2	8	0	2	0	0	8	23
Grand Total	228	223	201	169	165	185	171	163	390	175	2070

TABLE 1.1: Injuries By mode and incident year
[7]

Mode of Transportation	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	Grand Total
AIR	8	19	71	2	17	4	14	13	5	188	342
Highway	472	429	506	637	1131	602	495	596	622	432	5923
Railway	273	79	175	73	123	178	379	227	461	271	22339
Water	2	14	10	57	21	81	2	12	1	5	202

TABLE 1.2: Damage amounts by mode and incident year(All amounts in 10000 $)
[7]

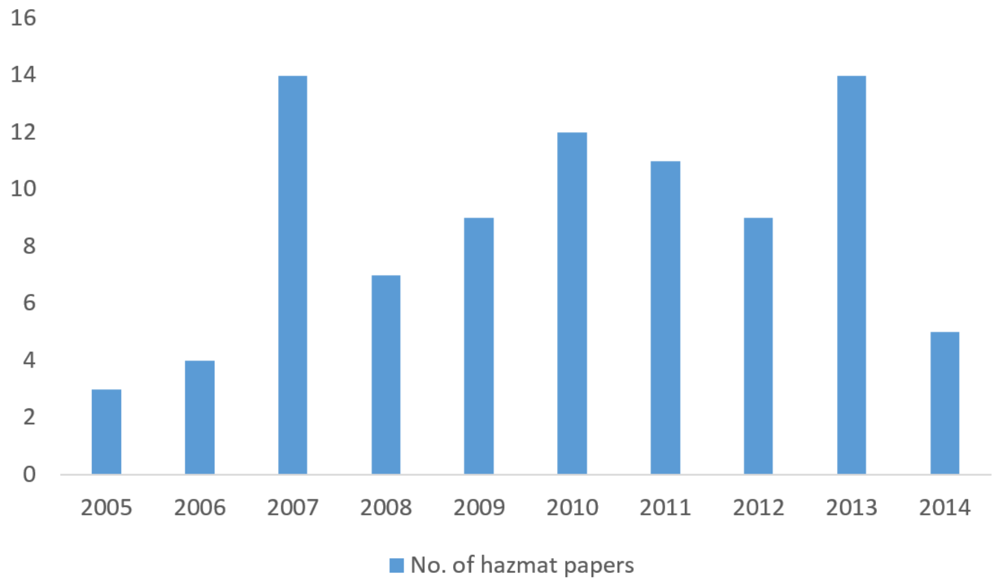

FIGURE 1.4: Number of hazmat-transportation related papers published in refereed Journals between 2005-2014

transportation. For example, gasoline is consumed by millions of cars, trucks and buses in the US but, needs to be transported from refineries/shipment points to gas stations. Gasoline is clearly hazardous in the sense that a truck carrying gasoline if involved in a collision, can result in casualties and serious damage to other vehicles and property. Federal Emergency Management Agency(FEMA) reports that various quantities of hazardous materials are manufactured, used or stored at an estimate of 4.5 million facilities in the US alone. This hazmat is again transported to various locations by different modes such as air, highway, railway and water. Travelers and shippers may choose to utilize more than 45,000 miles of interstate freeway, 300,000 miles of freight rail, nearly 10,000 miles of urban and commuter rail systems, or connect between 500 commercial-services and 14,000 general aviation airports [8]. Over the years, there have been many papers on the hazmat transportation as shown in the graph 1.4 [9].

1.3.1 Hazmat Routing Risk

Although the risk is a popular term in the media, and a popular topic with many authors, there is no universally accepted definition of risk. Most people would agree that risk has to do with the probability and the consequence of an undesirable event. Some authors define risk as only one of these terms (i.e., probability or consequence), it is more common to define risk as the product of both the probability of and the consequence of the undesirable event (Covello and Merkhofer [10]). Note that this is an expected consequence definition, and it is the definition that we refer to as traditional risk. We emphasize that, depending on the circumstances, it might make sense to use other definitions of risk.

Risk measurement in hazmat transportation is an important component for successful hazmat routing and modeling. Using the traditional risk definition, the risk of transporting hazmat B over a unit road segment A(such as 1-mile stretch) can be written as in 1.1

$$R_{AB} = p_{AB}C_{AB} \tag{1.1}$$

where p_{AB} is the probability of an incident occurring on the unit road segment A for hazmat B and C_{AB} is the consequence which is defined as population along the unit road segment A within the neighborhood associated with hazmat B.

The value of incident probability p_{AB} can be examined according to different modes, carrier types, vehicle types, road classifications, time of the day and weather conditions. For most hazmats, estimates of incident probabilities are between 0.1 and 0.8 per million miles. The consequence depends on population density near road segment and can be estimated by using the impact area for the hazmat under consideration. pEstimation tools for incident consequence typically take on the form of a "danger circle" [11] such that all individuals within the zone are determined to be exposed to a fatal hazmat incident. The impact area can be considered as a circle with the radius of circle varying from 0 to 7 miles based on the type of hazmat being carried. If we view the impacted area as the"danger circle"[11], we can easily visualize the hazmat transport activity as the movement of the danger circle along the path between origin and destination as seen in the figure 1.5. We can see that this forms a band with the width of the band as the diameter of the danger circle along the path. It is important to note that, depending on the time of day and area, population estimates may vary significantly from static figures such as census counts [12].

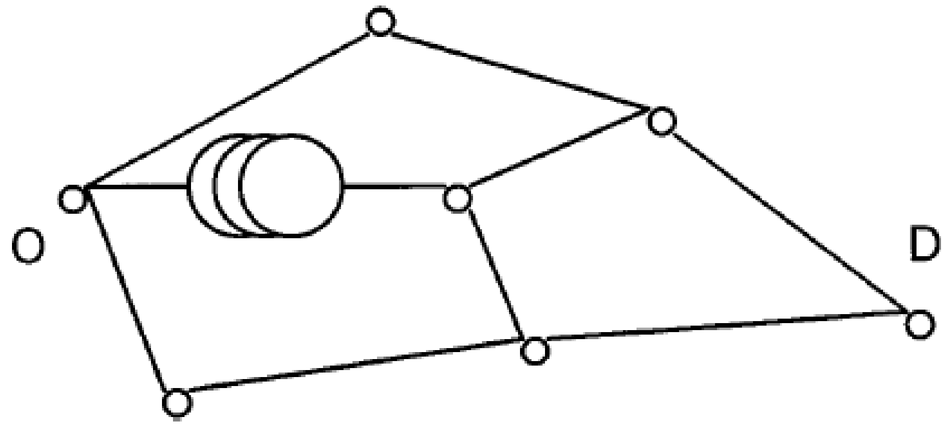

FIGURE 1.5: Depicition of hazmat transport between an origin(O) and destination(D) as the movement of a danger circle

Note that the equation 1.1 is valid for a unit road segment. In the construction of a network, it is assumed that an edge is a collection of n unit road segments each with same incident probability and population in (the danger circle) C. The vehicle will either have an incident in the first mile, or it will make it safely to the second mile. If it makes it safely to the second mile, it will either have an incident in the second mile, or it will not, and so on. We assume that the trip ends if an incident occurs. The tree in Figure 1.6 displays all possible outcomes of a trip along this edge.

The expected consequence(risk) associated with this edge can be expressed as 1.2 (variable interpretation is the same as above)

$$pC + (1-p)pC + (1-p)^2pC + \cdots + (1-p)^{n-1}pC \tag{1.2}$$

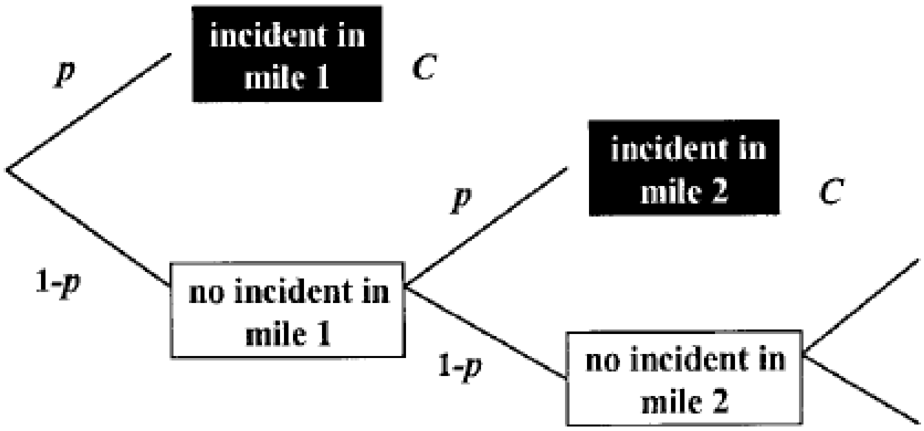

FIGURE 1.6: Partial probability tree displaying possible outcomes of a hazmat transport along an edge, where p= incident probability per mile and C= population impacted in the case of an accident

Note that, given p,n and C, it is easy to compute 1.2 and attach the value to the edge attribute to be used in route selections. However, since p (probability of a hazmat incident) is typically very small (on the order of one per one million miles), the 1.2 can be approximated as in 1.3 [12].

$$(pn)C \tag{1.3}$$

The risk of the edge can be redefined as in 1.4

$$R_i = p_i C_i \tag{1.4}$$

where p_i is the probability of an incident on edge i = (prob. of an incident on a unit segment of edge i)*(number of unit segments in edge i), and C_i is the number of people within the danger circle along edge i.

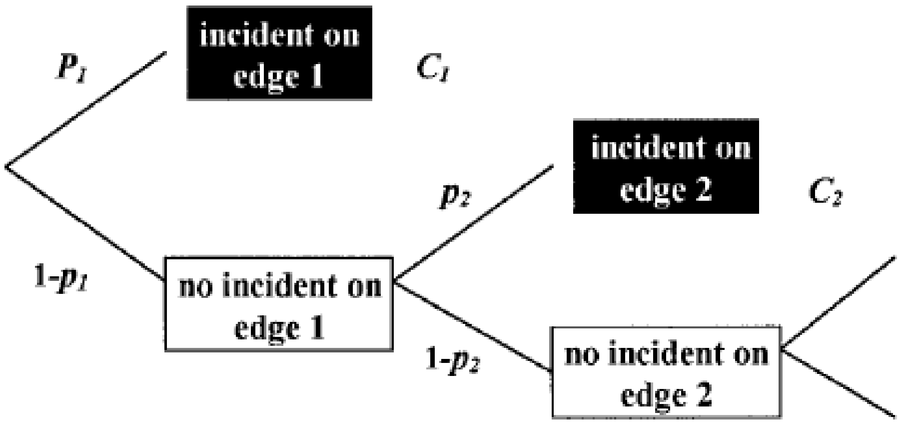

FIGURE 1.7: Partial probability tree displaying possible outcomes of a hazmat transport along a path, where p_i = incident probability along the i^{th} edge of the path and C^i = population impacted by an incident on the ith edge.

