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EMERGENCY RESPONSE FACILITIES ALLOCATION IN A TRANSPORTATION NETWORK INVOLVING HAZARDOUS MATERIALS (HAZMAT)

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ABSTRACT

Enormous volumes of hazardous materials are moving every day all over the world. Some are distributed to people's homes, such as petrol, while others are transported only between major industries and factories. Nonetheless, their presence within global transport networks is intense, and in the meantime, an accident involving any of them can be serious or even deadly. Their management, thus, is crucial. This diploma thesis seeks to formulate and solve a bi-objective mixed integer problem that belongs in the field of location-allocation problems; it also aims to provide the locations in which an operator should place emergency response stations that could deal with an incident involving some hazardous material in a given road segment. The optimal allocation of Emergency Response Facilities is vital; it can prevent accidents before their consequences become dangerous and catastrophic. This model raises three questions; where Emergency Response Facilities shall be located, with which emergency vehicles each of them must be equipped, and to what extent this allocation covers the potential demand, expressed in terms of non-coverage cost. The appropriate parameters, decision variables, objective functions, and constraints are defined. The aforementioned elements formulate an Integer Programming model, and a case study of this problem is, later on, solved in CPLEX Optimization Studio. Two well-known and widely used methods of bi-objective optimization, namely Weighted Sum Method and Epsilon-Constraint Method, are the computational tools of this study, and a Pareto front of non-dominated optimal solutions, is produced by each of these methods. Later on, the model's behavior on alterations of one of its parameters is investigated by examining various scenarios. In the scenarios discussed in the Sensitivity analysis chapter, we decrease or increase a facility's capacity and coverage ratio, alter lower acceptable demand coverage, and examine regions with uneven population distribution. Results for all different methods and scenarios are discussed, and ideas for further future research in this extremely interesting inter-disciplinary field are proposed.

Keywords: bi-objective, location-allocation, hazardous materials, Emergency Response Stations, Mixed Integer Programming, CPLEX, Pareto front, Weighted Sum Method, Epsilon-Constraint Method, sensitivity analysis



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Author,

Alexandros Liazos



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1 Introduction

In a more and more globalized world where we live, transportation of goods and its management has become complex and multi-factorial. Decision-makers can vary from private companies to sovereign nations, and challenges related to cutting down costs, keeping up with demands, optimizing carrying vehicles' capacities, and being on time, arise. The field of supply chain management, thus, is consistently in need of solving complex problems that affect the quality of the services provided. Supply chain management, above all, aims to mediate, in the best way possible, between supply and demand, within and between companies.

The field of hazardous materials management is considered a sub-sector of Supply Chain Management and plays a crucial role in ensuring people's safety in urban environments. People should always feel safe when a potentially dangerous substance is transported near where they live, adding this business goal to the ones of the Supply Chain Management, in general.

Similarly, Emergency Response Management deals with people's lives that are potentially threatened by a natural disaster, an accident, or an emergent health problem such as a heart attack. Time is money for this field of business, but on the other hand, resources are not infinite.

This thesis proposes a bi-objective model dealing with possible emergencies within the Hazardous Materials (Supply Chain) Management sector. It is organized into six chapters, including this of the introduction. In the second chapter, some background knowledge, necessary for the reader to better understand the modeling concept, will be provided. Terms such as location-allocation, optimization, multi-objective modeling, weighted sum, and epsilon-constraint method, will be briefly presented, along with some terminology relevant to hazardous materials and emergency vehicles. Later, in chapter three, a literature review will be presented. There one could find some of the incentives behind this thesis and what scientific papers, books, surveys, and studies have been published throughout the years in the relevant fields of location-allocation modeling and hazardous materials emergency management. In the fourth chapter of this study, the mathematical model we propose will be explicitly formulated, while in chapter five, one could see its implementation on a simple case study, as well as the results we reached by using two different heuristics appropriate for bi-objective programming. Sensitivity analysis will also be conducted in this part of the thesis, showing how the model results differentiate when some of its parameters change. Finally, in the sixth chapter, some conclusions that emerge from the previous chapters are provided, along with suggestions for future research.

2 Background knowledge

2.1 Hazardous materials: means of transport, classes, and correlation with

accidents

As hazardous materials or dangerous goods, one could define "objects or materials that, by nature, state, and characteristics, can be threatening to the public order and safety, and more specifically, to the life and health of people, animals and objects, throughout their transport procedure" (PHMSA, 2016). Hazardous materials are often abbreviated as HAZ-MAT (hazmat), and they will be referred to this way from now on in this thesis.

All means of transport have been utilized throughout the years to carry hazardous materials; trucks, railcars, container ships, aircraft, and pipelines, if we consider the latter as a means of transport in terms of logistics, can transport materials potentially harmful to the environment and human life. According to Census Bureau 2007, 55% of daily tons shipped in the US for 1997-98 were transported by trucks, followed by 28% that accounts for transportation via pipelines. In terms of ton-miles, though, truck and rail hazmat transport share approximately 30% of the total ton-miles shipped, with truck shipments having a slim lead of 33% versus 29% of the rail supply chain (US DOT & US DOC, 2012).

The most common origins of large shipments of hazardous materials include chemical manufacturers, gas distributors, and oil refineries, while smaller quantities of hazmat can originate from smaller industries and manufacturers, home heating fuel distributors, or hospitals (TRB, 2005). The route of a hazardous material usually involves many intermediate stops towards its destination, namely transfer points. Destinations of large shipments include factories and chemical plants, while gas stations, hospitals, some specialized retail outlets, service stations, convenience stores, and waste disposal sites can also be potential terminals of a hazmat route (TRB, 2005). Data from more than 5200 incidents recorded in Major Hazard Incident Data Service (MHIDAS), mainly from the United Kingdom and the United States, proved that about 39% of the total accidents involving hazardous materials seem to happen during their route from origin to destination, followed by 24.5% of incidents happening whilst cargo is stockpiled at the process plant (Vilchez et al., 1995).

In a more detailed manner, hazardous materials can be classified into nine classes, based on their properties, and mainly the physical, chemical, and nuclear ones:

- 1. Explosives, pyrotechnics: divided further into 6 divisions based on each substance's sensitivity in terms of fire and explosion
- 2. Gases: divided further into flammable, toxic, non-flammable, and non-toxic ones

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- 3. Flammable and combustible liquids
- 4. Flammable, combustible, and dangerous if getting wet, solids
- 5. Oxidizer and organic peroxides
- 6. Poisonous (toxic) and infectious substances
- 7. Radioactive materials
- 8. Corrosive (acidic or basic) materials
- 9. Miscellaneous, that do not belong to the above classes

(PHMSA, 2016)

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Out of the aforementioned hazardous materials categories, classes 2, 3, and 8 are the most shipped ones in terms of total tons transported (US DOT & US DOC, 2012), while substances belonging in classes 3, 6, and 8 are the most prevalent ones in dangerous accidental events, being involved in about 88% of the total hazmat transport accidents, according to data retrieved by the US Hazardous Material Information System (HMIS) and analyzed by Mullai and Larsson (2008). Class 3 substances (flammable and combustive liquids) were present at 43% of total accidents between 1993 and 2004, and they were closely followed by corrosive materials which corresponded to another 38% (Mullai and Larsson, 2008). Deaths and serious injuries are the most "expensive" factors in terms of risk-associated costs. Flammable liquids belonging to Class 3, seem to be contributing the most to these fatalities (PHMSA, 2004). Based on these statistics, Chakrabarti and Parikh (2012), in a relevant study, selected LPG (a flammable gas), petrol (a flammable liquid), and ammonia (a toxic gas) as representative hazardous materials and compared their risks.

2.2 Emergency Response Vehicles (ERVs)

When a disastrous event happens, time is a crucial factor, and wasted time can lead to major human loss. Emergency or relief logistics operators are responsible for planning, controlling, and managing the flows in a network after an event like that (Sheu, 2007). These logistics deal with estimation of commodities, equipment, or vehicles needed to treat injured, endangered, or even already dead people, as well as with transporting and distributing these commodities optimally, i.e., within a minimum time, to the proper people, via an optimal method (Ozdamar et al., 2004).

In an urban environment concept, the fleet of Emergency Response Services comprises ambulances, police cars, and fire trucks (Haghani & Yang, 2007). Nevertheless, each of those categories of vehicles falls under a different public sector department, namely the National Healthcare System, the Police Department, and the Fire Department, respectively. Fire trucks are the first that must reach a potentially deadly incident. Thus, the fire department vehicle sub-types will be examined in this thesis.

Each country's fire department features a fleet of specialized trucks that can intervene in a fire. Considering Greece, the Hellenic Fire Service (HFS) falls under the Ministry for Citizen Protection and is responsible for

- Protecting the lives and the properties of citizens and the State and the natural environment and forests from technological or natural disasters
- Creating and implementing operational plans to deal with floods and fires and providing support and assistance to people in threat
- Conducting the fire and rescue operations of the country's Civil Protection.

("Αποστολή – Αρμοδιότητες – Πυροσβεστικό Σώμα Ελλάδος")

The firefighting fleet consists of approximately 2500 trucks, 44 specialized aircraft, 20 helicopters, and 10 firefighting vessels. More specifically, the ground equipment includes 1500 fire engines and tenders, 800 auxiliary cars, and 200 special vehicles ("Hellenic Fire Service – Wikipedia").

Fire engines or pumpers are the most crucial vehicles in case of a fire scene. They are comprised of water tanks, water pumps, and long hoses. They carry the quantities of water that are needed to successfully intervene in an accident that includes fire ("9 Different Types of Fire Trucks"). Elaborating more on these vehicles, we refer to some indicative trucks:

VEHICLE	SUB-	DESCRIPTION	РНОТО
CATEGORY			
Type A fire engine		Fire engine with a water tank capacity of 500 to 1500 liters of water. Also features a foam tank.	
Type B fire engine		Fire engine with a water tank capacity of 2500 liters of water. Also features a foam tank.	

Type C fire engine	Fire engine with a water tank capacity of 5000 liters of water. Also features a foam tank.	
Type D fire engine	Fire engine with a water tank capacity of 10000 liters of water. Also features a foam tank.	

 Table 1: Indicative fire engines



Auxiliary vehicles, also known as firetrucks, transport the firefighters from the fire station facility to the place where the fire takes place and carry the necessary equipment. A typical auxiliary vehicle is equipped with a long ladder, first aid kit, and breathing apparatus such as a snorkel. Firetrucks, in other words, are responsible for the rescue of endangered people ("9 Different Types of Fire Trucks"). Some of these vehicles include:

VEHICLE	SUB-	DESCRIPTION	РНОТО
CATEGORY			
Arm firetruck		Auxiliary vehicles with equipped with an arm	
Ladder firetruck		Auxiliary vehicles armored with a ladder	



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Crane firetruck	Auxiliary trucks	armored	

Table 2: Indicative firetrucks

("Οχήματα – Αρχείο φωτογραφιών – Πυροσβεστικό Σώμα Ελλάδος")

The rest vehicles of the Fire Service Ground Fleet belong in the special vehicles category. The most well-known of them are the following:

VEHICLE	SUB-	DESCRIPTION	РНОТО
CATEGORY			
Ambulance		Vehicle specialized in providing first aid services to people that have undergone an injury or a scald	
Specialized vehicle		Truck utilized for collecting and separating chemical and toxic substances	

 Table 3: Indicative special vehicles of the fire department

("Οχήματα – Αρχείο φωτογραφιών – Πυροσβεστικό Σώμα Ελλάδος")

The speed of an ERV during an emergency does not always comply with the road rules. The actual conditions of a road network such as its density, combined with the scarcity of stations, can lead to limited demand coverage in many cases (Jezek et al., 2011). Fire trucks are bulky and, therefore, cannot reach high velocities even when running using a sirens system, but on average, assuming they are traveling on an asphalt road in good condition, they can reach an average speed of 60 km/h (Akay et al., 2012).

