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A bi-objective cash-in-transit pick-up and delivery problem with risk assessment methodology: a case study

Reza Ramezanain [1*], Meysam Arjmandfar [1], Darya Abbasi [2]

[1] *Department of Industrial Engineering, K. N. Toosi University of Technology, Tehran, Iran*

[2] *Department of Industrial Engineering and Management Systems, Amir Kabir University of Technology, Tehran, Iran*

**** Corresponding Author:** Reza Ramezanain (Email: ramezanian@kntu.ac.ir)*

Abstract *–In this paper, the Risk-constrained Cash-In-Transit Vehicle Routing Problem (RCITVRP) is addressed with time windows, pickups, and deliveries. It is crucial for Cash-In-Transit (CIT) companies involved in transporting valuable or hazardous goods to identify risks. Therefore, owing to the high level of risk in CIT operations (e.g., armed robbery or attack), a bi-objective mixed-integer non-linear programming (MINLP) model is used to minimize travel costs and the risks associated with transporting valuables. For risk minimization, a new risk measure is developed, which includes: (i) the level of vulnerability for each vehicle, and (ii) the threat probability on each route. In addition, multiple vehicles are considered with capacity limitations. The epsilon-constraint method, a multi-objective exact solution approach, is implemented to solve the proposed model. Furthermore, several numerical examples are generated to evaluate the model and the solution method, which clearly show the best route with minimum cost and minimum risk (cost value = 112, risk value = 64,600). Eventually, a case study is provided to investigate the applicability of the proposed model.*

Keywords*– Cash-in-transit Problem, Mathematical modeling, multi-objective, RCITVRP, risk assessment, robbery.*

I. INTRODUCTION

Over the past decade, the vehicle routing problem (VRP) has emerged as a major area of interest for researchers. Numerous variations of VRP have been developed to attempt to tackle real-life situations. One significant area of research that has not received enough attention as an essential VRP problem is related to security during the transportation of cash or valuable commodities between banks, large retailers, shopping centers, ATMs, jewelry, casinos, and other locations where large amounts of cash or valuable items are transmitted. Cash-in-transit (CIT) activities involve the physically transfer of cash in armored or non-armored vehicles. Cash includes banknotes, money, coins, jewels, bullion, securities, and other financial instruments. Many cash-in-transit companies have considerable experience in transporting valuable items between customers and one or more cash deposits or banks. However, due to the nature of cash transfers, criminal activities pose a constant challenge. CIT carriers are constantly threatened by risk factors, primarily from armed attacks and robbery. Attacks often result in serious injuries to CIT employees and can cause trauma to the people involved, including retail staff and customers.

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To highlight the significance of the Cash-in-Transit (CIT) sector, it is worth noting that in the United Kingdom alone, £500 billion is transported annually, which is equivalent to £1.4 billion daily. Certain high-profile thefts draw considerable attention from the media. For instance, in 2013, Foggia, Italy, witnessed the unlawful removal of 300 kilograms of gold. Shortly after, Brussels, Belgium, experienced a €50 million robbery, and in the same year, a criminal organization executed a €10 million heist in Varese, Italy. The funds acquired through CIT attacks serve as a substantial source of funding for organized crime. Statistics from the British Security Industry Association emphasize that assaults against CIT couriers remain a serious and escalating global issue (Talarico et al., 2015). Thus, companies need to make continuous investments to equip CIT vehicles with high-efficiency systems, advanced technologies, and equipment aimed at reducing the incidence (rate) of attacks and robberies. Although enhanced security equipment might be effective, ensuring secure and safeguarded transportation remains a complex task for CIT companies (Smith & Louis, 2010).

In various versions of the Vehicle Routing Problem, minimizing costs stands as a crucial objective. Consequently, substantial research has focused on decreasing routing expenses. However, prioritizing transportation security is more pivotal than simply reducing costs while dealing with the transport of cash, hazardous, and valuable items. Failing to incorporate secure planning may lead to significant human and economic losses. It is noteworthy to indicate that conducting a security analysis to mitigate risks often requires comprehensive high-level planning, which can drastically impact operating costs. Therefore, the simultaneous consideration of minimizing transportation costs while mitigating risks and threats is crucial (Talarico et al., 2017).