Having expressed the risk for the road segment and edge in 1.1 and 1.4 respectively, path risk can be expressed in a mathematical form using path risk and edge risk. A path is defined as the collection of edges. To get the expected risk of the path, The path is viewed as a probabilistic experiment as in 1.7. The expected consequence (risk) associated with this trip is expressed as 1.5

$$p_1C_1 + (1-p_1)p_2C_2 + (1-p_1)(1-p_2)p_3C_3 + \ldots\ldots \tag{1.5}$$

We see that (1-p_1)(1-p_2)…(1-$p_{k-1}p$)p_kC_k will be the edge attribute (impedance) of the k_{th} edge. Edge attributes are path dependent. Since the value of p is small, the (1-p_i) $\cong$ 1, for all i. Therefore the risk of the path is defined as 1.6 and 1.7

$$p_1C_1 + p_2C_2 + p_3C_3 + \ldots \tag{1.6}$$

$$\sum_{i=1}^{n} p_i C_i \tag{1.7}$$

It is this value that would be substituted in the objective function of the shortest path problem, creating an optimization problem that would return the path of minimum risk from an origin-destination (O-D) pair for the current network. This is a widely used approach, with the assumption that every line segment has uniform properties. Additional nodes that separate a link without uniform properties into its uniform components may be added, without influencing the optimal outcome. However, this approach is impractical for large networks and also increases the number of constraints in the optimization problem, potentially increasing computation time significantly. If this assumption cannot be made, then expected edge consequence may not be approximated as succinctly as in 1.7, preventing the shortest path approach [12].

The incident probability is directly proportional to the population around the link. The prominent way to calculate the population at risk is to calculate the risk for a given bandwidth and link is given by Chiu and Batta [13]. This method considers a population count within a buffer of given bandwidth. The individual link values of the total population at risk are summed to determine the total population at risk along a route from end to end. This method can be misleading as the population is counted twice if they are located at the corners. To avoid this double counting, a more elaborate method is developed as follows: A standard buffer is divided into three regions as shown in Fig 1.8: regions A and C are the buffer drawn around the ends of the link, while region B is the remaining part of the standard buffer. The total population at risk for a link is calculated as in 1.8:

$$\frac{1}{2}\text{ Population in region A} + \text{ Population in region B} + \frac{1}{2}\text{ Population in region C} \tag{1.8}$$

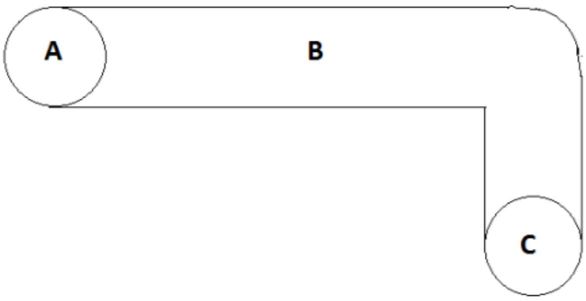

FIGURE 1.8: Regions of a link

Batta and Chiu [13] consider the problem of determining optimal paths for routing an undesirable vehicle on a network embedded on a Euclidean plane, considering discretely distributed demand points on straight-line links of the network. They considered a path that minimizes the weighted sum of lengths over which this vehicle is within a threshold distance λ of population centers, by varying λ. The routing objective becomes the minimization of expected damage, where accidental leakage of hazardous materials can inflict damage within a neighborhood λ of the accident site.

Abkowitz & Cheng[14] minimized risk and cost in hazmat transportation by focusing on risk estimation. Two types of damage were considered: direct and indirect. Direct damage occurs in the surrounding vicinity. The area of exposure for the indirect damage is determined using a formula which accounts for dispersion, horizontally and vertically, as well as wind speed and direction. Relative weights were used to combine the fatalities, injuries and property damages into a single overall measure of risk. This is then traded off against transportation cost to identify Pareto-optimal routes for individual O-D pairs.

On a similar note, Saccamanno and Chan[15] examined three strategies for routing of hazardous material shipments. These are:

1. minimize risk exposure
2. minimize accident likelihood
3. minimize operating costs

They also evaluate the sensitivity of route "performance" to random variations in certain environmental factors, such as pavement condition (wet vs. dry) and visibility (good vs. poor), and determine the incidence of benefits and costs (who gains and who loses) from each routing strategy.

ReVelle et al.[16] proposed a bi-objective formulation that considers: (1) minimization of the population covered (affected) by the path, and (2) minimization of the length of the path. The solution of the minimum covering/shortest path problem generates a trade-off curve of routes connecting a predetermined O-D pair. Sivakumar et al.[17] developed a related network model that routes shipments along the route that minimizes the sum of the arc losses, where the arc loss is defined as the cost of a hazmat release on that arc. Shipments continue to be routed along this path until an incident occurs. Although the minimization of the sum of the arc losses is a reasonable proxy for Damage limitation, it can lead to illogical routes (see Erkut 1995, for some examples of this). Routes which minimize the sum of the arc losses can nonetheless have an unacceptably high risk (sum of the products of the arc losses and their respective probabilities) or route incident probabilities. Consequently, Sivakumar et al. [17] minimized the sum of the arc losses subject to two side constraints; the risk of an incident is required to be less than some thresholds and the probability of an incident is required to be less than another threshold.

More recently a quantile-based methods such as value-at-risk and conditional value-at-risk have been used in hazmat routing to determine the risk of the route. Value-at-Risk(VaR) and Conditional Value-at-Risk(CVar) are generally the concepts used in measuring finance profit or loss measurement, has been recently applied in hazmat transportation for measuring the risk by following a specified route. Kang et al. [18] studied VaR in hazmat routing to measure a cut-off value for the risk of hazmat shipments. It was used to generate route choices for a hazmat shipment based on specified risk confidence level.

1.3.2 Hazmat Route Control

There are two issues in hazmat route planning. The first one is related to assessing the risk induced on the population by hazmat vehicles traveling on various segments of the road network, and the second involves the selection of the safest routes to take. Since the government can't impose the overall route for the hazmat carriers, there has been an intensive study on hazmat network design and toll setting policies. In network design, the government has the right to close certain road network or limit of hazmat traffic flow on certain network links by road bans and curfews. Whereas in toll setting, the government uses link tolls to deter the carriers from using certain network links and induce them constantly to route the shipment in less populated links of the network.

1.3.2.1 Hazmat transportation network design

The hazmat transportation network design models tries to reduce the equitable risk over the network. The main aim of the problem is to reduce the overall risk of the network by equitable risk distribution. The models are useful in finding a global routing plan for a hazmat carrier. In the generic Hazmat Transportation Network Design (HTND) problem it is assumed that an authority has the power to decide which links can be used for transportation of hazmat type $h \in H$. The problem is to force the carriers to route shipments on less risky links and hence minimizing the total risk induced by the hazmat shipments. The carriers will use the routes available on the network, minimizing their transportation cost.

General notations to follow in the rest of the section-

- G=(N, A) be a directed network with N being the set of n nodes(intersections in the road network) and A being the set of m directed links or arcs between pairs of nodes. The network is assumed unidirected.i.e in this case, let E be the set of unidirected links or edges of the network, and A= $\{(i, j), (j, i)|(i, j) \in E\}$ be the set of pairs of arcs related to the edges traversed forth and backward, with arc *(i,j)* $\in A$.

- C_{ij} be the transportation cost of arc *(i,j)* $\in A$. If the network is unidirected, the assumptions is that the travelling cost of the edge *(i,j)* $\in E$ does not depend on the direction in which the edge is traversed, and hence the costs of the arcs *(i,j),(j,i)* $\in A$ related to traversing that edge forth and backward, respectively, are assumed to be $c_{ij} = c_{ij}$ and equal to the edge travelling cost.

- H of hazmat types, we consider a set K of p carriers with with carrier $k \in K$ having to satisfy a single shipment order(commodity) of hazmat of type *h(k)* $\in H$ from origin node s^k to the destination node t^k.

- The amount of hazmat to be shipped by carrier k (i.e, the demand of k) is denoted with b^k and with n^k we denote the number of trucks used for the shipment. For the sake of simplicity, we assume that carrier k uses a fleet of the homogeneous truck (vehicles) each one of capacity q^k and traveling at full load (hence, we can assume that $b^k = n^k.q^k$).

- p_{ij}^h be the risk induced by a truck carrying hazmat of type h through link *(i,j)* $\in A$; typically, the risk does not depend on the direction in which a road segment is traversed. Therefore, the assumption is $p_{ij}^h = p_{ji}^h$

The modeling used to represent the HTND problem is a bilevel optimization problem, where the authority plays the role of the leader(first level) decision maker, and has the objective to select the minimum total risk network to open to hazmat shipments, taking into account the cost- minimizing behaviour of the carriers, that play the role of the follower (second level) decision maker.

In the HTND problem two set of variables are considered for modeling the decision of the authority and carrier, respectively:

- y_{ij}^h, the binary variables representing the decision of the authority. 1 if the arc *(i,j)* $\in A$ is open for the transportation of hazmat type h, 0 otherwise.
- x_{ij}^k, the binary variables modeling the decision if the carriers are equal to 1 if arc *(i,j)* $\in A$ is used by carrier k or the shipment, 0 otherwise.

Since the authority can open or close the links and no restriction (flow constraint) is assumed on open links, the decision of each carrier k results in selecting a route (with minimum cost) on the available subnetwork from the origin s^k to the destination t^k with all the amount of hazmat being shipped along the selected route (i.e unsuitable flow)

Although the main concern of the authority is the minimization of the risk while the carriers mainly address the minimization of the transportation cost, it is reasonable to assume that both the authority and the carriers take also into account at least i part objective of the other party Given the above discussion variables, the general version of the HTND problem [2] can be formulated as :

$$\min_{y_{ij}^h} \sum_{k\in K} \sum_{(i,j)\in A} n^k (p_{ij}^{h(k)} + w_1 c_{ij}) x_{ij}^k$$

$$\text{s.t.} \quad y_{ij}^h \in \{0,1\} \qquad\qquad \forall (i,j)\in A, h\in H$$

$$\text{where} \quad x_{ij}^k solve :$$

$$\min_{y_{ij}^h} \sum_{k\in K} \sum_{(i,j)\in A} n^k (c_{ij}^{h(k)} + w_2 p_{ij}) x_{ij}^k$$

s.t.

$$\sum_{\{j:(i,j)\in A\}} x_{ij}^k - \sum_{\{j:(j,i)\in A\}} x_{ji}^k = e_i^k \qquad\qquad \forall \quad i\in N, k\in K$$

$$x_{ij}^k <= y_{ij}^{h(k)} \qquad \forall (i,j)\in A, k\in K$$

$$x_{ij}^k \in \{0,1\} \qquad \forall (i,j)\in A, k\in K$$

where e_i^k is equal to 1, -1 or 0 depending on if node i is the origin, the destination or a transshipment node for carrier k. For the sake of generality, both the objective functions of the authority (the leader) and the carriers (the followers) consider the minimization of total risk (assuming additivity of impacts) and total transportation cost, with parameters w_1 and w_2 that allow the comparison between total risk and carriers total transportation cost i the objective functions of the leader and the followers, respectively.