2.3 Multi-objective optimization

Let the following optimization problem:

$$\min F(x) = \min(f_1(x), f_2(x), \dots, f_k(x)) (2.1)$$

Subject to:

 $x \in \Omega$ (2.2)

, where Ω is the feasible solutions space, and x is one of them. In fact, x is a vector of decision variables. Each of the f(x) functions evaluates a certain criterion, set by the decision maker. Let $x, y \in \Omega$ be a pair of feasible solutions for the above problem, assuming that there are k=2 criteria of optimization. Then y dominates x ($y \le x$), if $f_k(y) \le f_k(x)$ for every k, and $f_k(y) < f_k(x)$, for at least one value of k. A feasible solution that cannot be dominated by any other is a Pareto (non-dominated) solution. In other words, solutions belonging to the Pareto front, are better than the rest of the solutions of the search space, but they are worse than other solutions in at least one of the objectives (Srinivas & Deb, 1994). The Pareto front is a set of feasible, non-dominated solutions, depicted in the k-dimensional space.



Image 1: an example of a Pareto frontier, where both functions aim to minimize their decision variables (Di Somma, 2016).

Throughout the literature, various methods have been proposed to solve multi-objective optimization problems, and, therefore, find their respective Pareto fronts.

2.3.1 The Weighted Sum Method (WSM)

The simplest method that can solve a multi-objective problem, is the Weighted Sum Method (WSM). It was, at first, introduced by Zadeh (1963) and its basic functionality is to convert k

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objective functions into one, which becomes the object of a single-objective minimization or maximization. The weighted sum method uses, as its name reveals, weights w1, w2,..., wk, to indicate the relative importance of each of the objective functions. These weights are usually chosen such that their sum equals 1 (Di Somma, 2016).

This method can be mathematically described as follows:

$$\min F'(x) = \sum_{k \in K} w_k f_k(x) \ (2.3)$$

Where:

$$\sum_{k \in K} w_k = 1 (2.4)$$
$$w_k > 0, \forall k \in K (2.5)$$

In its more generic formulation, the latter constraint also includes the probability of w being equal to 0, although sometimes the solution extracted by these values of w is weakly Pareto optimal (Marler & Arora, 2010). If the problem is convex, i.e., each of its constraints and objective functions is convex on its own, the minimization (or maximization) of the weighted sum can provide a complete Pareto front. If at least one of them is not convex, WSM cannot spot solutions located at the non-convex parts of the front (Geoffrion, 1968). Nevertheless, this method has been applied in various models containing integer variables. The study of Snyder and Daskin (2005) provides a good example of creating a Pareto front by using the weighted sum method in a bi-objective logistics problem, namely the reliability P-median problem. In this case, some solutions in the non-convex (concave) parts of the efficient Pareto front may fail to be depicted, but nonetheless, the Pareto front is dense, seemingly convex, and provides many solutions. In a bi-objective problem of this type, where none of the objective functions is a priori more important than the other, finding all the Pareto front solutions may prove to add computational time without always adding significantly valuable information for the decision maker.

Normalization

Before using this method, in most cases, a normalization is required due to the different ranges and scales of the objective functions. This happens because a weight's value is relative to the other weights' values, but also relative to the objective function to which it corresponds (Marler & Arora, 2010). If there are k conflicting objective functions, they are normalized by using the following formula:

$$f_{k,norm} = \frac{f_k - f_{k,max}}{f_{k,min} - f_{k,max}}$$
(2.6)

The maximum and the minimum values of each of the k objective functions are calculated using the utopian (z^*) and the nadir point (z^{nad}) of a two-dimensional-Pareto frontier.



Image 2: a Pareto frontier showing the utopian (ideal), and nadir point (Di Somma, 2016).

The aforementioned method can find every solution of a convex Pareto front by appropriately varying the weights. In the case of a bi-objective problem, using a step (let it be δ), both w1 and w2 will be correctly altered in each iteration. If proper weights are selected, the utility function's gradient is parallel to the actual preference (objective) function's gradient; approximating this preference function is extremely important and, thus, one of the main reasons for using the weighted sum method (Marler & Arora, 2010). The Pareto optimal solution for each set of weights is constructed by finding where F(x), the weighted sum function with the lowest value, intersects with the boundary of the feasible criterion space. The F contours that different weights provide are linear and as a result tangent to the Pareto optimal front at the point where the solution is (Marler & Arora, 2010). The above also explains why this method cannot work with concave parts of Pareto fronts.

A more accurate representation of the optimal solutions located within the feasible solutions space can be obtained through the Adaptive Weighted Sum Method (AWSM), which Kim & De Weck (2005) introduced for bi-objective optimization problems. This approach can produce more evenly distributed packs of Pareto non-dominated solutions and explore concave regions of the feasible space by altering weights using exact numerical analysis methods. In a nutshell, this method solves sub-problems, zooming each time to the part of the feasible solutions space that has not, in the current iteration, given an optimal solution to construct the Pareto front.

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2.3.2 The Epsilon-constraint method (ECM)

Another computational method extensively used for years to generate Pareto fronts is the ε (epsilon)-constraint method (ECM). The innovation of ECM is that it optimizes only one of the objective functions of a multi-objective problem, putting the rest of them in the constraints section of the model (Mavrotas, 2009).

Given a multi-objective optimization problem:

$$\min F(x) = \min(f_1(x), f_2(x), \dots, f_k(x)) (2.7)$$

Subject to:

$$x \in \Omega$$
 (2.8)

Where x is one of the feasible solutions, belonging to Ω , the feasible solutions space.

The above must be converted as follows:

$$\min f_1(x)(2.9)$$

Subject to:

$$f_2(x) \le e_2 (2.10)$$

 $f_3(x) \le e_3 (2.11)$
...
 $f_k(x) \le e_k (2.12)$
 $x \in \Omega (2.13)$

The inequalities would have the opposite direction if the objective function converted to constraint was a maximization one.

This method is, obviously, extremely sensitive to changes of e_k and, as a result, the values of this parameter should be properly chosen to obtain a dense and accurate Pareto front. In a way similar to the one mentioned in Section (2.4.1), the appropriate value for this parameter should fluctuate between $f_{k,min}$ and $f_{k,max}$. Multiple iterations, in each of which the value of e_k will be ascending according to an a priori defined step, until covering all the aforementioned range, will lead to an equal number of solutions. Some of them will be Pareto optimal, while some will be neglected as they are dominated by other solutions already found.

The pseudocode for the epsilon-constraint method for two objective functions (bi-objective optimization) follows:

```
Let x<sup>1</sup> be an optimal solution of f<sub>1</sub>

A=\{x^{1}\}
e_{2}=f_{2}(x^{1})+\delta
while min{f<sub>1</sub>(x)|f<sub>2</sub>(x) \le e_{2}} is feasible

xx= min{f<sub>1</sub>(x)|f_{2}(x) \le e_{2}}

A=AUxx

e_{2}=f_{2}(xx)+\delta

Filter dominated solutions in A
```

The aforementioned method performs better than the simple weighted sum method in terms of Pareto front creation. Quite every run or iteration of the ECM leads to a new and different non-dominated solution being found, while this does not happen with WSM. Thus, ε -constraint can produce more solutions and a lot more central (non-extreme) ones, compared to weighted sum. Furthermore, due to its nature, ECM can handle non-convex regions of the Pareto front, which are common in integer or mixed-integer problems that contain binary constraints (Miettinen, 2012). Finally, the solutions obtained after using ECM do not need scaling and normalization; the latter is unavoidable while using WSM if objective functions have different ranges and scales (Mavrotas, 2009).



3 Literature review

Many researchers have dealt with hazardous material management, either on its own or as an intersection between Emergency Response Planning and Supply Chain-Logistics Management. The reason behind examining what happens in different scenarios of hazardous materials transportation is the nature of this type of cargo. Accidents happen seldom, but their consequences can be extremely serious, such as property damage, serious injuries, emergent evacuations, and even casualties. Thus, hazardous materials incidents are a typical case of High-Impact-Low-Probability risk events. Location-wise, they can happen either at the factory or industry of origin (or destination) or en-route between them; the reasons behind these road incidents are vehicular malfunctioning and human errors, and, to a lesser extent, failures in packaging goods (PHMSA, 2004).

3.1 Risk assessment on hazardous materials transportation

Operational research has dealt with hazardous materials transportation models in various ways. Many scientific papers and studies have been dedicated to hazmat related risk assessment, such as those conducted by Erkut & Verter (1998), Chakrabotry & Armstrong (1995), Zhang et al. (2000), and Abkowitz et al. (2001), to name some. In hazardous materials transportation models, the risk is a measure of the probability combined with the severity of causing damage to someone or something exposed to the hazmat, due to potential undesired events (Alp, 1995).

The research field of risk assessment is a challenging one considering the hazardous materials accidents nature. They happen extremely rarely compared to road accidents in general, but their impact and damage are greater than these of other road accidents. These types of events are called Low Probability/High Consequence (LP/HP) events, and finding their likelihoods a priori is, in general, a difficult task (Luxhjoi & Coit, 2006). The difficulties in problems involving events like the aforementioned arise because of the large numbers of contradictory objectives and perspectives and the many levels of decision making, such as tactical and strategic (Clemen, 1996).

More specifically, to complete a quantitative risk assessment, the following elements must be identified or calculated:

- Hazard and exposed receptor(s)
- Frequency
- Consequences, since being properly modeled

As mentioned above, the sources of dangerous releases must be identified, i.e., the types and quantities of compounds emitted during an incident. Afterward, the probability of an accident

must be calculated, along with the potential exposure level and the consequence severity, given the exposure level (Ang, 1979). In the most general case, Bayes' theorem is the appropriate tool to calculate the probability of a 'bad effect', e.g., an injury, caused by an accident related to a particular hazmat:

Let A be a hazmat incident, M the event of releasing hazmat and I the incident event:

$$p(A, M, I, D) = p(D|A, M, I) \times p(A, M, I) = p(D|A, M, I) \times p(I|A, M) \times p(A, M)$$

= $p(D|A, M, I) \times p(I|A, M) * p(M|A) * p(A)$
(3.1)

Some early studies used a model of this format (Bayesian) to predict the place and time of deadly nuclear incidents and estimate the risks associated with them. Glickman (1991) also performed risk estimation on highway transportation of flammable liquids.

Another measure of risk assessment, extensively used, is the FN-curve, i.e., the annual cumulative frequency of incidents with at least N people evacuating on the y-axis, dependent on the number of people (N) that actually evacuate during an undesirable event. According to Jonkman et al. (2003), some countries such as Netherlands, UK, and Denmark use appropriate values of the FN-curve to make their decision rules for hazmat installations.

In a more simplified type of modelling, expected loss is used as a measure of risk:

$$R_a = \sum_{m \in M} s_{am} p(M_m) c_{am}$$

(3.2)

 S_{am} is the number of (annual) shipments of hazmat m on road segment a, p(Mm) the probability of a release event of hazmat m, and c_{am} the non-desirable consequence due to this (a, m) incident. More abstractly, the expected loss is the product of the probability of an incident and its consequence (List & Mirchandani, 1991).

In general, if the probabilities of an incident happening on a road segment are a priori known, then one could use the concept of societal risk, which is the product of incident probability per unit length and incident consequence, modeled as the population living inside the impact area (Erkut and Verter, 1998).