The issue of "security" during the transportation of cash or precious goods as real-life vehicle routing problems has recently received considerable attention in the academic world. Various studies have explored methods for calculating risk, considering influential factors that affect risk in transportation networks during precarious conditions. Krarup (1995) and Ngueveu et al. (2009) proposed an approach which is so-called "peripatetic routing problems," which aims to reduce the risk of being attacked by building routes that are unforeseeable for criminals. Customers can be visited multiple times, but using the same route and road segment twice is explicitly prohibited. Calvo and Cordone (2003) defined specific time windows with a minimum and maximum time lag between two successive visits of the same customer to achieve unpredictable routes, which help to reduce the risk of being attacked. As a result, this method generates a wide variety of solutions for security reasons. Talarico et al. (2013) developed a variant of the VRP that uses a specific type of risk relevant to routing vehicles in the CIT industry. Also, a hard time window constraint is introduced in their model. To solve the medium and large instances of the problem, two meta-heuristic algorithms have been employed. Van Raemdonck et al. (2013) developed a framework to map the risks associated with hazardous material transport in Flanders, based on historical accident data. The mentioned approach permits establishing an overall risk map for the transportation of hazardous materials across different modes. In addition, they proposed a methodology to evaluate local accident risk, dividing the risk of a catastrophic hazmat incidents into two parts: (a) the general possibility of an incident occurring, and (b) the local possibility of an incident occurring. Talarico et al. (2015) presented a new risk index to model the vehicle routing problem in the CIT industry, where the likelihood of a robbery is presumed to be proportional to both the transported cash amount and the time or distance traveled by the cash-carrying vehicle. A mathematical formulation was presented for the Robbery Cash-in-Transit Vehicle Routing Problem (RCITVRP) along with a library including two sets of instances. Different meta-heuristics were developed to solve the problem. Meiyi et al. (2015) developed a location-scheduling optimization model for hazardous materials transportation, focusing on optimizing departure and dwell times for each depot-customer pair In this model, risks were considered as time-dependent fuzzy random variables. To minimize route and site risks, an expected value model and a modified particle swarm optimization algorithm were designed. For achieving an optimal global solution, the greedy method and adaptive genetic algorithm, integrated into the PSO algorithm, were applied. Later, Bozkaya et al. (2017) proposed a bi-objective route problem for transporting valuables and cash in-transit operations. The first objective of the model is to minimize the total transportation costs, and the second aims to minimize the security risks of transporting valuables along the determined routes. A combined risk metric is introduced, formed by assigning weights to two distinct risk elements: (1) traversing identical or highly similar routes, and (2) accessing areas with lower socioeconomic status on the routes. In addition, an adaptive, randomized, bi-objective path selection algorithm was developed to solve the problem. In another study, Talarico et al. (2017) proposed a multi-objective vehicle routing problem aimed at increasing security in the CIT sector. The first objective of the model is to minimize travel costs, while the second objective is to minimize the risk exposure to robberies. To calculate the risk value, the amount of cash transported and the distance traveled by the vehicle are considered. A progressive, multi-objective meta-heuristic was used to solve the problem. Radojičić et al. (2018) proposed a fuzzy version of the RCITVRP, where risk is established by applying a risk threshold to each route, and solutions with lower risk index values on their routes are regarded as better solutions. Furthermore, they developed two mixed-integer programming models of the proposed problem, utilizing the CPLEX solver for solving the model. Vahdat Zad (2018) presented a specific case of the two-echelon location-routing problem in the CIT sector. A multi-objective mixed-integer linear programming model is proposed, in which total transportation risk and cost are considered objective functions. To make the model more applicable, diverse real-life variants were considered in the model. The model was solved using an improved version of the ε-constraint method called AUGMECON2. Xu et al. (2019) introduced a new mixed-integer programming model to minimize the mix of various denominations of cash and build safe routes for CIT problems. A combined hybrid Tabu search meta-heuristic was used to solve the CIT model, demonstrating that the applied algorithm yields effective solutions. Rezaeipanah et al. (2019) addressed the Vehicle Routing Problem with Time Windows (VRPTW), an extension of the capacitated vehicle routing problem that includes specific service time constraints. They proposed a hybrid solution combining cuckoo search and greedy algorithms to optimize routes, minimizing total route costs and the number of vehicles used while maximizing customer satisfaction. Evaluations using various dataset sizes demonstrated the proposed method's superior performance compared to similar approaches. Ghannadpour and Zandiyeh (2020) developed a model for the vehicle routing problem with two objectives; the minimization of distance and risk. Game theory and multi-criteria decision-making were used in their presented method for the vulnerability estimation of an armed robbery, resulting in precise risk measurement. A multi-objective intelligent genetic algorithm, comprising different heuristics, was introduced to select the most efficient heuristic. Soltanzadeh et al. (2020)