The leader(outer) problem has no constraints(except for the binary constraints in the variables). The followers (inner) problem presents the flow balance requirements on each network node and for each carrier(shipment), and the constraint on the carriers decision variables implying that only the available links (decided by the leader) can be used by the carriers. One may control possible overload in the number of vehicles traversing any link by adding a constraint to the leader problem.

Constraint-

$$\sum_{k \in K} n^k x_{ij}^k <= w_{ij}$$

for each link *(i,j)*, with w_{ij} being the maximum total number of hazmat trucks allowed on link *(i,j)*. Addition of this constraint might not guarantee a feasible solution on a connected network. Without the addition of such constraints, there is no interaction between shipments of different hazmat types, and the followers' problem decomposes into —K— constrained shortest path problems.

Kara and Verter(2004) [2] were the first to study the hazmat transportation network design. They proposed a bi-level integer programming hazmat network design considering leader-follower relationship between government and carriers. In their paper, they assumed the carriers, represented by follower (second level) decision makers in the bilevel model, will always use the cheapest routes on the hazmat transportation network designed by the government authority. The authority plays the role of the leader (first level) in the bi-level model which has an objective to minimize the risk of the network, taking into account the cost- minimization behavior of the carriers. In this model, hazmat are grouped into categories based on risk, and a network for each group, without considering the interactions among the shipments of different hazmat categories. Since the follower's problem is linear, the bi-level integer programming problem is to reformulate as a single-level Mixed Integer Programming (MIP) problem by replacing the followers problem by its Karush-Kuhn-Tucker(KKT) conditions and by linearizing the complementary slackness constraints. They concluded that even though government intervention in the route choices reduces the transportation risk by a huge margin, the route may be undesirable for the carriers transportation cost.

Erkut and Gzara [19] studied a similar type of problem, where they generalized the model of Kara and Verter [2] by considering the unidirected network case and designing the same network for all the shipments. They considered the possible lack of stability of the solution of MIP model and proposed a heuristic solution method that always finds a stable solution. They extended the model to account for the cost/risk trade-off by including the cost in the objective function of the leader problem. In extension to their previous paper, Verter and Kara[20] introduced a single-level path-based formulation for hazmat network design, where the open links in the road network chosen by the regulator determine the set of paths that are available to the carriers. This facilitates the incorporation of carriers'cost concerns in regulators risk reduction decision.

Erkut and Alp [21] considered a single level hazmat transportation network model. In their model, they restricted the network to a tree, so that there is a single path between the origin and destination pair with a restriction that the carriers have no alternate paths on the tree. This restricted the carriers route selection giving them no freedom in route selection, with the result that the structure has a single level. They solved the integer programming problem with the objective of minimizing the risk. However, the solution had less risky paths, they gave circuitous and expensive routes. To avoid an economically infeasible solution for the carriers, the authors proposed a greedy heuristic that adds shortest paths to the tree so as to keep the risk increase to a minimum and allow the carriers to select the cheaper paths.

While most approaches discussed above assumed that the underlying network parameters are static or time invariant, Esfandeh et al. [22] extend the hazmat network design problem to account for the time-dependent road closure as a policy tool in order to reduce hazmat transport risk by altering carriers' departure times and route choices. In the model, they incorporated the risk implications of the carriers' least-cost route-time decisions into the design using a bi-level framework. They set an alternative for each shipment with each alternative being composed of a route and a departure time choice, giving them a single- level formulation for the bi-level framework. To solve this model, they suggested a column generation- based heuristic which generates the set of alternatives for each shipment by separately incorporating the perspectives of the regulator and the carriers.

All the above hazmat network design approaches considered the government and the carriers points of view, trying to mitigate the risk only from a macroscopic point of view, without considering the need to mitigate the risk in an equitable way over the region in which the transport network is embedded. Bianco et al.[23] analyzed a scenario, where local authority tries to minimize the risk over the populated links on the network, i.e. risk equity and regional area authority that aims to minimize the total risk over the network. Bianco et al.[23] also formulated their hazmat network design problem with a linear bilevel model, where at the higher (leader) level there is a meta-local authority that aims to minimize the maximum link risk over populated links of the whole network, that is risk equity, and at a lower (follower) level there is the regional authority that aims to minimize the total risk over the network. This corresponds to the existence of two decision makers, Regional authority, and the local authority. They reduce the bi-level problem to a single- level integer programming problem by replacing the follower problem with the KKT conditions and by linearizing the complementary slackness constraints.

Bell (2006,2007) proposed a min-max model which minimizes the maximum link risk, and looks for risk equity by balancing the risk through the links of the network.

1.3.2.2 Toll settings

Toll setting(TS) is a policy that is applied to hazmat transportation to regulate hazmat shipments. In this policy, the authority sets toll on all (or on a subset of) links of the network, in order to deter the carriers to use certain roads and encourage them to use the less populated ones.

In the TS problem two sets of variables are considered for modeling the decisions of the authority and carrier, respectively:

- t_{ij}^{h} are non-negative variables representing the tolls imposed by the authority on arc *(i,j)* $\in A$ for each truck transporting hazmat type $h \in H$.

- x_{ij}^{k}, the binary variables modeling the decisions if the carriers and equal to 1 if arc *(i,j)* $\in A$ is used by carrier k or the shipment, 0 otherwise.

where t_{ij}^{h} and x_{ij}^{h} are the variables controlled by the leader and the followers respectively. The other notations have the same meaning as in the hazmat network design.

While the papers discussed in previous sections were about the hazmat network design, the paper by Marcotte et al. [24] proposed toll setting method, discourage hazmat carriers from using certain road segments via placing tolls on certain links of the network. Toll pricing has been a regular method to control traffic congestion for a long time. When it is infeasible to increase the capacity of the transportation network, imposing appropriate tolls on roads can reduce traffic congestion because tolls can encourage travelers to detour or to travel during a less congested period. Besides, transportation agencies have commonly used tolls to generate revenue to offset infrastructure construction and maintenance cost. He proposed a bilevel model that minimizes the risk and costs including both transportation costs and tolls on the links. They reduced the bilevel problem to a single- level mixed integer problem by replacing the followers problem with optimality conditions and by linearizing the complementary slackness constraints. By imposing tolls on certain road segments in their model, the hazmat shipments are expected to be directed on less- populated roads according to carriers own selection. This gives carriers more flexibility than network design. The proposed model is the following NP-hard bilevel problem:

$$\min \sum_{k \in K} \sum_{(i,j) \in A} n^k (p_{ij}^{h(k)} + w_1(c_{ij} + t_{ij}^{h(k)})) x_{ij}^k$$

$$\text{s.t.} \quad t_{ij}^h >= 0 \qquad \forall (i,j) \in A, h \in H$$

$$\text{where} \quad x_{ij}^k solve:$$

$$\min_{y_{ij}^h} \sum_{k \in K} \sum_{(i,j) \in A} n^k (c_{ij}^{h(k)} + t_{ij}^{h(k)} + w_2 p_{ij}^{h(k)}) x_{ij}^k$$

s.t.

$$\sum_{\{j:(i,j) \in A\}} x_{ij}^k - \sum_{\{j:(j,i) \in A\}} x_{ji}^k = e_i^k \qquad \forall \quad i \in N, k \in K$$

$$x_{ij}^k \in \{0,1\} \qquad \forall (i,j) \in A, k \in K$$

In this model, the authority sets the tolls on the arcs in such a way to minimize a weighted combination of population exposure and carriers'cost into account. For certain value of tolls, carriers choose the minimum cost routes.

It can be shown that HTND model and TS model are equivalent in case there is a single carrier or when each carrier transports a different type of hazmat since the model is inseparable by hazmat type.

Bianco et al. [25] extended Marcotte et al.[24] model of toll setting policy to regulate hazmat transportation, where the regulator (e.g., a government authority) aims at minimizing not only the network total risk, but also spreading the risk in an equitable way over a given road transportation network. The idea is to use a toll setting policy to discourage carriers transporting hazmat from overloading portions of the network with the consequent increase of the risk exposure of the population involved. Specifically, they assumed that the toll paid by a carrier on a network link depends on the usage of that link by all carriers. Therefore, the route choices of each carrier depend on the other carriers choices, and the tolls deter the carriers from using links with high total risk. The [24] considered a mathematical programming problem with equilibrium constraints (MPEC), where the inner problem is a nash game having as players the carriers, each one wishing to minimize their travel cost (including tolls); the outer problem is addressed by the government authority, whose aim is finding the link tolls that induce the carriers to choose route plans that minimize both the network total risk and the maximum link total risk among the network links (in order to address risk equity).

Wang et al. [26] assumes that both hazmat traffic and regular traffic affect population safety, since congestion increases the accident probability and delays. His idea was to control regular as well as hazmat traffic through toll setting policies. They proposed a dual toll pricing problem with the following assumptions: (1) congestion included by the traffic flow of hazmat trucks can be ignored; (2) to simplify the model, the users have perfect information of the current status; (3)

All the model parameters are deterministic; (4) single type of hazmat is considered; (5) travel delay is a linear function of traffic congestion; (6) risk is linearly affected by travel delay. The authors provided a bilevel formulation, where the first stage is a non-convex quadratic programming problem and the latter is a linear programming model.

Esfandeh et al. [27] studied on regulating hazmat by dual toll pricing which was an extended work of Dual toll pricing for hazmat material transport with linear delay by Marcotte et al by considering the non linearity in the travel delay. In this paper, they proposed a dual toll pricing model with a linear delay function to reduce the hazmat transportation risk. They provided a bi-level formulation and then provided an equivalent two-stage problem with an assumption that the number of hazmat trucks is relatively small so that the congestion induced by the hazmat trucks can be ignored. While the second-stage problem was linear programming problem, the first-stage problem is a non-convex quadratic problem. They suggested two methods to solve the first stage problem: the branch and bound, and the null space active set method. They concluded that the dual toll can reduce the hazmat transportation risk significantly, while it limits the increase of transportation costs to a reasonable level.

1.3.3 Routing hazardous materials when considering risk

Shobrys[28] and Robbins[29] represent the earliest efforts to deal explicitly with multiple objectives. Shobrys considers two objectives:

1. minimize ton miles traveled
2. minimize population exposure-tons

He points out that the optimal decisions must come from the Pareto-optimal solution set figure 1.9. By using various weights to combine the two objectives, Shobrys was able to use a hybrid distance-population cost for each link, and hence, use the shortest path algorithm to obtain several Pareto-optimal solutions.