3.2 Hazardous materials impact zones

The aforementioned consequences are, mathematics-wise, a function of an incidents' impact area (exposure zone) as well as population, property, and environmental parameters characteristic of the region where the accident happens. In most cases, the volume and shape of an impact zone depend on the material or substance carried, the weather conditions, and the regional topography. Different methods of a priori modeling have been used. One could indicatively refer to a fixed-width band around a road segment (Batta & Chiu, 1988), the so-called *danger circle*. This circle's radius depends on the hazmat carried and its center is the actual incident location (Erkut & Verter, 1998, Kara et al., 2003). Another widely used approach is an ellipse based on the Gaussian plume model (Chakabotry & Armstrong, 1995).

Since an arc is a part of a network and, also, of one or more routes, if one considers the danger circle of Kara et al. (2003) as an impact area for a node, then the impact area of an arc will be semicircular, with the same radius as the circle.



Image 3: an example of semi-circular exposure zone around link $a(i_3j)$ (Kara et al., 2003).

A truck following a route will collide in the first arc of the path it follows or in the second, etc., or it will reach its destination without an accident happening until there. Let p be the probability of an incident, n the number of arcs, c the consequence, expressed in a quantitative way (such as cost), and assuming that when an incident happens, the trip ends, the risk associated with an edge i could be:

$$pc + (1-p)pc + (1-p)^2pc + \dots + (1-p)^{n-1}pc$$
(3.3)

Assuming, furthermore, that the incident probability p is less than 10^{-6} per trip per kilometer (Harwood et al., 1993), p^s $\rightarrow 0$ for s >1, and, thus, the above sum becomes equal to:

$$pc + pc + \dots + pc = npc$$
(3.4)

, and as a result, for edge i:

$$r_i = p_i c_i$$

(3.5)

This risk modeling assumes that incident probabilities and consequences are distributed uniformly along an arc. This can be the case for dense urban networks, where road segments between two nodes (intersections) are not too long. The danger circle seems to be the most practical and widely used exposure zone modeling; moving this circle across an arc of the road network results in a fixed-width approximation (Kara et al., 2003). In many relevant studies, the radius is a function of the material a truck carries, and thus, during a shipment procedure, it is considered constant. Assuming that every person within the dangerous zone will be equally exposed to a hazardous materials release, and nobody outside this region will have an impact, we can introduce an evacuation distance metric. According to the PHMSA (2004), if a truck carries a flammable hazmat and an incident occurs, people residing within 0.8 km of the accident location must evacuate, and if this hazmat is also explosive, this distance equals 1.6 km.

Some other researchers have emphasized the environmental footprint of the different hazardous materials, and therefore, the evacuation zone for each one of them. Margai (2001) used ALOHA (Areal Location of Hazardous Atmospheres) software to model the impact zones for the worstcase accidents in two New York counties, after inputting relevant data of ten years such as local weather conditions and type and amount of chemicals released, and generated the footprints for each incident scenario. The threat zones for the different chemicals ranged from 150 yards to 3.2 miles, and furthermore, due to the uniqueness of each transportation, different surrounding communities lead to the creation of different impact zones. Thus, the author used an average footprint size of 1.4 miles (2.25 km), regardless of the material. In a more recent study, Chakrabarti & Parikh (2011) aimed to design vulnerable zones, i.e., regions within which properties and people are going to be affected if an incident takes place there. As far as it may concern fire and explosion, they viewed danger circle as an appropriate approximation, while wind conditions were taken into consideration concerning the impact zone of an incident's toxic emissions. Multiplying the impact area volume by the local population density, one could extract the number of affected persons. (Zhang et al., 2000). Chakrabarti & Parikh estimated that if a truck containing 10,000 kg of ammonia crashes, being 949 m away from the accident's location downwind could lead to a 1% lethality probability due to toxic dispersion. The respective threshold for a truck carrying 17,500 kg of 1,3-butadiene was equal to 233 m. The latter study also examined the worst-case scenario for explosion, flashfire, and toxic dispersion and thus calculated and drew an impact zone of 0.053 km2 for 17,500 kg of 1,3-butadiene and 0.076 km2 for 10,000 kg of ammonia.

After estimating spatial factors such as impact area, quantitative risk modeling is required, and, therefore, several studies have been published on this. Undesired consequences can be injuries and deaths (population exposure), property damage, cleanup cost, traffic delays, product loss, environmental disaster, to name some of them (Abkowitz et al., 2001). These consequences must be, if possible, converted to the same monetary unit (Erkut et al., 2007).

The costs associated with population exposure can be direct or not. The direct ones include emergency treatment, some initial medical costs, long-term treatment, insurance cost, etc., while the most prevalent indirect cost is the loss of productivity of the people involved in the incident. These costs are not easily measured because they are a matter of human life. Analyzing 1996 figures, though, a fatality could cost about 913,000 \$, according to National Highway Transportation Safety Administration (1996), while the respective fatality cost estimated by National Safety Council (NSC) for 2003 was 3,610,000 \$, and the same, as calculated by PHMSA was at about 2,800,000 \$ to avoid a fatality (Erkut et al., 2007). From the above figures, one could conclude that researchers and Organizations do not agree on a universal 'cost of death' after an accident.

3.3 Facility Location Problems

Location-allocation problems belong to a category of Operational Research problems, in which the decision maker aims to locate a set of new facilities in a way that the transportation cost from facilities to customers is the minimal one, and an optimal amount of facilities should be located to satisfy the customers' demand. Cooper (1963) first proposed this problem in his paper. Examples of facilities can be warehouses, distribution centers, production facilities, or other facilities which offer homogeneous services (Azarmand & Neizhabouri, 2009). The formulation of the location-allocation problem (LAP) in general has various applications in sectors such as health care, telecommunications, supply chain networks, car-sharing systems, and emergency services (Fan et al., 2019). De Almeida Correia & Antunes (2012), for example, used a mixed integer programming (MIP) model, aiming to maximize the profit of a car-sharing organization, by optimally locating depots and vehicles. As far as emergency facility locations problems can be concerned, given some demand points and possible facility (depots/stations) sites, an appropriate subset of the potential sites which minimize the total cost must be selected by the model used (Li et al., 2011).

3.3.1 The Location Set Covering Problem

The first study that dealt with emergency facility location coverage was the Location Set Covering Problem (LSCP), introduced by Toregas et al. (1971). The original model aims to find the minimum number of facilities that must be allocated to cover all demand points in full. The latter is practically impossible in most cases (Li et al., 2011).

The mathematical formulation behind the Location Set Covering Model is the following:

$$min\sum_{i\in I}x_i \ (3.6)$$

Subject to:

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$$\sum_{i \in N_j} x_i, \forall j \in J (3.7)$$
$$x_i \in \{0,1\}, \forall i \in I (3.8)$$

(Toregas et al., 1971)

In this simple formulation, there are I candidate facility sites, and J demand nodes. For every demand node j, Nj is the coverage set of this node, i.e., the set of facilities that can cover this node, or in other words, the set of facilities that are no longer than S meters away from j. The decision variable, xi, is binary and equals 1 when a facility site opens at node i and 0 when it does not.

3.3.2 The Maximal Covering Linear Problem and an extension of it for large-scale emergencies

Three years later, Church & ReVelle (1974) developed a model that, given a limited number of facilities, maximizes the coverage offered to a set of points, each of which summarizes a population center, using the concept of the centroid. That was the initial effort of modeling and solving the Maximal Covering Linear Problem (MCLP). This problem can be formulated as of below:

$$max \sum_{j \in J} d_j \, y_j \ (3.9)$$

Subject to:

$$\sum_{i \in N_j} x_i \ge y_j, \forall j \in J \ (3.10)$$

$$\sum_{i \in I} x_i = P (3.11)$$
$$x_i \in \{0,1\}, \forall i \in I, j \in J (3.12)$$

(Church & ReVelle, 1974)

This formulation intends to maximize the total coverage, as per its objective function. The latter is a weighted sum, where the binary variable of coverage is multiplied by the demand of each point which corresponds to its weight, to force the model to prioritize places with high demand compared to lower demand ones. According to the constraints, demand point j is covered if, and only if, at least one facility is placed close to it. Resources are limited to P units to maintain an economically feasible solution.

Jia et al. (2007) extended the MCLP for solving Emergency Medical Service (EMS) problems on a large scale, considering various quality levels of service (LoS), or/and various facilities at each quality level. They also proposed that quality levels should depend on population and the probability of an emergency incident happening at each demand point (Li et al., 2011). Their model was the following one:

$$max \sum_{k \in K} \sum_{j \in J} c_k d_j y_{jk} (3.13)$$

Subject to:

$$\sum_{i \in I} x_i \le P (3.14)$$
$$\sum_{i \in N_{jk}} x_i \ge Q_{jk} y_{jk} (3.15)$$
$$x_i \in \{0,1\}, \forall i \in I (3.16)$$
$$y_{jk} \in \{0,1\}, \forall j \in J, k \in K (3.17)$$

(Jia et al., 2007)

, where ck is an importance factor for demand points having quality level k, y_{jk} is a binary variable, equal to 1 if and only if the demand point j is covered at quality level k, and Q_{jk} is the minimum number of facilities that must be able to serve demand point j to achieve services of level k. Finally, N_{jk} is the set of points (facility sites) that can cover point j at a quality of service equal to k.

3.3.3 The Fixed Charge Facility Location Problem

This problem is one of the most classical location-allocation one and has many applications in the supply chain industry. Being introduced by Balinski (1965), it can be formulated as follows:

$$\min \sum_{i \in I} f_i x_i + \sum_{i \in I} \sum_{j \in J} h_j c_{ij} y_{ij}$$
(3.18)

Subject to:

$$\sum_{i \in I} y_{ij} = 1, \forall j \in J (3.19)$$
$$y_{ij} \le x_i, \forall i \in I, j \in J (3.20)$$

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$$x_i \in \{0,1\}, \forall i \in I (3.21)$$

 $y_{ij} \ge 0, \forall i \in I, j \in J (3.22)$

(Balinski, 1965)

A mixed sum of fixed costs for each facility and transportation (or shipment) costs, must be minimized. In the meantime, every demand node must be assigned to a facility, and a facility should be open at the appropriate site to perform an assignment. This formulation assumes unlimited capacity, and that's why it is also called Uncapacitated Fixed Charge Location Problem (UFCLP).

3.3.4 Conflicting objectives of facility location problems and previous related work

In real-life systems, there is a conflict between cost minimization and coverage maximization, and several studies on fields of engineering such as transportation and telecommunication networks, have tried to find tradeoffs between these two. Given the limitations in investments in facilities, the goal of achieving at least a level of coverage confronts these limitations (Church & ReVelle, 1976). Some evident tradeoffs concerning the location-allocation problems of the healthcare facility sector are those between accessibility, coverage, and equity. The goal of minimizing the total distance from a sited facility to the location where an incident happens, leads to increased accessibility and Level of Service (LoS), while the maximization of the population being close to at least one facility leads to more people being possibly assigned to this facility, and thus, a worse LoS. If a solution performs well on accessibility and coverage, it will probably lack equity (Zhang et al., 2016).

Models aiming to optimize more than two objective functions have been proposed throughout the literature. Current et al. (1990), in their review article, referred to quite all the possible objective functions that had been used until then for solving facility location problems. They referred, more specifically, to:

- twelve different objective functions for cost minimization,
- four objectives related to demand satisfaction,
- four objectives about minimizing environmental impacts, and
- three objectives leading to profit maximization.