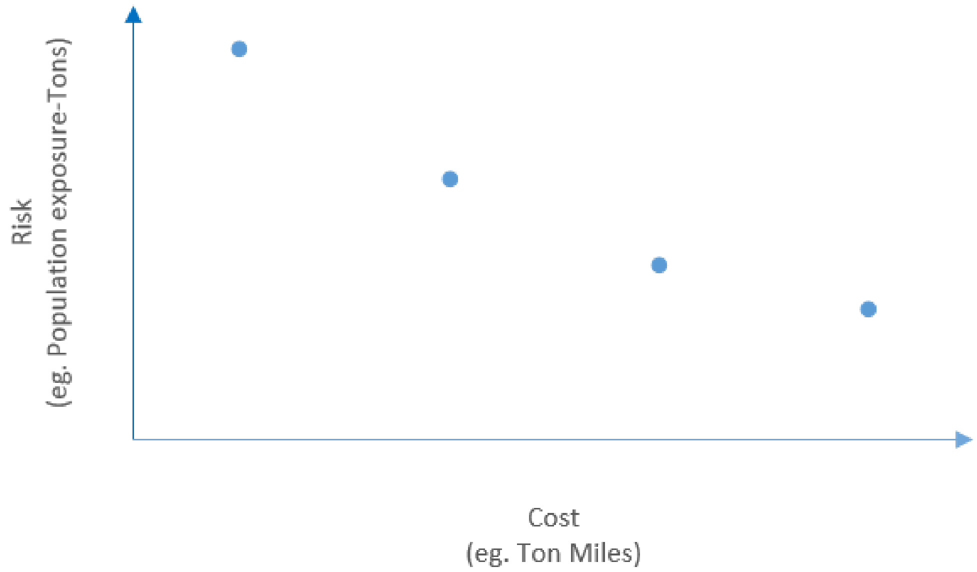

FIGURE 1.9: Pareto-optimal routes for objectives (1) minimize risk and (2) minimize cost. (Each point represents a route)

Robbins[5] used a sample of 105 O-D pairs connected by the interstate highway system to test the Null Hypothesis: For an equal number of shipments, the expected number of people affected by accidents on a minimum population route does not differ significantly from the number of people affected by accidents on a minimum distance route. The null hypothesis was rejected; leading to the conclusion that the minimum population route can reduce the minimum population route can reduce the number of people potentially affected by hazmat release by a significant amount.

An alternate approach with time consideration is discussed in [30], where a p-dispersion problem is used to generate a candidate set of routes for unmanned military aircraft and a Quadratic Semi-Assignment problem employed to filter out undesirable routes and ensure that each vehicle routed is assigned to only one route. Instead of safety, however, this approach relies on the identification of dissimilarity between routes through a proposed metric, and maximizes the minimum dissimilarity through the use of the optimization of the p-dispersion problem [30]. Heuristically, the approach is similar to the tabu search described above. Initial solution construction is carried out, and a local search component strives to improve the solution.

Motivation for the above problem lies in the observation that, when seeking multiple paths between an origin and destination, most k-shortest path algorithms will return routes without significant variation. The paper by Akgun, Erkut and Batta [1] study the procedure for finding the dissimilar paths. They study the differences in the solutions in iterative penalty method, gateway shortest path and minimax method. To find the set of dissimilar paths, they propose to use p-dispersion problem to the k-shortest paths and Iterative penalty method to find the dissimilar paths. The 1.10 displays a typical result of dissimilarity application, where both routes roughly cover similar mileage, but where commonality between the two is small.

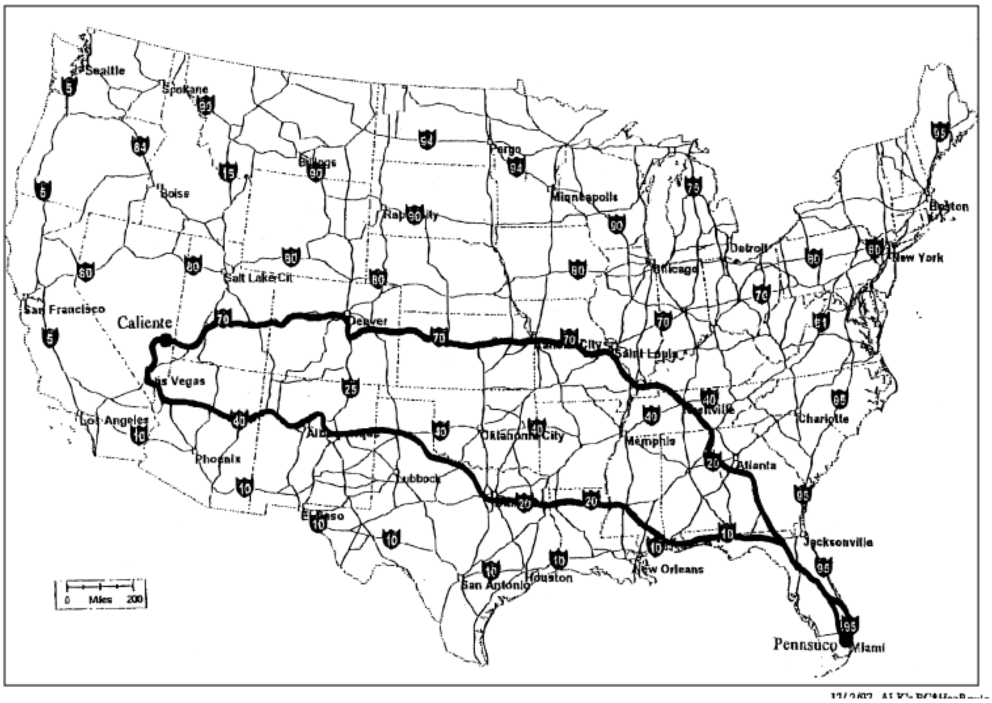

FIGURE 1.10: Dissimilar paths by dissimilarity application [1]

1.3.3.1 Most closely related to the scope of this work

The strategy proposed by P Cappanera, M Nonatowhich [31] is an alternative to the direct control on each shipment. They proposed a method that uses rule based scenario. In this the hazmat carrier has to pass through at least one gateway location from the origin to destination. The gateway points are placed in such a manner that it diverts the vehicles from the shortest path. This new strategy involves the solution of a new challenging combinatorial optimization problem, the Gateway Location Problem (GLP). It proposes a methodology to easily compute the best trade off solutions between risk and cost, by making the hazmat shipment pass through these gateway locations. In this method they used the gateway location problem for diverting vehicles from their risky shortest path from origin to destination by assigning a fixed gateway to be crossed along its itinerary. The gateways are chosen from the candidate solution. The candidate solution is assumed to be given. Given this method, the carrier will have to take the shortest route which goes through the assigned gateway. They used the dynamic setting where demand varies with time. As the demand varies, gateway locations and allocation decisions vary at each period. Such rules not only must be easy to implement but must be devised in such a way that carriers response will result in a less risky set of itineraries.

The current research differs from the above method by taking into one more constraint that each vehicle needs to pass through the inspection station (Gateway) after every K miles and we also consider that the final destinations for the hazmat vehicles as inspection stations to keep check on the carriers that they follow this route or else they can be penalized accordingly. Once we have the inspection stations set up, the carriers will then try to minimize their cost by following the regulations.

1.4 Chapter Summary and Road Map of thesis

This chapter was devoted to the literature review of different methods for controlling hazmat transport and the motivation behind choosing the problem. Relevant terminology was introduced to the reader. The different controlling strategies such as hazmat network design, toll setting and gateway location problem are discussed in detail. The present solution methodology was outlined in this chapter.

The remainder of this thesis is organized as follows. In Chapter 2 we describe a exact solution method for this problem and why it is difficult to implement on real road network problem. Chapter 3 explains in details the different methods to solve the problem using heuristics. Chapter 4 concentrates on the implementation of heuristics on real world case study. In our thesis we took a road network of Ravenna, Italy to check the solution methods. Chapter 5 summarizes the work done and then make suggestions for future work.

Chapter 2

Exact Solution Method

In this section, we discuss one of the exact solution methods for placement of inspection stations. It can be found that the exact solution for this problem is possible only through total enumeration.

Claim 1: The Inspection placement problem can be solved exactly through total enumeration.

Justification of claim: We are concerned with the problem of optimally placing inspection stations with a distance constraint such that for a given set of candidate set, we need to find m number of inspection stations which will give the least risk path when carriers take the shortest path through the inspection station with the distance constraint. Let's introduce some mathematical notation.

Let $V = \{ 1 \ldots n\}$ be the vehicles set. For each v, the pair (o_v, d_v) denote its origin and destination. Let $O = \{o_v, v \in V\}$ be the set of origins and, Likewise, let $D = \{d_v, v \in V\}$ denote the destination set. Let N be the total set of nodes and N^{cs} be the candidate set from nodes, where $N^{cs} < N$. A weighted graph *G=(N,A)* models the network such that for each arc set A, there is a positive cost coefficient c and a non negative risk coefficient r. Let K be the distance, after which every vehicle needs to pass through an inspection station.

We can find all the K-shortest loopless paths (Yen's Algorithm) for all vehicles as shown below

$$v_1 = P_{11}, P_{12}, \ldots\ldots, P_{1l_1}$$

$$v_2 = P_{21}, P_{22}, \ldots\ldots, P_{2l_2}$$

$$v_3 = P_{31}, P_{32}, \ldots\ldots, P_{3l_3}$$

$$\vdots$$

$$v_n = P_{n1}, P_{n2}, \ldots\ldots, P_{nl_n}$$

In the above P_{ij} denotes the path for i^{th} vehicle and j^{th} alternate path. All the paths are in increasing order of cost, i.e cost$(P_{11}) < cost(P_{12}) < cost(P_{13}) \ldots$ where the cost of the path is calculated as the sum of the cost of each link that is visited in the path. The risk of the path is also calculated similarly by summing of risks for each link that is visited.

If we want to choose m inspection stations from N^{cs} locations, we can select m inspection stations in $\binom{N^{cs}}{m}$ ways. For a given K and set of m inspection stations in $\binom{N^{cs}}{m}$ we choose the first feasible path for each vehicle such that

$$\sum_{j=1}^{l_i} Y_{ij} = 1 \qquad \forall i$$

$$Y_{ij} \in \{0, 1\} \qquad \forall i, j$$

where Y_{ij} is the j^{th} path chosen for i^{th} vehicle and

$$\sum_{i=1}^{n} v_i = n \qquad \forall i$$

Where n is the total number of vehicles.

This similarly can be done with all other $\binom{N^{cs}}{m}$ instances such that the risk of the path is the least. By doing this we get the least risk path by choosing m inspection stations for N^{cs} candidate set.The above procedure is illustrated with the example in figure 2.1.

In the fig. 2.1, each arc contains the (cost,risk). For each v, the pair (S_v, D_v) denote its origin and destination. Nodes *a,f,g* are given as the candidate set and we set K as 3 units. The alternate paths for vehicle V_1 by K-shortest loopless

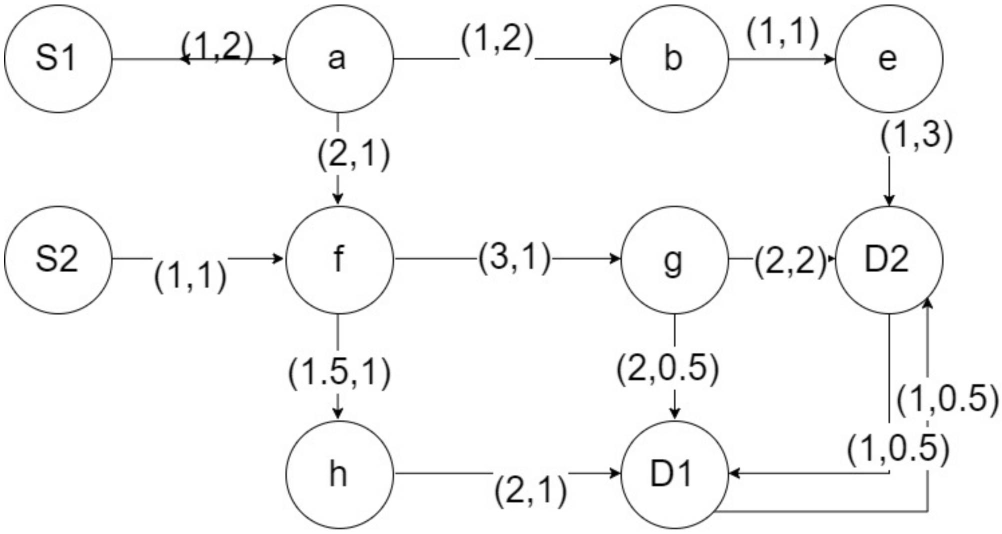

FIGURE 2.1: Hazmat transportat network

paths would be

$$P_{11} \to S1, a, b, e, D2, D1$$

$$P_{12} \to S1, a, f, h, D1$$

$$P_{13} \to S1, a, f, g, D1$$

$$P_{14} \to S1, a, f, g, D2, D1$$

Similarly, for V_2 the paths would be

$$P_{21} \to S2, f, h, D1, D2$$

$$P_{22} \to S2, f, g, D2$$

$$P_{23} \to S2, f, h, D1, D2$$

If we want to choose 3 inspection stations, then we can choose in $\binom{3}{3}$ ways. That is we can have the inspection stations at all the candidate sets. Then the vehicle V_1 would choose the least cost path P_{11} and similarly, vehicle V_2 would choose path P_{21}. This way the total cost be P_{11} (1+1+1+1+1=5) + P_{21} (1+1.5+2=4.5) and total risk would be risk for P_{11} (8.5) + risk for P_{21} (3.5). The total cost incurred by the vehicles would be 9.5 and the risk would be 12 units.

Similarly, if we were to choose 2 inspection stations, we can choose in $\binom{3}{2}$ ways. The different combinations of inspection stations are *af, fg* and *ag.*

Case 1: When we have *a,f* as inspection stations. Then the vehicle V_1 would choose the least cost path P_{11} and similarly, vehicle V_2 would choose path P_{21}. This way the total cost would be P_{11} (1+1+1+1+1=5) + P_{21} (1+1.5+2=4.5) and total risk would be, risk for P_{11} (8.5) + risk for P_{21} (3.5). The total cost incurred by the vehicles would be 9.5 and the risk would be 12 units.

Case 2: When we have *f,g* as inspection stations. Then the vehicle V_1 would choose the least cost path P_{13} and similarly, vehicle V_2 would choose path P_{22}. This way the total cost would be P_{13} (7.8) + P_{22} (5.8) and total risk would be P_{13} (4.5) + risk for P_{22} (4). The total cost incurred by the vehicles would be 13.6 and the risk would be 8.5 units.

Case 3: When we have g,a as inspection stations. Then the vehicle V_1 would choose the least cost path P_{11} and similarly vehicle V_2 there is no path with distance constraint k and g,a as inspection stations. There are no paths for V_2 with the given inspection stations.

Hence with 2 inspection stations, we get the least risk path by choosing inspection stations at f and g.

Given a set of n vehicles, each associated with the origin- destination pair (o_i, d_i) for i= 1,...,n. Let O={o_i:i=1,...,n} and D={d_i:i=1,...,n}. The set of candidate set is given by N^{cs} which is a subset of N. Firstly, we observe that if the graph is big, the 1st step of creating all k- loopless alternate paths becomes a computationally challenging problem for a directed graph with nodes greater than 40 Nodes.

Corollary: The total enumeration solution for Placement of inspection stations is a a computationally challenging problem on large networks.

The corollary follows immediately with the fact that for large directed graphs, finding the alternate loopless shortest paths along with finding all combinations of inspection stations for a given candidate set is a computationally challenging problem.

Chapter 3

Heuristic solution method

In this chapter, we study the methods to place the inspection stations through different heuristics. We first discuss the greedy heuristic and in later sections, we discuss how other heuristics are developed from the exact solution to reduce the candidate set by finding the alternate dissimilar paths and then use the greedy heuristic to find a lower risk.

3.1 Greedy heuristic to place the inspection stations

For placement of inspection stations, we use the greedy heuristic algorithm. In this algorithm, it removes the node from the candidate set, until there is no route possible for all O-D pairs. After removing the node, we find the shortest paths for all O-D pairs through the inspection stations with the distance constraint and find the number of nodes visited in the candidate set. The algorithm removes the node by which we get the least risk in the next iteration. The algorithm is explained in the pseudo code below.

```
Result: To reduce the risk of the path using Greedy heuristic
initialization;
clist ←candidate set of nodes;
dist_constraint← Distance constraint;
while clist is not empty do
    find the shortest routes through clist with distance constraint for each O-D
      pair;
    N ← Unique clist nodes from shortest paths;
    initialize empty risk array;
    for  i in N do
        k← infinity (K stores risk values);
        remove i from clist;
        find the shortest path through remaining clist and find the overall risk of
          the path and store it in k;
        if k = infinity then
            There is no path possible without i for this distance constraint and
              that node cannot be removed;
        else
            Store the value of risk in k with the clist in risks array;
        end
        append i to clist;
    end
    Select minimum risk from risks array and remove the node from clist;
    Remove all nodes from ;
    if all the values in risk array are infinity then
        break;
    end
end
```

Algorithm 1: Greedy algorithms

To explain the working, assume the flow of the hazmat in 3.1 with two OD pairs S1-D1 and S2-D2, where S1, S2 being source and D1, D2 being destinations. The candidate set for the following example is given by C1, C2 and C3. Numbers in the bracket define the (distance, risk) for each link. It can be seen that for a distance

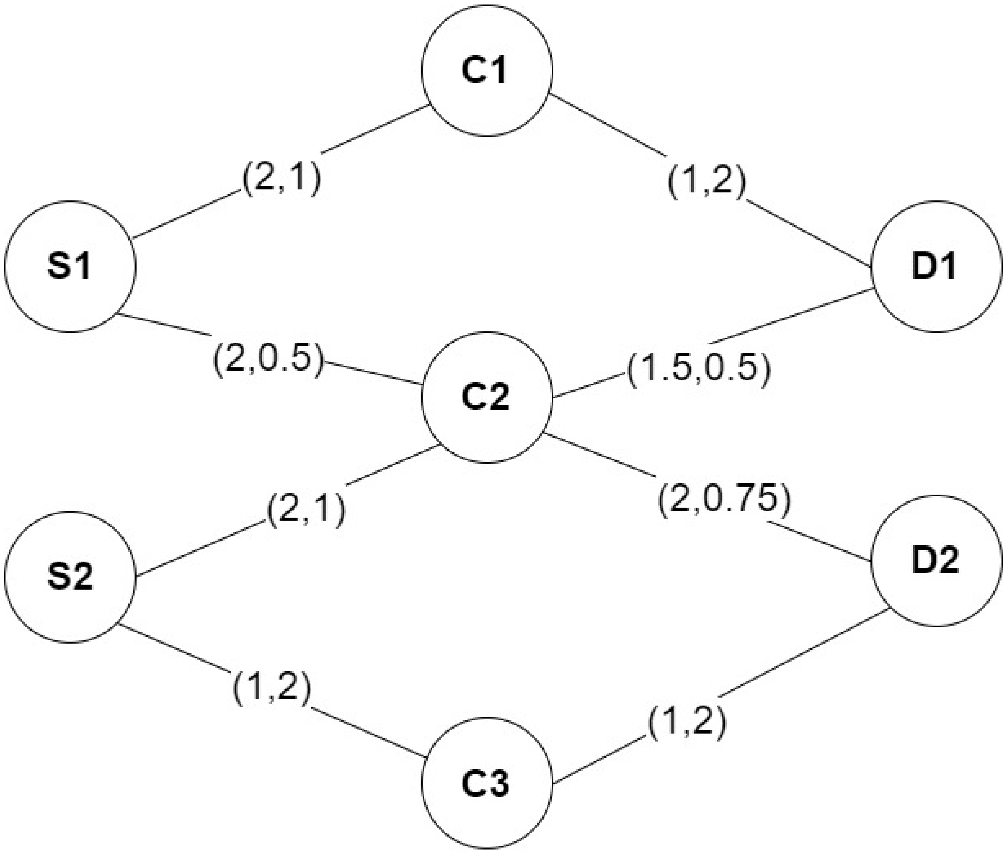

FIGURE 3.1: Network

constraint of 2 Units, the carrier traveling from S1-D1 will take the least distance path, i.e S1-c1-D1 and similarly S2-D2 carrier will take S2-C3-D2.

By implementing the greedy algorithm, the algorithm will check the risk when C1 is removed and then when C3 is removed. It is visible that the overall risk reduces when candidate C2 is removed. Similarly, in the next step C1 is removed and we can have the least risk path through C3. Even though this algorithm gives a reduced risk path, it doesn't guarantee the least risk path for the following distance constraint.

By following the greedy heuristic we can find the number of nodes needed to find the least risk path and the distance for that path.

3.2 Heuristics derived from Exact method

The major component in this problem is to place the inspection station such that we can reduce the risk of the network by rerouting the carriers from going through the risky path. In this, we try and find the alternate paths through the candidate set instead of finding all the alternate paths. In the 1st heuristic, we generate all the alternate routes through the candidate set such that it follows the distance constraint and select the least risk path for each O-D pair. In the 2nd heuristic, we generate all the alternate least risk routes.