Cost minimization could be achieved either by minimizing distances between demand points and facilities or more indirectly by minimizing costs; maximization of the demand satisfied is a result of reaching high LoS by maximizing coverage and demand assignment to each facility.

Cetin & Sarul (2009) intended to simultaneously minimize the total fixed location cost, the total time of travel, as well as inequalities in distribution of blood banks at hospitals and other health.

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care facilities. Nuclear accidents were the epicenter of the multi-objective optimization problem introduced by Papazoglou & Christou (1997). Their goal was to produce an optimal Emergency Response Plan, consisting of the evacuation of the region around the nuclear plant where the incident takes place, succeeding in costing the minimum possible, both money-wise and society-wise, by limiting the number of instant deaths and latent injuries. The evacuation process has also been the epicenter of the study performed by Saadatsersesht et al. (2009), who, using a multi-objective Evolutionary Algorithm, managed to provide a Pareto front of solutions. The goals they had set were the minimization of the distance an affected person had to walk to the closest safe location, along with the minimum excess of these locations' capacities, taking for granted that at least one facility's capacity would exceed because of the emergency.

Some multi-objective location-allocation problems within the wireless telecommunications field share a modelling concept with the ones belonging in the emergency evacuation field. One could refer to the study of Kumrai et al. (2013), who implemented an evolutionary heuristic algorithm to find the best places for sensors within a Wireless Sensor Network (WMS). The area (in m²) not covered by any of the sensors was the object of minimization, and the objective function included a region-dependent cost and a node-dependent cost. They proposed a binary decision variable to represent coverage and calculated the total area that can be considered as covered, by making some logical assumptions and using cost constraints.

In the transportation and logistics sector, a limited number of studies have been conducted to find optimal tradeoffs between these two conflicting aims of the decision maker. Nozick & Turnquist (2001) suggested a modified inventory cost function for the classic fixed-charge facility location (FCFLP) model, and they extended this model by adding a coverage minimization objective function. They solved this bi-objective model by weighting with various W values the non-coverage minimization sub-problem. Some other relevant initiatives were taken by Badri et al. (1998), who used a goal programming method for multi-objective optimal location of fire stations in Istanbul. Previously, Osleeb & Ratick (1983) had formulated a mixed-integer multi-objective model appropriate to find tradeoffs between several costs and unloading time efficiency in several coal industries in New England. More recently, Villegas et al. (2006) applied a MCLP along with a FCFLP, to examine where to locate possible depots and purchasing centers of the Colombian supply chain network, dealing with the contradictory objectives of the two aforementioned problems.

The emergency response facility location problem, including hazardous materials or not, dealing with uncertainties or not, has not received much attention in the literature. Berman et al. (2007) highlighted that covering arcs (links) is the key for solving problems like that, instead of covering nodes, as has previously been the case in many location problems. They designed

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and proposed a deterministic model to locate a finite number of emergency response stations, and their objective is to maximize the total arc length covered, by solving the maximal-arc location problem (MALP), which had been introduced by Church & Meadows (1979). The formulation of the latter is based on the Network Interest Point Set (NIPS), a finite set of points within which an optimal solution of the problem exists. The authors defined these points as "any point that is R units of distance from any node i in N, along with the nodes themselves". Any segment lying between two adjacent points of NIPS is a segment of equal coverage (SEC). They assume that there are k NIPS on a network.

Lastly, the concept of maximizing coverage, using non-coverage cost as a metric of it, while maintaining allocation and operation costs at a minimal level, is, amongst other parameters, proposed in the study of Vaezi et al. (2021) for rail transport networks. They use scenarios whose probabilities are estimated by analyzing incidents data of the last 15 years.



4 Problem description and formulation

A person's safety is possible to be endangered when a truck carrying hazardous substances crosses a road of the dense urban environment where he lives, walks, drives, etc. After also concluding that accidents involving hazardous materials are rare but deadly events that Supply Chain Management cannot solve without applying to Emergency Response Management, the idea of constructing a bi-objective model intending to simultaneously optimize efficiency and cost and find the tradeoffs between them, was born.

The Fixed Charge Facility Location Problem, referred to in Chapter (3.3.3), is a fundamental one in terms of Facility Location problems in general, and its objective is to minimize the costs of opening a facility by opening the least sites possible and selecting the cheapest ones, too. Considering a set of points, where a facility can be placed, the model we propose shall select the subset of the most cost-efficient points. Simultaneously, the original FCFLP formulation aims to minimize the transportation cost between the origin of a vehicle and its destination. Since our formulation is applied to the context of Hazardous Materials accidents, a HILP type of event, the actual probability of an event happening is extremely slim, and, as a result, there is no need to calculate such a cost. Furthermore, the coverage ratios of possible Emergency Response Stations (ERS) are a priori known and, even in case a vehicle must respond to an incident assigned to the station it is located at, the route it must follow will be a short one, traversing at most two road segments until reaching the demand destination. Thus, we can assume that transportation cost is negligible compared to the fixed one. As per the operation cost, it will be added to our cost minimization objective function. Once an ERS is open, one or more Emergency Response Vehicles (ERV) of different types can be placed there. Those are emergency vehicles, and as such, they must always be ready to intervene in an accident, and not be decommissioned. Therefore, their maintenance cost must be taken into consideration. Furthermore, for safety reasons, the stations should be monitored and this encompasses another cost added to the operation process.

On the contrary, the MCLP, referred to in Chapter (3.3.2), aims to maximize the coverage or the service level provided by a fleet of cars. The ERVs must be able to serve, at any given time, the demand that can occur anywhere in the region they are responsible for. The concept of maximizing demand coverage is vital for an emergency service; in the optimal scenario, nobody should be endangered due to an inconvenient or inadequate allocation of a station, or due to the absence of a specialized firefighting vehicle when it is needed. The definition of the problem parameters is highly dependent on the decision maker and, thus, subjective. The population in danger in case an accident happens, and the amounts of hazardous materials crossing a road, are considered reliable parameters for the maximal coverage in the context of this emergency

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hazardous materials facility location model. One could also consider this function as a risk minimization one.

Thus, this emergency facility location problem consists of two contradictory objectives; cost and coverage. The cost within the whole network should be the minimal one, both for installing a station and for operating vehicles of a certain type on it. On the other hand, as much as possible of the predictable incidents happening in any road segment (link/arc) and involving any type of hazardous material, should be *coverable*, i.e., possible to be covered by the installed stations and vehicles on them. After studying many problem formulations that dealt with facility location, risk minimization, maximal coverage, and hazardous materials network design, which have already been referred to in Chapter 3, we can unfold this bi-objective model in the following paragraphs.

<u>Sets</u>

The problem's geographical background is an urban transportation network, consisting of roads that intersect, topologically speaking, in certain points. The road segments are represented as arcs or links of a graph, where accidents can happen, while the intersecting points are the graph nodes, where we assume that an Emergency Response Vehicle station can be located. These two sets of arcs and nodes, A and I respectively, describe the network topology.

One of the key elements of the problem are the different types of hazardous materials, namely M, that can cause a deadly incident, and therefore each of them must be treated in a different way, due to their different natural, chemical and nuclear properties.

The Emergency Response Vehicles (ERV) fleet consists of K different types of vehicles related to fire extinguishing. All hazardous materials accidents involve an explosion, and therefore, a fire will break out. Fire engines carry large quantities of water or/and foam and if they reach the incident's location immediately the fire's expansion will be limited. Auxiliary ladder trucks transport the firefighters, in other words, the personnel needed to put out a fire. Finally, ambulances located in a fire station are specialized cars undoubtedly vital in every accident where people are possibly involved and endangered, to ensure that nobody residing or walking in the region won't have respiratory issues after the accident, as well as that, assuming a collision between vehicles or a crash in general, the injured people will be transported in time to the closest hospital.

All the above can be mathematically defined as follows:

I: set of candidate facility locations (nodes)

M: set of hazmat types

K: set of emergency response vehicle types

A: set of possible hazmat incident locations (arcs)

Na: set of response facilities (i) that can cover arc a

 D_m : set of emergency response vehicle types (k) that an incident involving hazardous material of type m, requires.

Parameters

In the context of a facility location problem, each possible station is characterized by its cost of opening (installation), often referred to as setup cost, which depends on the topography, i.e., slope, soil texture, and the proximity to other stations, amongst other parameters. Meanwhile, each vehicle costs in terms of maintenance while being on hold at the station, waiting for an incident. Transportation cost has not been introduced in this model, due to the rarity of dangerous events, which is a characteristic of the problems dealing with hazardous materials management.

Furthermore, stations cannot accommodate more than C vehicles, and at the same time, this is a maximal coverage problem and as a result, a constraint on a minimum amount of demand being covered in any case should be added.

The different types of ERVs do not contribute in the same way to treating a hazardous materials incident; this can depend on the type of incident. Some incidents do not immediately call for ambulances of the Fire Department, especially if there is no known injury. In most cases, though, a fire engine is in primary need, because it is assumed that the worst possible case happens each time, including a major or minor fire and explosion. The above can be described in the two-dimensional D_{mk} table. This parameter results from D_m set (see Sets section above).

The coverage table (cov_{ai}) has been created running a shortest path finding algorithm (Breadth First Search) I times, defining each time the respective node i as the source node, and finding the breadth-first tree of this node, up to its second level, i.e., the arcs which are part of the paths that connect the source node with nodes up to 2 distance levels away from it. These arcs' cov_{ai} values were equal to 1. Coverage table is the two-dimensional binary depiction of N_a set (see Sets section above).

In many models dealing with Emergency Vehicles Location problems, such as the one introduced by Nelas & Dias (2020), the concept of Substitution Table is applied. This table gathers the information of what types of vehicles can substitute others if the first choice is not available. Let k' the vehicle type that is practically able (both in terms of crew and equipment) to replace a vehicle of type k, if needed, then $c_{kk'}$ would be a binary variable, equal to 1, if k's

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can substitute k, and to 0, if not. We should note that $c_{kk'}$ is not the same as $c_{k'k}$ in any case. To be more precise, though, in our model, the aforementioned Substitution Table is blank; each of the vehicle categories considered is simultaneously useful, and it is obvious that a fire engine cannot substitute a ladder fire truck or an ambulance, and vice versa.

Another parameter we should consider, as it applies to many Emergency Vehicles Location problems, is the Incompatibility table, which, in its simplest form, is a binary parameter, let it be i_{aa} . This, as a result of its definition, equals 1 when an incident at road segment a happens partially or fully at the same time as an incident at road segment a'. We can assume that, due to the extreme rarity of the hazardous materials incidents in general, combined with the quite limited urban network this study has been set on, this is never the case in this model, and, thus, this parameter is always equal to zero. Therefore, in practice, this parameter won't be used, although it, theoretically, exists.

As far as it may concern the isolation zone, it can be calculated as follows, for every possible accident; on its own, a possible accident is characterized by its location (road segment where it may happen (a), and the hazardous material involved (m):

$$iz_{am} = \pi(r_m)^2 + 2r_m l_a, \forall m \in M, \forall a \in A (4.1)$$

The assumption made for the impact zone, is the semi-circular one, as it was introduced and modelled by Kara et al. (2003) and defined in Chapter 2. In the long run, there are two semicircles of radius r_m , or, equivalently, a whole circle of radius r_m , and a rectangle l_a long and $2*r_m$ wide.

Afterwards, the potentially affected or endangered population is calculated using the following equation:

$$pop_{am} = iz_{am}dens_a, \forall m \in M, \forall a \in A (4.2)$$

, given that each arc (road segment) lies within a statistical region whose population and population density have been calculated in the most recent census. We can consider urban municipalities with known population and area, and as a result, known population density. We can assume that in an urban environment, there is equity in the population density, and, thus, all segments that are located within the same statistical region, e.g., a municipality, have the same population density. If a road link lies at the boundary of two different statistical regions, its population density will be the median of the two population densities of these regions.