The major components of these heuristics is to select a method to find the alternate paths. To find the set of alternate paths we use the method discussed in finding the dissimilar paths [1]. We use the preprocessing of the paths by finding the alternate routes between the origin and destination by using the iterative penalty method. This method is based on a repetitive application of the shortest path algorithm and adding a cumulative penalty percentage on all links in the resulting shortest path. Hence, repeated selection of the same set of links is discouraged and as a result, we get k-loopless dissimilar paths. If a repeat shortest path is found at an iteration, penalties are applied to the links even though this path is rejected. Fig 3.2 from [1] shows the number of rejected paths generated when attempting to find 20 distinct paths for various penalty percentage.

It can be seen that with higher penalty factor results in smaller rejected paths since they alter the selection severely than lower penalty factors. For penalty factors above 20%, the number of rejected paths is quiet low. It was seen that with

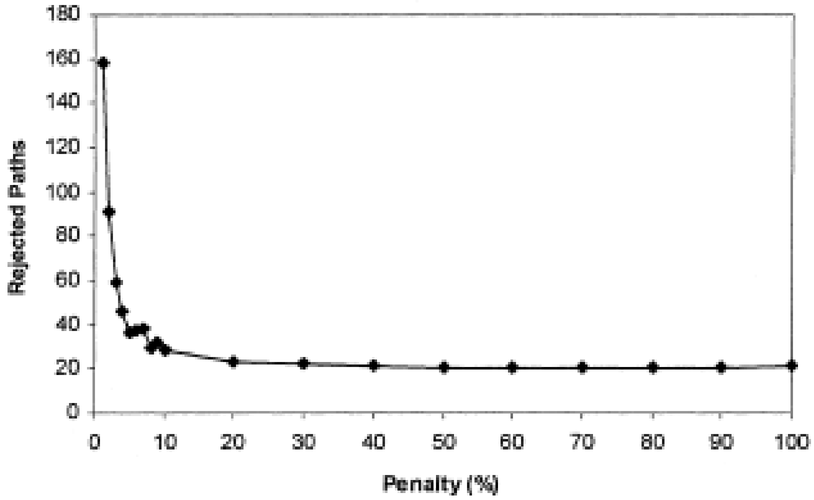

FIGURE 3.2: Number of rejected paths as a function of the penalty factor

an increase in a number of paths generated, there was a gradual increase in the average path length. The rate of increase of average path length is almost constant when the penalty factor is varied between 1% to 10%. However, the average path length increases faster when the penalty factor is increased from 10% to 100%.

We select a penalty factor and then use the p-dispersion on the solution of to find the set of dissimilar paths. By this method, we find the alternate shortest paths for the given O-D pairs.

3.2.1 Heuristic-1

In this heuristic, for a given candidate set we consider n alternate paths through the candidate set with the given distance constraint for each O-D pair as shown below.

$$OD_1 = P_{11}, P_{12}, \ldots\ldots, P_{1l_1}$$

$$OD_2 = P_{21}, P_{22}, \ldots\ldots, P_{2l_2}$$

$$OD_3 = P_{31}, P_{32}, \ldots\ldots, P_{3l_3}$$

$$\vdots$$

$$OD_n = P_{n1}, P_{n2}, \ldots\ldots, P_{nl_n}$$

In the above P_{ij} denotes the path for i^{th} OD pair and j^{th} alternate path. The risk of the path is calculated by summing of risks for each link that is visited.

Then we select the least risk path for each OD pair and now find all the unique nodes visited. Now we select this unique node set as the new candidate set and solve the problem using the greedy heuristic.

For the same example problem in Fig 3.1, we can find the alternate paths from S1-D1 and S2-D2. For the given distance constraint of , we will have the alternate path P_{11} as S1- C1 -D1 with distance 3 and risk as 3 units and path P_{12} as S1-C2-D2 with distance as 3.5 and risk as 1 Units.

Similarly for S2-D2, we will have alternate paths P_{21} -S2-C3-D2 and P_{22}- S3-C2-D2 with distances of 2,4 and risk 4, 1.75 respectively.

By implementing this algorithm, we will choose least risk path, i.e paths, P_{12} and P_{22}. Which gives us a reduced candidate set C3. By this algorithm we can have a reduced candidate set and implementation of greedy heuristics can be quick and can give different results.

3.2.2 Heuristic-2

In this heuristic, we try to find the alternate least risk paths through the candidate set with the given constraint. Then we try and find the minimum number of nodes that span the entire graph.

To solve the problem, we must first find a method to reduce the candidate set.

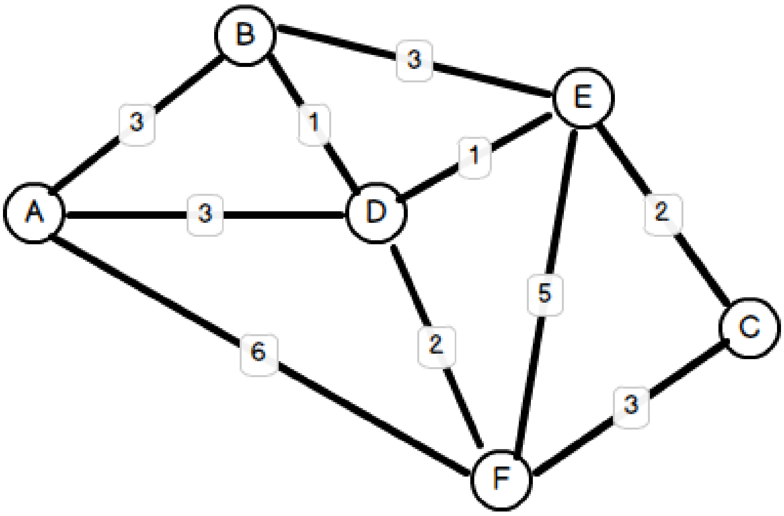

FIGURE 3.3: distance weighted graph

To illustrate the following problem lets take the example in the figure 3.3 where the numbers indicate the distance between the nodesin the graph. Let's assume that the nodes A and B are the origin and nodes C and F are the destinations respectively, forming two OD pairs. If we take the shortest path from origins to destinations ({A-D-E-C} and {B-D-F}) we have 6 different nodes{A,B,D,E,C,F}. But if we consider an alternate route for the OD pair AC i.e A-D-F-C , then we have 5 unique nodes from which we can have routes to all O-D pairs. By selecting an alternate shortest path we have reduced the size of the candidate set.

This problem can be expressed as

1. To find the alternate paths for all the OD pairs and
2. Find the combination of path for OD pairs such that we have the minimum number of the candidate set.

We can find the minimum no. of common nodes from all origin to destinations by

1. Iterating to all the combinations of the alternate paths for all O-D pairs which is a brute force method
2. Using an iterative heuristic

Iterating through all combinations of alternate paths to find a candidate set becomes a computationally challenging problem. Imagine a 10 OD pair network and we created 9 alternate paths from Section 2.1, then it will take 9^{10} iterations to find the initial candidate set. The number of iterations will grow exponentially as the number of OD pairs or the number of alternate paths selected increase. Hence, we propose an iteration heuristic to solve this problem.

Imagine all alternate risk paths for origin destination pairs through the candidate set be as shown below-

$$OD_1 = P_{11}, P_{12}, \ldots\ldots, P_{1l_1}$$

$$OD_2 = P_{21}, P_{22}, \ldots\ldots, P_{2l_2}$$

$$OD_3 = P_{31}, P_{32}, \ldots\ldots, P_{3l_3}$$

$$\vdots$$

$$OD_n = P_{n1}, P_{n2}, \ldots\ldots, P_{nl_n}$$

In the above P_{ij} denotes the path for i^{th} OD pair and j^{th} alternate path. The risk of the path is calculated by summing of risks for each link that is visited.

To reduce the number of inspection points we use the below heuristic. In this heuristic, instead of considering all the combinations of paths to reduce the

After reducing the number of the candidate set, we then apply the greedy algorithm to the new candidate set and compare the results.

For the same example problem in Fig 3.1, we can find the alternate paths from S1-D1 and S2-D2. For the given distance constraint of , we will have the alternate path P_{11} as S1-C2-D2 with distance as 3.5 and risk as 1 Units and path P_{12} as S1-C1 -D1 with distance 3 and risk as 3 units and .

Similarly for S2-D2, we will have alternate paths P_{21} -S3-C2-D2 and P_{22}- S2-C3-D2 with distances of 4,2 and risk 1.75, 4 respectively.

By implementing this algorithm, we will choose least risk path, i.e paths, P_{11} and P_{21}. Which gives us a reduced candidate set C3. By this algorithm we can have a

Result: To reduce the candidate set
initialization;
unique points ← length of candidate set;
improvement number ← unique points;
dict ← A dictionary with OD pairs as key and path numbers as values (Path numbers are 0 initially);
iteration number ← 0;
while *iteration number* $\leq$ *5* **do**
    for *i in OD pair* **do**
        for *j in paths* **do**
            Compare i^{th} OD pairs j^{th} path with remaining OD pairs paths from dict;
            calculated points ← all unique nodes from all the paths above;
            if *unique points* $\geq$ *calculated points* **then**
                update dict OD pairs key value as j;
                unique points ← calculated points;
            end
        end
    end
    if *improvement number* $\leq$ *unique points* **then**
        iteration number ← 0
    else
        iteration number ← iteration number +1;
    end
end

Algorithm 2: Iteration heuristic to reduce the candidate set

reduced candidate set and implementation of greedy heuristics can be quick and can give different results.

Chapter 4

Case Study

In this chapter, we discuss how the previously discussed method affects the total risk with distance constraint and the overall distance traveled with the subject to a number of inspection stations. Each of the above methods discussed in the previous chapter provide a valid solution, However, the different granularity of their decision variables, i.e, arcs, paths and candidate set, makes each of them either more or less adaptive.

While we have performed the experiment, there are few conjunctures concerning the impact of the solution, that is

1. for a fixed number of m inspection stations, the same level of risk mitigation can be achieved by a smaller number of inspection stations by way of information guided selection.

Risk		Distance	
Upper Bound	Lower Bound	Upper Bound	Lower Bound
167179	138548	776977	602852

Table 4.1: Upper and lower bounds for Risk and cost

2. Conversely, for the same size of the candidate set, an information guided policy may reach, on the average, a lower threshold than a purely random selection policy.

3. The solution is dependent on the way the candidate set is chosen.

4.1 Solution Methodology

For testing the above algorithms, we have used the data set used in [31] and [19]. The test data is a graph with 105 nodes and 134 arcs, being an abstraction of the road network of Ravenna (Italy), as well as a cost(or distance for this particular instance) and risk function, not collinear, defined on the arcs. It has 35 vehicles with their origin-destination pairs. On this network, we generated a candidate set by finding the least risk path for each vehicle and collected the set of unique nodes as the candidate set.

On this network, the least risk path is considered the lower bound for the risk and the upper bound for the distance. And the shortest distance path is considered as the lower bound for distance and upper bound for the risk. The values of upper and lower bounds are presented in table 4.1.

The numerical experiment was coded in Python. All the testing was done on i5 processor with 8GB ram and 2.20GHz Processor. For the heuristic-1, 15 alternate paths were generated with 0.15 as penalty factor and for heuristic-2 5 alternate paths were generated with penalty factor as 0.15. The testing was done separately for each distance constraint and on average the greedy algorithm took 589 seconds more than heuristic-1 and heuristic-2. The greedy heuristic run time for each distance constraint was 1hr. In the next section we discuss more about the results.

4.2 Results

In table 4.2 we see how the number of visited nodes, distance traveled and the overall risk varies with respect to the distance constraint. We can see from the graphs in 4.1 4.2 4.3 on how the distance constraint impact the number of nodes visited, distance traveled and the risk when we do not use any heuristic and consider all the candidate set as inspection stations.

Distance Constraint	No. of Inspection Stations	Risk	Distance Travelled
6184	32	149887	685217
7000	31	151545	681839
8000	23	151142	677661
9000	20	161701	616078
10000	18	161701	616078
11000	18	164981	615017
12000	18	167179	602852
13000	12	167179	602852

Table 4.2: No of nodes visited in candidate set when the carriers take the shortest path with distance constraint

It is evident from the graphs in 4.1, as the distance constraint increases the government needs to install less number of check points and if they want to control the risk flow to a higher degree they can reduce the distant constraint and the trade

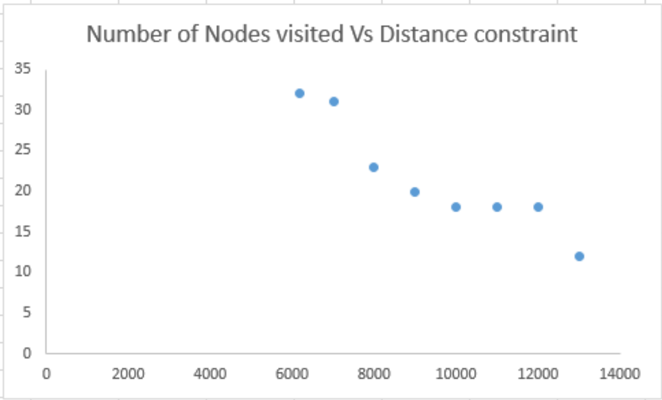

FIGURE 4.1: Number of nodes visited vs Distance constraint

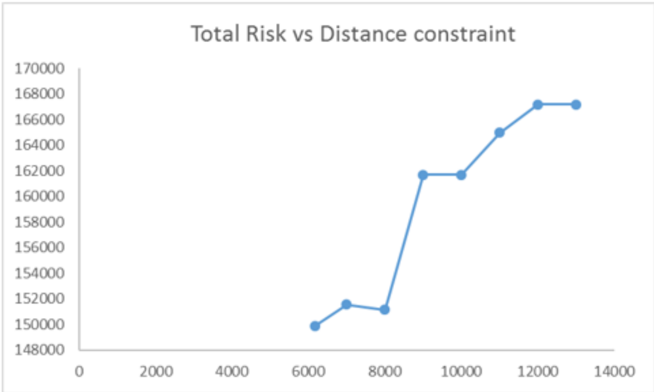

FIGURE 4.2: Total Risk vs Distance constraint

off between the risk and distance constraint is given in 4.2. Similarly, carriers need to take longer routes when there is a greater restriction on distance constraint.

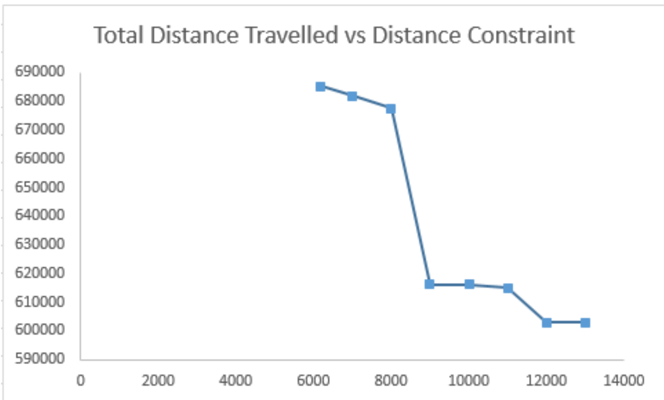

FIGURE 4.3: Total Distance tavelled by carriers vs Distance constraint

Even though we have the exact solution, it is computationally difficult to implement the method for a large graph. In this section we have implemented the greedy heuristic and heuristics from exact solution methods and compared the solutions with different distance constraints and studied the effect of risk, distance and no. of nodes visited. While implementing these heuristics, the minimum distance constraint is the maximum link distance, without which there is no path possible. For this network the minimum distance without which there is no feasible path is 6184 units. Various results of Distance constraint with respect to the total risk of the graph and Distance traveled are posted.

4.2.1 Distance Constraint = 6184

The effect of risk with different heuristics vs distance when every carrier must visit an inspection station after every 6184 units is shown in the following tables. It can be seen that the risk varies with maximum value 149887 to minimum value 142513 in greedy heuristic, maximum value 149783 to minimum value 141752 in heuristic-1 and maximum value 154889 to minimum value 143997 in heuristic-2. It can be seen that with the process of reducing the risk, the distance keeps on increasing. The risk and distance remain same when we take 35 nodes or 16 nodes in greedy, 28 to 16 in heuristic-1 and 23-15 in heuristic-2. Hence it would be a better choice to take the least number of nodes as there is the same cost associated with setting up each inspection station.

Distance constraint - 6184		
Nodes	Risk	Distance
35	149887	685277
36	144576	689511
35-16	142783	689940
15	142513	697540
14	142956	697733
13	143948	701999

TABLE 4.3: Greedy results with Distance Constraint -6184

Distance Constraint - 6184		
Nodes	Risk	Distance
32	149783	685697
31	144472	689911
29	142679	690340
28	142204	692637
28-16	141752	693699
15	141948	693871
14	142700	698966
13	143692	703233

TABLE 4.4: Heuristic-1 results with Distance Constraint -6184

Nodes	Risk	Distance
25	149308	687994
23-15	143997	692208
14	144986	701323
13	145978	705590
12	154889	759752

TABLE 4.5: Heuristic-2 results with Distance Constraint -6184

4.2.2 Distance Constraint = 7000

The effect of risk with different heuristics vs distance when every carrier must visit an inspection station after every 7000 units is shown in the following tables. It can be seen that the risk varies with maximum value 151545 to minimum value 145619.59 in greedy heuristic, maximum value 149153 to minimum value 145269 in heuristic-1 and maximum value 152996 to minimum value 149308 in heuristic-2. It can be seen that with the process of reducing the risk, the distance keeps on increasing. The risk and distance remain same when we take any node in between 29-16 nodes in greedy, 30-14 in heuristic-1 and 23-13 in heuristic-2. Hence it would be a better choice to take the least number of nodes as there is the same cost associated with setting up each inspection station.

Distance constraint - 7000		
Nodes	Risk	Distance
31	151545	681839
30	147958	682697
30	146300	686155
29-16	145721	688852
16-14	145619	689390
13	145873	689922
12	146214	692354

Table 4.6: Greedy results with Distance Constraint -7000

Distance Constraint - 7000		
Nodes	Risk	Distance
31	147958	682697
31	146300	686155
30	145721	688852
30-14	145269	689848
13	145465	690086
12	145958	693588
11	149153	713297

Table 4.7: Heuristic-1 results with Distance Constraint -7000

Nodes	Risk	Distance
23- 13	149308	687994
13	149460	689064
12	149801	691496
11	152996	711205

Table 4.8: Heuristic-2 results with Distance Constraint -7000

4.2.3 Distance Constraint = 8000

The effect of risk with different heuristics vs distance when every carrier must visit an inspection station after every 8000 units is shown in the following tables. It can be seen that the risk varies with maximum value 151545 to minimum value 145721 in greedy heuristic, maximum value 151142 to minimum value 145269 in heuristic-1 and maximum value 149308 to minimum value 145721 in heuristic-2. It can be seen that with the process of reducing the risk, the distance keeps on increasing. The risk and distance remain same when we take any node in between 23-12 nodes in greedy, 22-14 in heuristic-1 and 19-11 in heuristic-2. Hence it would be a better choice to take the least number of nodes as there is the same cost associated with setting up each inspection station.

Distance constraint - 8000		
Nodes	Risk	Distance
23	151142	677661
23	147555	678519
24	146976	681217
23-12	145721	688852
11	145881	692908
10	146222	695339

Table 4.9: Greedy results with Distance Constraint -8000

Distance Constraint - 8000		
Nodes	Risk	Distance
22	151142	677661
22	147555	678519
22-14	145721	688852
14-13	145269	689848
13	145462	692215
12	145610	692518
10	145806	692518
9	146042	696537

Table 4.10: Heuristic-1 results with Distance Constraint -8000

Nodes	Risk	Distance
18	149308	687994
19-11	145721	688852

Table 4.11: Heuristic-2 results with Distance Constraint -8000

4.2.4 Distance Constraint = 9000

The effect of risk with different heuristics vs distance when every carrier must visit an inspection station after every 9000 units is shown in the following tables. It can be seen that the risk varies with maximum value 161701 to minimum value 143545 in greedy heuristic, maximum value 161701 to minimum value 141752 in heuristic-1 and maximum value 161525 to minimum value 145269 in heuristic-2. It can be seen that with the process of reducing the risk, the distance keeps on increasing. The risk and distance remain same when we take any node in between 17-11 nodes in greedy, 14-11 in heuristic-1 and 15-9 in heuristic-2. Hence it would be a better choice to take the least number of nodes as there is the same cost associated with setting up each inspection station.

Distance constraint - 9000		
Nodes	Risk	Distance
21	161701	616078
21	151142	6776661
20-19	145832	681875
18-17	144576	689511
17-11	143545	693204
10	143664	695214
9	143978	697462
8	144470	700963
7	15028	713128

Table 4.12: Greedy results with Distance Constraint -9000

4.2.5 Distance Constraint = 10000

The effect of risk with different heuristics vs distance when every carrier must visit an inspection station after every 10000 units is shown in the following tables. It

Distance Constraint - 9000		
Nodes	Risk	Distance
24	161701	616078
23	151142	677661
22-20	150563	680358
19-18	145253	684572
17-16	143459	685001
16-14	142204	692637
14-11	141752	693633
11	141761	695644
10	141957	695882
9	142252	696011
8	142694	705445

TABLE 4.13: Heuristic-1 results with Distance Constraint -9000

Nodes	Risk	Distance
17	161525	622953
16	150966	684536
17	149308	687994
15	148856	688990
15-9	145269	689848
9	145387	691858
8	145701	694106

TABLE 4.14: Heuristic-2 results with Distance Constraint -9000

can be seen that the risk varies with maximum value 161701 to minimum value 145669 in greedy heuristic, maximum value 161122 to minimum value 146780 in heuristic-1 and maximum value 161597 to minimum value 144895 in heuristic-2. It can be seen that with the process of reducing the risk, the distance keeps on increasing. The risk and distance remain same when we take any node in between 18-12 nodes in greedy, 14-10 in heuristic-1 and 14-11 in heuristic-2. Hence it would be a better choice to take the least number of nodes as there is the same cost associated with setting up each inspection station.