As for the incident probability, this can be modelled using the available data for the region studied. In this problem, one could consider the total volume of hazardous materials (in tons) that have travelled through the whole network, as a measure of incident probability. The bigger

the volume of a hazardous material (m) that has traversed an edge throughout a predetermined period (such as last year), the more prone this edge is to an incident. Each road arc a, in this period, has been a part of the origin-destination route of hazardous material m. The amount of transported tons of m through this edge accounts for this arc's weight. For more convenience, instead of using the actual tons of a hazmat (m) transported via an edge, we use its percentage of the whole hazmat tons transported via the urban network of study for one year:

$$fr_{am} = \frac{ton_{am}}{\sum_{a \in A} \sum_{m \in M} ton_{am}}, \forall a \in A, m \in M$$
(4.3)

And as a result:

$$\sum_{a\in A}\sum_{m\in M}fr_{am}=1\ (4.4)$$

Summing up, the parameters used in this problem are the following ones:

 FC_i : fixed cost (in euros) of opening a response facility at site (location) i

 OC_k : cost (in euros) to (acquire) and operate an emergency response vehicle of type k

C: number of vehicles each site can support (site capacity)

perc: percentage of the total demand (in ton-kilometers) that shall be covered according to the decision maker

 D_{mk} : number of emergency response vehicles of type k that are needed to treat an incident involving hazmat m..

 ton_{am} : total weight (in tons) of hazmat of type m that has been transported through arc a, within a certain period (e.g., last year)

 fr_{am} : tons of hazmat m that has been transported via arc a, divided by the total tons of all hazardous materials in every arc of the road network

 pop_{am} : endangered population around arc a (considering a danger circle with certain radius), due to an incident that involves hazmat of type m.

 cov_{ai} : 1 if candidate station at i can cover arc a; 0 otherwise.

 l_a : length of road segment (arc) a

 $dens_a$: population density of the region within which arc a lies

 r_m : isolation radius when a hazmat of type m occurs (threshold distance for hazmat m, for evacuation of people living around an arc)

 iz_{am} : area (in m²) around arc a that must be evacuated (and therefore, its population must be considered) when an incident of hazmat type m occurs.

M: A big integer value which is used in some constraints to activate or de-activate them.

Decision variables

 Y_i : 1 if a facility opens at site i; 0 otherwise

 U_{ik} : number of vehicles of type k that are sited at node (possible location) i

 Z_{am} : 1 if arc a is covered for incidents involving type m hazmat; 0 otherwise

Objective Functions

$$\min f_{1} = \min(\sum_{i \in I} FC_{i} Y_{i} + \sum_{i \in I} \sum_{k \in K} OC_{k} U_{ik})$$
(4.5)

$$\min f_2 = \min(\sum_{a \in A} \sum_{m \in M} (1 - Z_{am}) * pop_{am} * fr_{am})$$
(4.6)

Equation (4.5) seeks to minimize the total cost and incorporates a location-based cost for each station the model chooses to open and use and a vehicle-based operation and maintenance cost for each type of vehicle bought and placed in a station. This cost should be kept minimal within the whole network. Via equation (4.6), we intend to minimize the non-coverage cost for incidents in road segments where they are more probable to happen and in road parts where more people will be exposed and affected when they happen. The objective function (4.5) connects stations with vehicles, while (4.6) connects road segments with hazmat incidents.

Constraints

$$\sum_{k: D_{mk} \ge 1} U_{ik} \le C * Y_i, \forall i \in I, \forall k \in K$$
(4.7)

$$\sum_{i:cov_{ai}} U_{ik} \ge Z_{am} * D_{mk}, \forall a \in A, \forall m \in M (4.8)$$

$$z_{am} * M \ge \sum_{k: D_{mk} \ge 1} U_{ik} - D_{mk} - 1, \forall a \in A, \forall m \in M, \forall k \in K$$
(4.9)

$$\sum_{m \in M} \sum_{a \in A} (l_a * ton_{am} * Z_{am}) \ge perc * \sum_{m \in M} \sum_{a \in A} (l_a * ton_{am}) (4.10)$$
$$U_{ik} \ge 0, \forall i \in I, k \in K (4.11)$$

 $U_{ik} \in Z, \forall i \in I, k \in K$ (4.12)

 $Y_i \in \{0,1\}, \forall i \in I \; (4.13)$

 $Z_{am} \in \{0,1\}, \forall a \in A, m \in M (4.14)$

According to (4.7), the total number of emergency vehicles located at emergency service station i should be at most equal to the capacity of this station. This constraint is active when there is a station at node i, and inactive when there is not; i.e., if Y_i is equal to 0, no vehicles should be assigned to this station. Constraints (4.8) and (4.9) act simultaneously to force the decision variable of coverage (Z_{am}) to be True (equal to 1) when the total ERVs of type k sited in any of the stations (i) that cover arc a are more than the ERVs of this type needed to cover an accident of hazardous material m plus one; then it is clear that accident in road arc a, involving hazmat m, is covered. Meanwhile, when there are not enough ERVs at the appropriate stations to cover the demand for hazmat m, the decision variable is forced to 0. If the covering vehicles are just as many as needed, the decision variable can be equal to either 0 or 1. The total number of *covered* ton-kilometers must be at least equal to a user-defined percentage of the total tonkilometers within the network, according to the inequality (4.10). Finally, restrictions (4.11) and (4.12) force the number of vehicles to be a non-negative integer number, while constraints (4.13) and (4.14) force the respective decision variables to be binary.



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5 Application of the model on a case study and experimental results

5.1 The CPLEX optimization Studio

The IBM ILOG CPLEX Optimization Studio is a software used for mathematical modelling and efficiently solving optimization problems. Its name derives from the Simplex method, combined with the programming language it was originally implemented in by Robert E. Bixby in 1988, the C programming language ("CPLEX – Wikipedia"). Since then, the software has seen major improvements; there have been released about 20 versions, with the latest one (20.1) being released in December 2020. CPLEX can solve integer programming (IP) problems, large linear programming (LP) problems, as well as quadratic programming (QP) problems, either convex or non-convex ones ("IBM Docs – IBM Documentation").

When aiming to solve a Mixed Integer Programming (MIP) problem, such as the one this study deals with, CPLEX internally uses the branch-and-cut search algorithm. The latter solves a search tree consisting of nodes; every node, on itself, is a linear or quadratic sub-problem waiting to be solved, checked for integrality, or analyzed to lower tree levels, and, thus, sub-problems. The algorithm runs through the tree in a top-down way, processing its active (not yet processed) nodes until all the nodes are inactive or until enough time has passed. A branch occurs when a parent node creates two child nodes, one for the lower and one for the upper bound of a variable. The more we descend the tree, the stricter these bounds become, leading to an exact solution after some iterations. Then the node is solved. A cut is a constraint that the algorithm adds to the model to reduce the branches needed to solve the problem, resulting, thus, to reducing the feasible solutions space ("CPLEX CP Optimization").

To produce models using this software, one needs to import or enter the appropriate datasets and connect each of these to a parameter of the model, having assigned the dimensions properly in these parameters. Each CPLEX project includes a .dat tab and a .mod tab, the data and the model, respectively. To be more illustrative, if one wants to import the lengths of all arcs of a road network, he must utilize a parameter named, for example, l[a] in the .mod tab. Then, CPLEX optimization studio will connect it with a one-dimensional table that should also be named l[a], found in the .dat tab, where each arc length is saved as an element of the table. The Optimizer connects these tabs using the parameter's name (l[a]) as a key. In the same way, CPLEX can also support two-dimensional arrays; e.g., the parameter cov[a][i] in the model (.mod) tab, should be connected with a two-dimensional table with a rows and i columns, found in the data (.dat) tab. A and i are parameters whose dimensions must also be appropriately defined in the data tab as integer values.

5.2 Case study description and data



In the context of the bi-objective problem, a simple urban network with 19 road segments, and thus 19 possible incident locations, and 12 nodes-possible emergency response facilities, is created to test the model and interpret the results. More specifically, the a priori known data of the problem, which should be inputted or imported into the .dat tab of a CPLEX project, are the following:

1) The fixed cost (in euros) of opening a response facility at site (location) i (FC_i)

Fixed cost (in Euros) of opening a facility at	1	2	3	4	5	6	7	8	9	10	11	12
node i(FCi)	10000	12000	7000	8000	12000	8000	10000	11000	6000	9000	9000	12000

2) The cost (in euros) to acquire, maintain, and possibly operate an emergency response vehicle of type k (OC_k)

Operational cost (in Euros) for one unit of	1	2	3
type k (OCk)	10000	6000	8000

3) The length (in meters) of each arc (l_a)

Arc length (in m)	1	2	3	4	5		6	7	8 9	10
	180	150	120	140	150	1	210	90 1	10 140	130
	11	12	13	3	14	15	16	17	18	19
	180	170	120) 1	70	140	120	140	150	200

4) The radius (in meters) within which there is danger of explosion, fire, or serious toxic release for hazardous material m, and people must evacuate (r_m)

Evacuation radius (in m) for hazmat m, r(m)	1	2	3	4
	800	1000	1100	1400

5) The population density (in people per square kilometer) of the statistical region in which arc a lies $(dens_a)$

Population density around roas segment a	1	2	3	4	5	6		7	8 9	10
(people/km2)	9000	9000	9000	10000	10000	10000	950	0 900	0 9000	9000
	11	12	2 13		14	15	16	17	18	19
	9000	9000	9000	9.	500	9000	9000	9000	9000	9000

6) The total tons of each hazmat m that were transported through arc a throughout last year (ton_{am}) , which can be used as a measure of probability for an (a, m) incident happening.

	Tons of hazn	Tons of hazmat m that go annually through road segment a									
	1	2	3	4							
1	200	0	400	0							
2	200	300	100	0							
3	300	100	100	100							
4	100	200	0	100							
5	0	100	100	100							
6	0	100	100	0							
7	100	0	200	100							
8	200	100	0	200							
9	0	100	200	200							
10	100	200	100	0							
11	700	200	100	0							
12	0	100	300	100							
13	300	200	0	200							
14	300	0	100	100							
15	100	200	200	0							
16	0	100	200	0							
17	200	200	0	400							
18	200	100	0	100							
19	200	200	100	300							



7) The number of emergency response vehicles (ERV) of type k that are needed to treat an incident involving hazmat of class m, according to the nature of the substance released, and to what each of the different ERV can offer to this type of accident (D_{mk})

	Number of k vehicles needed for m incidents (Dmk)							
	1	2	3					
1	5	3	0					
2	1	0	1					
3	1	0	3					
4	1	3	1					

8) A binary table showing which possible emergency response facilities (i) can cover road segment a (cov_{ai}) .

lvl=2				Possi	ble station	locations	(i) that can	cover an i	ncident on	road segm	ent a		
		i=1	2	3	4	5	6	7	8	9	10	11	12
1 to 3	a=1	1	1	1	0	0	0	0	1	1	0	0	0
1 to 4	2	1	0	0	1	1	0	1	0	0	0	0	0
3 to 4	3	0	1	1	1	1	0	1	0	1	0	0	0
2 to 3	4	1	1	1	1	0	0	0	1	1	1	1	0
2 to 10	5	0	1	1	0	0	0	0	0	0	1	0	0
3 to 9	6	1	1	1	1	0	0	0	0	1	0	1	0
3 to 8	7	1	1	1	0	0	0	0	1	0	0	0	1
4 to 8	8	0	0	0	1	1	0	1	1	0	0	0	0
4 to 5	9	1	0	1	1	1	1	1	1	0	0	0	0
5 to 6	10	0	0	0	1	1	1	0	0	0	0	0	0
6 to 7	11	0	0	0	0	1	1	1	0	0	0	0	1
4 to 7	12	1	0	1	1	1	0	1	0	0	0	0	1
7 to 12	13	0	0	0	0	0	1	1	1	0	0	1	1
8 to 12	14	0	0	1	1	0	0	0	1	1	0	0	1
8 το 9	15	0	0	0	0	0	0	0	1	1	1	1	1
11 το 12	16	0	0	0	0	0	0	1	0	0	1	1	1
9 το 11	17	0	0	1	0	0	0	0	1	1	0	1	0
9 το 10	18	0	0	0	0	0	0	0	1	1	1	0	0
10 το 11	19	0	1	0	0	0	0	0	0	0	1	1	1

- 9) The capacity of each station is defined by the decision maker and is equal to 10 vehicles per station.
- 10) The percentage of the least acceptable percentage of total transport work of the network, expressed in ton-kilometers, is also user-defined to 50%.

5.3 Heuristics implementation

5.3.1 WSM implementation

All the model elements are now clearly defined and the decision variables are ready to be calculated by the CPLEX software, leading to many different optimal solutions for different weight values, respectively. Still, the objective functions must be normalized beforehand using the method referred to in Chapter 2. The minimum and maximum values of these functions are calculated as of below:

$$f_{1,norm} = \frac{f_1 - 141000}{1220000 - 141000} = \frac{f_1 - 141000}{1080000}$$
(5.1)

When only f_1 is minimized, its value equals 141000 (euros); this happens because we impose a minimum coverage of at least 50% of the total ton-kilometers (see equation 4.5). On the contrary, when we optimize only f_2 , f_1 gets its maximum value which is equal to 1220000. The above values are utilized to compute $f_{1,norm}$.

$$f_{2,norm} = \frac{f_2}{17300} \ (5.2)$$

Respectively, when only f2 is minimized, its value is equal to 0, because the whole demand is covered. On the other hand, when only f1 is minimized, f2 gets its maximum value of 17300 (euros), and that's how $f_{2,norm}$ is computed.

Using the aforementioned, normalized, objective functions as optimization material and generating weights from 0 to 1, with a step of 0.01, i.e., 100 different combinations of w_1 and w_2 , some of the optimal solutions are computed, using, in practice, the Weighted Sum Method. The result is, as anticipated, a convex Pareto front. The solutions depicted in this graph are equivalently optimal, i.e., none of these is better than the others; some of them satisfy the cost objective while others are better in terms of coverage. If no other criterion is set, the choice between them is up to the decision maker.



Figure 1: Pareto Front of optimal solutions, created by the weighted sum method (WSM).

The above front of solutions includes only dominant solutions, which are not dominating each other. The installation and operation cost fluctuates between 0 and 0.2 monetary units, while the non-coverage cost lies within the range [0, 0.9] cost units.

5.3.2 ECM implementation

The problem formulated in Chapter 4 includes integer and binary decision variables. That means it is not a convex one, and, thus, the Pareto front of optimal solutions arising from solving this model is also non-convex. Although the WSM can correctly spot a subset of the optimal solutions, it cannot provide the whole picture. As a result, we will implement the epsilon-constraint method which is also referred to in Chapter 2. The extreme values of 0 and 17300 of the 2nd objective function, which in this case is not necessary to be normalized, form the range of the epsilon parameter.

$$0 \le e_2 \le 17300 (5.3)$$

After testing the data, a step equal to 200 is considered a good choice to create a dense front without missing nearly any of the non-dominated solutions. Using the values derived from this implementation, we can create a Pareto front consisting of convex and concave parts.



Figure 2: Pareto Front of optimal solutions, created by the epsilon constraint method (ECM).

Undoubtedly, the ε -constraint method is a far better way to treat this problem; it provides 24 equally optimal solutions, compared to just 6 of the weighted sum method, leaving the decision.

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maker a bigger solution pool from which he can choose the one that matches his preferences. Via the Weighted Sum method, the most prominent solutions of the convex parts are spotted, concentrated mainly on the upper left and the lower right regions of the Cartesian quadrant. The upper left solutions cost about 150000 to 180000 euros while their non-coverage cost is high, fluctuating between 12000 and 15000. In the range [180000, 230000] euros of the horizontal axis, the Pareto front is significantly concave. The solutions located there are not actually profitable; e.g., comparing solutions p_8 =(178000, 11800) and p_9 =(196000,11750), to decrease the non-coverage cost by 50 monetary units, the installation and operation cost should be increased by 18000 euros. Further interpreting this means that, despite the different scale and range of the two objective functions, selecting p_9 instead of p_8 is not profitable for hardly any decision maker. The same applies to all concave parts of the Pareto front. Thus, although Figure 2 is a more detailed and accurate depiction of the relationship between the two objectives, the far simpler and seemingly incomplete Pareto front created by the Weighted Sum Method also provides some reliable solutions.

We will compare two indicative solutions of this Pareto front. Let them be $p_4=(154000, 13400)$ and $p_{19}=(286000, 3000)$. These two solutions indicate significantly different strategies applied by the decision maker.

5.3.3 An indicative high-risk Pareto-optimal solution (p₄)

In the first case, more emphasis is put on maintaining operational costs at a low level, due to financial restrictions. The fact that hazardous materials accidents are rare, can make the decision maker think that, in the long term, he cannot afford to maintain and constantly monitor a fleet of vehicles that is highly likely to remain out of use for a long time. In general, this is the case for all the emergency vehicles' or security forces' fleets, which seem 'costly' when no fires, pandemics, wars, or other emergent situations happen. So, a decision maker may prefer to leave some of the demand uncovered if he has to decide at the peak of an economic crisis or when dealing with other financial restrictions. He will also go for a lower budget, higher risk choice in case he, somehow, knows that at the current period, the probabilities of a hazmat accident happening are slimmer than in the past or in the future. This indicative solution leads to potentially leaving some incidents unprotected, but the decision maker, in this case, can rely on the constraint that requires at least half of the ton-kilometers to be coverable, which could mean that even in this case, which is considered a *high risk* one, the uncovered area is not that extended.

Four stations are built in the whole network, and they are equipped with a total of 7 ERVs of type 1, 3 ERVs of type 2, and 4 ERVs of type 3. Schematically:



Image 4: an indicative low cost-high risk solution for the facility location problem.

Emergency response stations have been placed in nodes 3, 7, 8, and 10. Node 3 is the least expensive of the network in terms of fixed cost, nodes 7 and 10 have a moderate cost, while node 8 is not a cheap one for placing a station there. Nonetheless, node 8 is a strategic point; it covers many arcs, some of which are not coverable by other potential sites, and this explains why the optimization model chose it. While placing stations in these sites, only 1 out of 19 road segments (5-6) is not coverable by any of the stations.

As for the ERVs, type 1 vehicles, although being the most expensive ones in terms of stocking and maintaining them, while being on alert to intervene if an incident happens, they are also the most useful ones. According to the table (5.7), at least one of them is needed to treat incidents, whatever the type. Furthermore, for the first class of hazardous materials considered in our model, 5 of them are required. Consequently, even in the case of paying more attention to minimizing the operating costs of the fleet and stations, some expenses are unavoidable. On the

UNIVER OMIKO contrary, type 2 ERVs are useful for 2 out of 4 classes of hazmat (and the incidents they are involved in, consequently), and that's why only 3 of them are bought for the whole network. All vehicles will be located at the station that delivers better coverage to roads where hazmat classes 1 and 4 are present. In this case, this coverage is adequate while limiting the expenses.

Considering this is a high-risk solution, a coverage of 43 out of 76 possible incidents (a, m) is achieved, which leads to a 56.5% success. We have, though, to take into consideration that some of the 33 non-coverable incidents have zero accident probability, and therefore, the actual percentage is a little higher.

5.3.4 An indicative low-risk Pareto-optimal solution (p₁₉)

In this case, more emphasis is given to protecting people and the environment as much as possible, without caring so much about the operating costs. The decision maker cares more about the high consequences of a hazardous materials incident than their low probability of happening. This may seem more like a conservative way of planning but a more risk-aware one. The amount of incidents remaining non-coverable is low; numerous stations and vehicles are sited, seeking to cover any potential demand, no matter how low the probabilities of a disastrous event are, for example, in roads where just 1% of the total amount of hazardous materials have been transported throughout the last year. The solution described above is a *low-risk* one.

In the case of the dense and urban small network where we are working on, opening 6 Emergency Response Stations seems to be an excessively big number, and the same could hold true for the 33 vehicles (15 of type 1 ERVs, 9 of type 2, and 9 of type 3) that will be purchased, maintained for always being ready to fight an incident, and monitored. This solution is depicted in the following scheme:



Image 5: an indicative high cost-low risk solution for the facility location problem.

Nodes 5 and 12 have been selected for placing Emergency Response Stations, despite their fixed cost being the highest amongst all the candidate nodes. They cover arcs that are not coverable by other potential sites according to the table (5.7), and, consequently, they can potentially cover incidents happening at these arcs. In this solution, the operation cost is considered a minor objective. Every road arc of the network is coverable in this solution of the facility location problem.

The pattern of usable ERVs selection is the same as in p4 (see Section 5.3.3). Type 1 vehicles are of much use in all accidents and, as a result, at least one of them must be located at every station the model has selected for opening. It is worth noting that vehicles are equally distributed throughout the stations; in most stations, there are 2 or 3 vehicles of type 1 and 1 or 2 vehicles of types 2 and 3. This equal distribution is the optimal one, taking for granted, on the one hand, that these 6 stations are necessary to cover every possible incident requiring type 1

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emergency vehicles, and on the other hand, that the differences in costs between the stations are not excessive (the most expensive stations are also the most strategic ones, covering many road segments).

This possible optimal choice covers 96.5% of possible incidents (a, m), or 73 out of 76. This percentage could be even closer to 100% considering that these 3 incidents may have zero tons of uncovered hazmat class being transported through the uncovered road segment, and the amount of hazmat transported in the past through a road link is used as a quantification of probability in this study.

As for the very 'conservative' solution of the Pareto front, which leads to zero cost of noncoverage, the respective percentage is 100%. That means that every possible accident, even the ones that may never occur, will be covered, and that is the reason the low-risk decision maker may lean towards a solution costing about 300000 instead of the extreme one.



5.4 Sensitivity analysis

A mathematical model where every parameter holds a certain value constitutes a scenario. Whenever one or more of these parameters change, a different scenario develops. Sensitivity analysis, as evidenced by its name, investigates how sensitive is the model to any alteration, i.e., how much does every parameter affects the model results. Some changes may prove insignificant, while others can lead to completely different solutions than those of the original scenario when their values decrease or increase. The following alternative scenarios will be examined:

5.4.1 Capacity of stations

Increasing capacity C of the stations to 15:

This alteration in capacity results in a looser constraint, meaning that one could anticipate in general a lower installation cost, as each station can now accommodate more vehicles. Some Emergency Response Stations (ERS) locations, though, are crucial. As a result, they will open if no other facilities can cover the desired demand. Assuming that it is highly unlikely for two incidents to happen simultaneously, due to the low probabilities of the hazmat events and the undersized network we are working on, only a few stations will be needed, but each of them will be hosting more vehicles.

Decreasing capacity C of the stations to 5:

Decreasing the maximum capacity leads to a stricter constraint than the original one. Each station will not be very costly, but inevitably, more stations will be built, because otherwise, the non-coverage cost will undergo a significant increase due to the low capacity of each station which can easily be exceeded.