Distance constraint - 10000		
Nodes	Risk	Distance
20	161701	616078
19	157650	652132
18	151142	677661
18-12	147439	680396
12-11	147337	680933
11	147233	681333
11-9	146758	683630
8	146780	684444
7	145669	688297
6	149751	715383

Table 4.15: Greedy results with Distance Constraint -10000

Distance Constraint - 10000		
Nodes	Risk	Distance
18	161122	618776
16-15	150563	680358
14-10	146860	683630
10-8	146780	683630
7	146780	684448
6	145669	688297
5	149751	715383

Table 4.16: Heuristic-1 results with Distance Constraint -10000

Distance Constraint - 10000		
Nodes	Risk	Distance
19	161597	616478
18	157545	652532
17	151038	678061
17	150563	680358
16-15	150307	691592
15	146626	685145
14-11	144997	685806
10 7	144895	686343
6	145413	689531
5	149495	716617

Table 4.17: Heuristic-2 results with Distance Constraint -10000

4.2.6 Distance Constraint = 11000

The effect of risk with different heuristics vs distance when every carrier must visit an inspection station after every 11000 units is shown in the following tables. It can be seen that the risk varies with maximum value 164981 to minimum value 148275 in greedy heuristic, maximum value 164981 to minimum value 148580 in heuristic-1 and maximum value 164981 to minimum value 159069 in heuristic-2. It can be seen that with the process of reducing the risk, the distance keeps on increasing. The risk and distance remain same when we take any node in between 13-10 nodes in greedy, 20-7 in heuristic-1 and 17-7 in heuristic-2. Hence it would be a better choice to take the least number of nodes as there is the same cost associated with setting up each inspection station.

Distance constraint - 11000		
Nodes	Risk	Distance
18	164981	615017
19-13	161701	616078
13	160904	618119
13-10	160089	618450
10	159985	618849
10-8	159510	621147
7	159628	623157
6	157222	629643
5	148275	688854
4	148580	690994

TABLE 4.18: Greedy results with Distance Constraint -11000

4.2.7 Distance Constraint = 12000

The effect of risk with different heuristics vs distance when every carrier must visit an inspection station after every 12000 units is shown in the following tables. It

Distance Constraint - 11000		
Nodes	Risk	Distance
17	164981	615017
17-14	161701	616078
16	160904	616078
13	160904	677661
13-11	151142	680358
10-7	150563	680358
6	150682	682368
5	150986	684508
4	148580	690994

Table 4.19: Heuristic-1 results with Distance Constraint -11000

Nodes	Risk	Distance
17	164981	615017
18	161122	618776
17-7	160866	620009
6	161171	622149
5	161475	624289
4	159069	630775
2	162559	639795

Table 4.20: Heuristic-2 results with Distance Constraint -11000

can be seen that the risk varies with maximum value 167179 to minimum value 158734 in greedy heuristic, maximum value 167179 to minimum value 158734 in heuristic-1 and maximum value 167179 to minimum value 158734 in heuristic-2. It can be seen that with the process of reducing the risk, the distance keeps on increasing. The risk and distance remain same when we take any node in between 17-7 nodes in greedy, 14-9 in heuristic-1 and 16-5 in heuristic-2. Hence it would be a better choice to take the least number of nodes as there is the same cost associated with setting up each inspection station.

Distance constraint - 12000		
Nodes	Risk	Distance
18	167179	602852
18	164555	603701
19	162345	614907
17-7	161701	616078
8-7	161597	616478
7-5	161122	618776
7	161131	620787
5	158734	629284
4	159147	631423
3	159443	631551
2	162815	638562

TABLE 4.21: Greedy results with Distance Constraint -12000

Distance Constraint - 12000		
Nodes	Risk	Distance
14	167191	603811
14	163911	604872
14-9	161597	616478
8-6	161122	618776
5	158734	629284
4	159147	631423
3	159443	631551
2	162815	638562

TABLE 4.22: Heuristic-1 results with Distance Constraint -12000

Nodes	Risk	Distance
16	167179	602852
16	164555	603701
16	161597	616478
16-5	161122	618776
6	161140	322798
5	158734	629284
4	159147	631423
3	159443	631551
2	162815	638562

TABLE 4.23: Heuristic-2 results with Distance Constraint -12000

4.2.8 Distance Constraint = 13000

The effect of risk with different heuristics vs distance when every carrier must visit an inspection station after every 13000 units is shown in the following tables. It can be seen that the risk varies with maximum value 167179 to minimum value 158734 in greedy heuristic, maximum value 167179 to minimum value 158114 in heuristic-1 and maximum value 167179 to minimum value 158114 in heuristic-2. It can be seen that with the process of reducing the risk, the distance keeps on increasing. The risk and distance remain same when we take any node in between 8-6 nodes in greedy, 8-5 in heuristic-1 and 8-4 in heuristic-2. Hence it would be a better choice to take the least number of nodes as there is the same cost associated with setting up each inspection station.

Distance constraint - 13000		
Nodes	Risk	Distance
12	167179	602852
12-9	164555	603701
9	162345	614907
8	161701	616078
8-6	161597	616478
5	161122	618776
5	161131	620787
4	158734	629284
4	159147	631423
3	159443	631551
2	162815	638562

Table 4.24: Greedy results with Distance Constraint -13000

4.2.9 Results Summary

We can get the minimum risk for each distance constraint as seen in tables. It is evident that as the distance increases, the minimum number of nodes to place

Distance Constraint - 13000		
Nodes	Risk	Distance
12	167179	602852
12-9	163911	604872
9-8	160324	605730
8-5	158114	616937
5	158123	618948
4	158320	622321
3	158911	622578
2	165740	652964

TABLE 4.25: Heuristic-1 results with Distance Constraint -13000

Nodes	Risk	Distance
11	167179	602852
11-8	161701	616078
8-4	158114	616937
3	159029	624588

TABLE 4.26: Heuristic-2 results with Distance Constraint -13000

inspection stations for minimum risk decreases as can be seen from the table. If there is a significant cost incurred by the government in setting up inspection stations, it is better to place a minimum number of inspection stations by taking a higher degree of distance constraint. But if the government objective is to strictly minimize the risk for that particular part, then they can implement a tighter distance constraint and reduce the risk significantly.

The values of least risk and the number of inspections stations needed to set up for different distance constraint is given in tables

With heuristic, we get the minimum risk for each distance constraint as seen in tables. It is observed with distance constraint 6184 and 9000, we can achieve the minimum risk by using this method. But given this scenario, it might be more economical to place the inspection stations with distance constraint of 9000 units as less number of inspection points are placed and carriers have bit more freedom in choosing the route.

Distance Constraint	No. of Inspection Stations	Risk	Distance Travelled
6184	15	142513	697540
7000	14	145619	689390
8000	12	145721	688852
9000	11	143545	693204
10000	7	145669	688297
11000	5	148275	688854
12000	5	158734	629284
13000	4	158734	629284

Table 4.27: No. of inspection stations required with respective minimum risk and distance travelled for greedy heuristic

Distance Constraint	No. of Inspection Stations	Risk	Distance Travelled
6184	16	141752	693633
7000	14	145269	689848
8000	13	145269	689848
9000	11	141732	693699
10000	6	145669	688297
11000	4	148580	690994
12000	5	158734	629284
13000	5	158114	616937

Table 4.28: No. of inspection stations required with respective minimum risk and distance travelled for heuristic-1

Distance Constraint	No. of inspections Stations	Risk	Distance
6184	15	143997	692208
7000	13	149308	687994
8000	11	145721	688852
9000	9	145269	689848
10000	7	144895	686343
11000	4	159069	630775
12000	5	158734	629284
13000	4	158114	616937

Table 4.29: No. of inspection stations required with respective minimum risk and distance travelled for heuristic-2

Chapter 5

Summary and Future Scope

5.1 Summary

In this thesis we proposed an alternative method to reduce the risk of the network for hazmat shipment by strategic placement of inspection stations. In this we had observed that by the placement of inspection stations, the risk can be significantly reduced without increasing the distance by a huge margin. The government can give carriers freedom in choosing the paths while reducing the risk of the network.

In the following table 5.1, each bold term gives the minimum risk for that distance constraint and the values in the brackets indicate the number of inspections stations required for achieving that risk.

From the table we can see that the minimum risk is generally achieved at 6184 and 9000 distance constraint. It would be a better choice for both government to have a distance constraint of 9000 Units so that equal amount of risk reduction

Distance Constraint	Greedy	Heuristic-1	Heuristic-2
6184	142513 (15)	**141752(16)**	143997(15)
7000	145619(14)	**145269(14)**	149308(13)
8000	145721(12)	**145269(13)**	145721(11)
9000	143545(11)	**141732(11)**	145269(9)
10000	145669(7)	145669(6)	**144895(7)**
11000	**148275(5)**	148580(4)	159069(4)
12000	**158734(5)**	**158734(5)**	**158734(5)**
13000	158734(4)	158114(5)	**158114(4)**

Table 5.1: Minimum risk for all heuristics

can be obtained with minimal number of inspection stations. The higher distance constraint also gives the carriers some freedom in choosing the path.

In general it can be seen that heuristic-1 gives minimum risk paths. This heuristic can be used when minimizing the risk is the main objective and the cost of setting up the inspection station is minimal. But if the set up cost for setting up inspection station is very high and the major objective is to minimize the number of inspection stations, heuristic-2 would be a better approach.

5.2 Future scope

In this section of thesis, we discuss the various future research scope for this problem and how it can be improvised.

5.2.1 Location of Candidate set

In our model, we have assumed that the candidate set for the network to be already provided. But in general, we can also create a model to generate optimal candidate sets which can in turn be used to decrease the risk of the network. As we have seen that different candidate sets produce different results, it is very important to have a proper choice of candidate set.

5.2.2 Integration of previous hazmat network control methods and Inspection stations

The future scope of this problem can be extended to using the placement of inspection stations along with the road band/curfews and with toll setting. The combinatorial problem of the two methods can have a serious impact on reducing the overall risk of the network. This method will also help to reduce the overall risk to minimum amount without making the carrieres take the longest route.

5.2.3 Use of Genetic algorithms and other search techniques

The proposed solution methodology uses greedy heuristic to reduce the risk. Even in the other two heuristics, we use different combinations of paths to reduce the candidate set and then apply the greedy heuristic. It might be possible in future considerations to apply some meta heuristic techniques to improve the solution and get the global optima.

5.2.4 Working of inspections stations with time factor

We know that the traffic conditions vary with time. We can take the time factor and use that to open certain inspection station at certain time and try to reduce the risk with varying time.

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