Running the model with C=15 and C=5 respectively, without altering anything else, creates two new Pareto fronts, the first being the result of WSM and the second after implementing the ECM. Those fronts, along with the one of the original scenario, are presented below:





Figure 3: Graph comparing the weighted sum model results in case of allowing up to 5, up to 10, and up to 15 emergency response vehicles being located at a station.



Figure 4: Graph comparing the epsilon-constraint model results in case of allowing up to 5, up to 10 and up to 15 emergency response vehicles being located at a station.

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Analyzing the above, we can conclude that reducing the capacity of each station leads to more costly solutions, both in terms of operational and non-coverage cost, with the first one being affected more severely. The epsilon-constraint method gives far more accurate results, while the weighted sum method showcases a general tendency. In the case of increased station capacities, zero installation and operation cost is achieved by spending 11000 monetary units less. When trying to cover everything, capacity constraints are fully exploited and given that a station can host up to 15 vehicles, fewer stations open. All the solutions of the (C=15) Pareto front are dominating the (C=10) front, but not in a stable way. Many solutions are concentrated in the feasible region of low coverage and high installation and operation cost. When decreasing each station's ability to host ERVs, the results are significantly worse than in the original scenario, especially when it comes to high non-coverage costs. In this sub-region, the Pareto front is sparse; only two optimal solutions cost less than 302000 in terms of installation and operation, while in the (C=10) case only two solutions are more expensive than this value. When the operational cost is equal or close to zero, the differences are diminished; the (C=5) scenario is 23000 more costly than the original one.

The table that follows, except for the above, showcases that once decreasing the maximum station capacity to 5, approximately 3.5 ERVs correspond to each station, while in the case of a maximum capacity of 15 vehicles, 6.5 to 7 ERVs are sited at each location. By this, we could conclude that, on average, the threshold of 15 is not fully exploited, at least in this case study.

	Objective	Objective	Number of	Number of	Percentage of
	function f1	function 2	stations	emergency	demand in
	(installation	(non-	installed	vehicles	ton-
	- operation	coverage		placed	kilometers
	cost)	cost)			covered
Station	379000	0	10	35	100%
capacity=5	199000	17400	5	18	50%
Station	345000	0	5	36	100%
capacity=15	127000	14200	2	13	50%

Table 4: Sensitivity analysis on stations coverage.

5.4.2 Minimum ton-kilometers to be covered

Increasing the required percentage of ton-kilometers to be covered to 80%:

In other words, whatever the cost, at least 80 out of 100 units of transport work (ton-kilometers) must be covered in any case. This alternative constraint would limit the range of the non-coverage cost function because even in the worst case, a significant majority of the tons transported should be coverable in case of an incident.

Decreasing the required percentage of ton-kilometers to be covered to 20%:

Altering this parameter shall increase the range of the non-coverage function; the model will now be able to choose solutions that weren't allowed in the original case, which are characterized by significantly low cost and insufficient coverage (less than 50%) too.

Running the model with perc=0.8 and perc=0.2 respectively, without varying anything else, creates two new Pareto fronts (products of WSM and ECM, respectively), which, in comparison with the original scenario, are presented below:



Figure 5: Graph comparing the weighted sum model results in case of requiring at least 20%, at least 50%, and at least 80% of total demand to be covered.





Figure 6: Graph comparing the epsilon-constraint model results in case of requiring at least 20%, at least 50%, and at least 80% of total demand to be covered.

The Pareto front corresponding to a minimum coverage of 80% is a compressed version of the original one, consisting of a limited number of solutions. On the contrary, the outcome of demanding the coverage of at least 20% of the transport work is a more spread-out Pareto front; it is an extension of the original Pareto front and seems like predicting the tendency of the two costs if a high-risk decision maker is in charge. A dense concave part of this Pareto extension lies within 125000 and 135000 monetary units of operational cost, while the non-coverage cost increases, reaching 20000 cost units. In its most extreme case, when only 20% of the total transport work is coverable, the cost of not covering possible incidents rises to 29000. When using the stricter version of constraint (80% of minimum coverage), 4.5 ERVs correspond to each station, while in the case of a looser constraint, 2 ERVs, on average, are assigned to each station.

It is, thus, up to the decision maker, which of the objective functions he should prioritize; if the risk reduction, expressed in non-coverage cost reduction, then he should consider increasing

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the minimum coverage level, knowing that it will cause an increase to more stations being installed as well as more vehicles in each of them.

	Objective	Objective	Number of	Number of	Percentage of
	function f1	function 2	stations	emergency	demand in
	(installation	(non-	installed	vehicles	ton-
	- operation	coverage		placed	kilometers
	cost)	cost)			covered
At least	356000	0	6	36	100%
20%					
2070	54000	28800	2	4	20%
coverage					
At least	356000	0	6	36	100%
800/					
00%	233000	6100	5	23	80%
coverage					

The results of the epsilon-constraint method, summarized, appear in the following table:

Table 5: Sensitivity analysis on minimum transport work coverage.

5.4.3 Coverage ratio of a station

Increasing to 3 the level of BFS for which one could consider an arc as coverable:

By accomplishing this, the coverage table (cov_{ai}) will be denser in "1" values; every station can now cover more incidents. As a result, the same level of service (LoS) can be achieved by spending less. But we should have in mind that in this case, the model assumes that incidents on two road links a station can cover are impossible to happen simultaneously. The probability of something like this happening remains slim in our case study, where a 4-level BFS tree of each potential site covers the entire network. Nonetheless, if a network is more extended than ours and we decide that any arc located six breadth-first-search tree levels away of a node is coverable, this can result in up to 25 or 30 road links being simultaneously coverable. The above raises the probability of hazmat incidents happening simultaneously in at least two of these arcs, and if we extend this even more to a large metropolitan area network, the probabilities can be even less negligible. In a case like this, another approach, such as the Double Standard Model (DSM), introduced by Gendreau et al. (1997), can be implemented. In this model, two distance standards, namely r1 and r2, are introduced and intend to maximize the demands covered twice within the r1 distance. The demand in this model is nodal, i.e., the demand of a whole region is represented by a centrally located node; DSM, furthermore, doesn't strictly assume that only one facility can be placed at a potential site (Li et al., 2011).



Decreasing to 1 the level of BFS for which one could consider an arc as coverable:

In that case, only the arcs adjacent to the source node will be coverable. That scenario seems to be realistic in terms of probabilities of incidents of the coverable road segments happening simultaneously, but too expensive and difficult to function on a large-scale network on the other hand as hardly any decision maker would consider this feasible. It has to be investigated, though, mathematics-wise.



Figure 7: Graph comparing the weighted sum model results in case of each station being able to cover incidents happening at arcs 1, 2 and 3 levels away of its location.





Figure 8: Graph comparing the epsilon-constraint model results in case of each station being able to cover incidents happening at arcs 1, 2 and 3 levels away of its location.



As one can easily see, changing the radius of possible coverage for each facility can lead to dissimilar Pareto fronts. If a station can cover arcs that are located farther away, the total cost decreases significantly; e.g., for solutions costing approximately 4000 units in terms of non-coverage, when a single station can serve incidents within a 3-arcs radius, the corresponding installation and operation spendings equal 215000 monetary units, 45000 less than in the original case. The differences fluctuate between 20000 and 95000, and the increased facility coverage scenario obviously performs better. As far as the case of limited coverage is concerned, when a facility can only cover the arcs adjacent to it, it carries an operational cost of about 180000 or even 250000 monetary units more, for the same level of non-coverage cost. The Pareto front shifts slightly to the left in case of increased station responsibilities, and significantly to the right, in case of limited responsibilities.

Furthermore, in the case of 3-levels coverage, an average of 5-5.5 ERVs are assigned to each station, while this number is less stable in the case of 1-level coverage, fluctuating between 4 to 5.5 vehicles per station.

The summary of the above can be found in the following table, where the numerical results of the epsilon-constraint method (which have not undergone normalization) are presented:

	Objective	Objective	Number of	Number of	Percentage of
	function f1	function 2	stations	emergency	demand in
	(installation	(non-	installed	vehicles	ton-
	- operation	coverage		placed	kilometers
	cost)	cost)			covered
1-level	663000	0	12	66	100%
coverage	289000	17600	7	27	50%
3-levels	261000	0	5	26	100%
coverage	112000	17000	2	11	50%

Table 6: Sensitivity	[,] analysis on	potential station	coverage.
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5.4.4 Population distribution

The population of a region that mostly consists of urban sub-areas such as city districts or neighborhoods leans towards a uniform density. In the original scenario, population density fluctuates between 9000 and 10000 people per square kilometer, which are realistic values within a continuous urban environment without huge and abrupt differences between residential places and industrial zones. Although the grid of this study is not that huge, we could see what would happen if some sub-areas of the region were more sparse in terms of density for various reasons. A decreased population density of an inhabited area also means a low population density of the roads located within this area.

Considering three levels of population density, 13000 (people/sq. kilometer), 9000 and 5000, the modified table is the following one:

Population density around roas segment a	1	2	3	4	5	6		7	8 9	10
(people/km2)	9000	9000	9000	5000	5000	5000	900	0 1100	0 13000	13000
	11	12	1	3	14	15	16	17	18	19
	13000	13000	1100	- D 90	000	9000	9000	7000	5000	5000

Running the model again, ceteris paribus, the results of this scenario, compared with the respective results of the original one, are presented in the following graphs:



Figure 9: Graph comparing the weighted sum model results in case of the population being quite uniformly and quite non-uniformly distributed.





Figure 10: Graph comparing the epsilon-constraint model results in case of the population being quite uniformly and quite non-uniformly distributed.

The case of an unbalanced urban environment, population-wise, leads to less costly solutions, especially when it comes to the non-coverage cost objective function weighted as the primary one, according to the WSM, which produces a simplified Pareto front. An analysis of the optimal solutions front obtained by ECM, though, could prove that the relationship between a uniform and a non-uniform population distribution is more complicated; the most costly, installation and operation-wise, solutions are the same in both cases. Nevertheless, in the feasible region of significantly low operation costs and more difficulties in covering possible incidents, the solutions belonging in the Pareto front of unevenly distributed population scenario fully dominate the ones of the uniform density scenario.

Locating Emergency Response Stations closer to the more densely inhabited urban areas results in the coverage of a great deal of the total demand, which means opening and operating fewer stations. A non-coverage cost of the least expensive solution in terms of operational costs, due to the nature of the optimization process itself, will place the stations needed near the road segments with the most extended impact zones around them; the impact zones, though, are dependent on population density, since no other factor has changed. Thus, while in the case of equity in population density, some of the road segments connected with a population density of approximately 9000 people/square kilometer were left uncovered, in the case of uneven distribution, the respective left out possible incident locations will be those, associated with

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population densities equal to 5000 or 7000 people/square kilometers. Thereafter, not covering these roads (and incidents possibly occurring there) means less risk since non-coverage depends on the population around a road segment exposed to danger, according to objective function (4.2).



6 Conclusions – Future search

In this thesis, we proposed and solved a bi-objective model for an Emergency Facility Location Problem for Hazardous Materials Management, combining decision variables and parameters used extensively in literature with newly introduced ones. The contradictory objectives of cost minimization and coverage maximization had not been, until now, the research object of many studies and papers in hazardous materials and emergency management fields, and this thesis aimed to dig into it and highlight it a bit more.

Two different methods, the weighted sum method and the epsilon-constraint, were intended to investigate the form of the Pareto optimal front of a problem like this, examine its convex and concave parts, and propose different strategies for different risk-awareness levels of decision makers. The different scenarios investigated, highlighted the model's sensitivity on the, known in advance, coverage ratio of the Emergency Response Stations, its less but significant, sensitivity on their vehicular capacity.

The results of this study are not conflicting with what one could anticipate; the creation of a Pareto front, many optimal solutions, tradeoffs, and difficulty to choose one solution that stands out. Nevertheless, the fact that two fundamental facility location problems were combined with a spatial risk modelling, a fleet of emergency vehicles, and hazardous materials classes treated differently, was indeed a good reason for me to follow this research topic until the very end, and, hopefully, to have provided something significant research, engineering and businesswise.

6.1 Further research perspectives

Although this thesis could be an incentive for future research, much work needs to be done by future researchers in the field to acquire relevant data. Obtaining information from a dense urban transportation network where each road segment, according to its road category and class, is characterized by a different speed limit, would be of much use for accurate calculations of coverage tables. The latter could, furthermore, be enriched with real-time traffic data to help evaluate the Level of Service of the entire network; this would prove helpful both for calculating the potential coverage ratio and for spotting the roads where delays could be fatal for a person in need after a severe hazmat incident.

The concept of emergency calls prioritization has also been widely used in past Operational Research studies, even though not much in hazardous materials problems. The rules of prioritization, though, shall be strict and thoroughly examined before being applied. Otherwise, they could be too subjective, leading to arbitrary results that could prove dangerous for the people and the environment.

Equity in the possible demand events should also be motivated and maximized by researchers that will dig into this field in the future. One or more extra constraints would lead to a model that treats as fairly as possible everyone in need, concurrently maintaining cost at high levels. As per sensitivity analysis, alterations in parameters such as demand distribution, examining networks where only a few roads are utilized as a part of hazmat trucks routes, which is a realistic scenario, and more detailed research on evacuation radius for different hazardous materials, could prove to be potential improvements to the existing model.

Finally, more advanced exact algorithms could lead to groundbreaking results, along with the availability of large real datasets. Evolutionary algorithms such as NSGA-II as well as ant colony optimization techniques turn out to be key tools in the research field of multi-objective optimization and can lead to improved and interesting, research-wise, results.





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Appendix: IBM LOG CPLEX Optimization Code

<u>Data</u>

* OPL 12.10.0.0 Data

* Author: alex1

* Creation Date: 18 Noε 2021 at 12:25:27 π.μ.

nodes=12;

hazmats=4;

vehicles=3;

arcs=19;

big_b=10000;

capacity=10;

perc=0.5;

```
fixed_install_cost=[10000, 12000, 7000, 8000, 12000, 8000, 10000, 11000, 6000, 6000, 9000, 12000];
```

```
oper_cost=[10000, 6000, 8000];
```

w1=0.76;

ton=[

[200, 0, 400, 0],

[200, 300, 100, 0],

[300, 100, 100, 100],

[100, 200, 0, 100],

[0, 100, 100, 100],

[0, 100, 100, 0],

[100, 0, 200, 100],



[200, 100, 0, 200],

[0, 100, 200, 200],

[100, 200, 100, 0],

[600, 200, 100, 0],

[0, 100, 300, 100],

[300, 100, 0, 200],

[300, 0, 100, 100],

[100, 200, 200, 0],

[0, 100, 300, 0],

[200, 200, 0, 400],

[200, 100, 0, 100],

[200, 200, 100, 300]

];

fraction=[

[0.02, 0.0, 0.04, 0.0],

[0.02, 0.03, 0.01, 0.0],

[0.03, 0.01, 0.01, 0.01],

[0.01, 0.02, 0.0, 0.01],

[0.0, 0.01, 0.01, 0.01],

[0.0, 0.01, 0.01, 0.0],

[0.01, 0.0, 0.02, 0.01],

[0.02, 0.01, 0.0, 0.02],

[0.0, 0.01, 0.02, 0.02],

[0.01, 0.02, 0.01, 0.0],

[0.06, 0.02, 0.01, 0.0],

[0.0, 0.01, 0.03, 0.01],



[0.03, 0.01, 0.0, 0.02],

[0.03, 0.0, 0.01, 0.01],

[0.01, 0.02, 0.02, 0.0],

[0.0, 0.01, 0.03, 0.0],

[0.02, 0.02, 0.0, 0.04],

[0.02, 0.01, 0.0, 0.01],

 $\left[0.02,\,0.02,\,0.01,\,0.03\right]$

];

D=[

[5, 3, 0],

[1, 0, 1],

[1, 0, 3],

[1, 3, 1],

];

cover_table=[

[1, 1, 1, 0, 0, 0, 0, 1, 1, 0, 0, 0],

[1, 0, 0, 1, 1, 0, 1, 0, 0, 0, 0, 0],

[0, 1, 1, 1, 1, 0, 1, 0, 1, 0, 0, 0],

[1, 1, 1, 1, 0, 0, 0, 1, 1, 1, 1, 0],

[0, 1, 1, 0, 0, 0, 0, 0, 0, 1, 0, 0],

[1, 1, 1, 1, 0, 0, 0, 0, 1, 0, 1, 0],

[1, 1, 1, 0, 0, 0, 0, 1, 0, 0, 0, 1],

[0, 0, 0, 1, 1, 0, 1, 1, 0, 0, 0, 0],

[1, 0, 1, 1, 1, 1, 1, 1, 0, 0, 0, 0],

[0, 0, 0, 1, 1, 1, 0, 0, 0, 0, 0, 0],

[0, 0, 0, 0, 1, 1, 1, 0, 0, 0, 0, 1],



[1, 0, 1, 1, 1, 0, 1, 0, 0, 0, 0, 1],

[0, 0, 0, 0, 0, 1, 1, 1, 0, 0, 1, 1],

[0, 0, 1, 1, 0, 0, 0, 1, 1, 0, 0, 1],

[0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 1, 1, 1],

[0, 0, 0, 0, 0, 0, 1, 0, 0, 1, 1, 1],

[0, 0, 1, 0, 0, 0, 0, 1, 1, 0, 1, 0],

[0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 1, 0, 0],

[0, 1, 0, 0, 0, 0, 0, 0, 0, 1, 1, 1]

];

isol_r=[800, 1000, 1100, 1400];

leng=[180, 150, 120, 140, 150, 210, 90, 110, 140, 130, 180, 170, 120, 170, 140, 120, 140, 150, 200];

density=[9000, 9000, 9000, 5000, 5000, 5000, 9000, 11000, 13000, 13000, 13000, 13000, 11000, 9000, 9000, 9000, 7000, 5000, 5000];

The weighted sum method (WSM)

This pice of .mod produces one solution of the weighted sum method. Altering the weights utilizing a step equal to 0.01 results to multiple Pareto front solutions that are located in the convex part of the front.

* OPL 12.10.0.0 Model

* Author: alex1

* Creation Date: 18 Noε 2021 at 12:25:26 π.μ.

//Sets

int nodes=...; //no of nodes

int hazmats=...; //no of hazmats


int vehicles=...; //no of vehicles int arcs=...; //no of arcs range ii=1..nodes; range mm=1..hazmats; range kk=1..vehicles; range aa=1..arcs;

//Parameters

int big_b=; //number used to break or maintain inequalities in constraints
int capacity=;
float perc=;
int fixed_install_cost[ii]=;
int oper_cost[kk]=;
int D[mm][kk]=;
int cover_table[aa][ii]=;
int isol_r[mm]=;
int leng[aa]=;
int density[aa]=;
float fraction[aa][mm]=;
int ton[aa][mm]=;
float w1=; //the weight of the first objective function
//Variables
dvar int+ vehs[ii][kk];
dvar boolean located[ii];
dvar boolean z[aa][mm];
dvar int isol_zone[aa][mm];



dvar float pop[aa][mm];

//Objective Functions

dexpr float v1= w1*(((sum(i in ii) (fixed_install_cost[i]*located[i])+sum(i in ii, k in kk)(oper_cost[k]*vehs[i][k])-141000)/1083000));

dexpr float v2= $(1-w1)^*((sum(a \text{ in } aa, m \text{ in } mm))((1-z[a][m])^*fraction[a][m]^*pop[a][m])/17300));$

minimize v1+v2; //the model optimizes a weighted and normalized sum of the two objective functions

//Subject to constraints:

subject to {

```
forall (i in ii) {
```

sum(k in kk) vehs[i][k]<=capacity*located[i];</pre>

}

```
forall (a in aa, m in mm, k in kk) {
```

sum(i in ii: cover_table[a][i]==1) vehs[i][k]>=z[a][m]* D[m][k];

 $z[a][m]*big_b >= sum(i in ii: cover_table[a][i]==1) (vehs[i][k])-D[m][k]-1;$

}

```
forall (a in aa, m in mm) {
```

isol_zone[a][m]==3.14*isol_r[m]^2+2*isol_r[m]*leng[a];

```
pop[a][m]==isol_zone[a][m]*density[a]/1000000;
```

}

sum(a in aa, m in mm) (leng[a]*ton[a][m]*z[a][m])>=perc*sum(a in aa, m in mm)
(leng[a]*ton[a][m]);

}

The ε-constraint-method (ECM)

This piece of .mod is the code that produces one solution of the ε -constraint method, and altering the value of parameter e each time, with a step of 200, within the range [0, 17400], multiple Pareto-optimal solutions are provided.

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* OPL 12.10.0.0 Model

* Author: alex1

* Creation Date: 18 Noε 2021 at 12:25:26 π.μ.

//Sets

int nodes=...; //no of nodes

int hazmats=...; //no of hazmats

int vehicles=...; //no of vehicles

int arcs=...; //no of arcs

range ii=1..nodes;

range mm=1..hazmats;

range kk=1..vehicles;

range aa=1..arcs;

//Parameters

int big_b=...; //number used to break or maintain inequalities in constraints

int capacity=...;

float perc=...;

int fixed_install_cost[ii]=...;

int oper_cost[kk]=...;

int D[mm][kk]=...;

int cover_table[aa][ii]=...;

int isol_r[mm]=...;

int leng[aa]=...;

int density[aa]=...;

float fraction[aa][mm]=...;



int ton[aa][mm]=...;

float pop[aa][mm]=...;

int e=...; //an upper bound for the objective set as constraint, the epsilon parameter

//Variables

dvar int+ vehs[ii][kk];

dvar boolean located[ii];

dvar boolean z[aa][mm];

dvar int isol_zone[aa][mm];

//Objective Function

```
dexpr float v1= sum(i in ii) (fixed_install_cost[i]*located[i])+sum(i in ii, k in
kk)(oper_cost[k]*vehs[i][k]);
```

minimize v1;

//Subject to constraints:

subject to {

```
forall (i in ii) {
```

sum(k in kk) vehs[i][k]<=capacity*located[i];</pre>

}

```
forall (a in aa, m in mm, k in kk) {
```

sum(i in ii: cover_table[a][i]==1) vehs[i][k]>=z[a][m]* D[m][k];

z[a][m]*big_b>=sum(i in ii: cover_table[a][i]==1) (vehs[i][k])-D[m][k]-1;

}

```
forall (a in aa, m in mm) {
```

isol_zone[a][m]==3.14*isol_r[m]^2+2*isol_r[m]*leng[a];

}

sum(a in aa, m in mm) (leng[a]*ton[a][m]*z[a][m])>=perc*sum(a in aa, m in mm)
(leng[a]*ton[a][m]); //the 2nd objective function set as constraint

sum(a in aa, m in mm)((1-z[a][m])*fraction[a][m]*pop[a][m])<=e;</pre>

}