Proposed a model for routing electric and conventional vehicles to minimize greenhouse gas emissions. The model included recharging and battery swapping and was solved using GAMS and a multi-objective particle swarm optimization algorithm. The results indicate that the model reduces both costs and emissions, with higher greenhouse gas taxes increasing electric vehicle use. Tikani et al. (2021) presented new CIT models, including deterministic and stochastic time-varying traffic congestion. Additionally, a novel formula was proposed to calculate the risk of travel, considering the presence of parallel links with varying levels of traffic congestion, and a model was studied in multigraph networks. Solution methods were developed using novel flexible restricted dynamic programming and a self-adaptive caching genetic algorithm. As risk is pivotal for companies with CIT activities, Yildiz et al. (2022) considered the criteria to define the risks associated with routes for each CIT vehicle. These criteria were weighted by the Interval-Valued Intuitionistic Fuzzy Analytical Hierarchy Process, and risk assessment was made to alternative routes in accord with these weighted risks. The routes were assessed by Interval-Valued Intuitionistic Fuzzy Technique for Order Preference by Similarity to Ideal Solution methodology, which identifies paths with the lowest and highest risks. Momeni et al. (2022) developed a mathematical model to optimize routes for autonomous vehicles (AVs) considering traffic congestion. Using GAMS software, they demonstrated that optimal routes can be determined, but network congestion poses challenges when many vehicles choose the same route. Sensitivity analysis showed that increased traffic time raises costs and service times. They suggest that government allocation of specific road segments to AVs could improve network performance. Ge et al. (2023) proposed a two-objective and a goal programming model for risk-constrained multi-depot vehicle routing problems employing real-time traffic data to address CIT sector routing issues. In their study, risk was defined using a distance-based method. To solve the bi-objective model and the goal programming model, a self-constrained hybrid genetic algorithm and a hybrid genetic algorithm with intensification procedures were developed, respectively. According to the prior studies, different factors and constraints are considered in the risk calculation for CIT vehicle routing problems (CTVRP). Most studies in the literature focusing on risk calculation in risk-constrained CIT vehicle routing problems emphasize distance-based methods, in which the likelihood of a CIT vehicle being robbed is positively related to the travel distance (or duration) along the routes, and probability-based methods are utilized to evaluate the probability of robbery and loss after a successful robbery. In risk measurement for CTVRP, very little attention has been paid to risk related to the CIT vehicle and the threat probability existing on routes. To overcome these limitations, a new bi-objective model was developed for the pick-up and delivery CIT vehicle routing problem, considering real-life constraints such as multiple vehicles, capacity limitations, and time windows for pick-up and delivery. In this study, two novel effective parameters for evaluating risk exposure are taken into account: the level of vulnerability for each vehicle and the threat probability on each route. These new parameters in the risk measurement for the RCITVRP offer a more realistic assessment by considering route-specific threat levels and vehicle-specific vulnerabilities. This approach, distinct from traditional distance-based methods, acknowledges the dynamic nature of risk, incorporating cumulative cash on board and providing a comprehensive measure. It enhances accuracy in risk assessment and aids in optimizing routes to minimize the risk of CIT vehicle robberies. Additionally, to demonstrate the applicability of the proposed model, a real case study is provided on the optimization of transporting CIT operations in a series of bank branches and Virtual Teller Machines (VTMs) in Tehran (the capital city of Iran). The rest of the paper is organized as follows: Section two describes the problem and the assumptions that were considered, which includes an explanation of the risk assessment index and its evaluation, as well as its mathematical modeling. In Section three, an appropriate approach is presented with the steps for solving the problem. In Section four, using testing data and modeling in different sizes, the contradictions in the target functions are investigated. Additionally, this section presents a real case study to evaluate the performance of the model and the proposed solution approach. Finally, Section five describes the conclusions and suggestions for future studies.

II. PROBLEM STATEMENT

Network $G = \{V, A\}$ is considered, where $V = N \cup S \cup E$ is the set of nodes and $A = V \times V$ is the set of available arcs. Set N includes n customers who should be visited. Each customer may have a pickup or delivery request; hence, set N is divided into two distinct sets, namely sets P and D which contain pickup and delivery nodes for customers, respectively ($N = P \cup D$). Set S includes the depots that the vehicle routes depart (starting depots), and set E contains the depots from which vehicle routes end (ending depots). c_{ij} is a non-negative travel cost from node i to node j for each arc (*i*,*j*). In this model, it is presumed that there are multiple vehicles with limited capacity. Each vehicle moves from an origin depot with a certain amount of cash and after delivery and pickup from customers, delivers the remaining amount of cash to the destination depot. The aim of this study is to specify v vehicle routes, where travel costs and risk of getting robbed or attacked must be minimized simultaneously, while considering pick-up and delivery operations and time windows. It should be mentioned that each customer must be assigned to exactly one of the p routes, and vehicle capacity CA must not be exceeded. Vehicle capacity shows the maximum number of valuables that a vehicle, based on its features, is permitted to haul.

A. Risk measure

In this subsection, we provide a detailed description of the developed risk measure and the procedure for calculating this measure. To measure risk, it is assumed that a vehicle can pick up and delivers cash at customer's locations. Thus, R_j^v as the risk index for each customer j when visited by vehicle v is described as follows:

$$R_j^v = R_i^v + M_i^v \cdot Q^v \cdot T_{ij} \cdot c_{ij} \tag{1}$$

Where c_{ij} is the travel cost between two successive customers i and j and M_i^v is the amount of money on board of the vehicle v when it leaves customer (node) i. M_i^v is specified for each customer, and is the cumulative amount of cash carried by the vehicle v from the depot $s \in S$ until customer i. Since, the calculation of risk has a significant impact on the optimal route selection and solution finding, two further parameters have been added to the formula of risk calculation in comparison with prior works, including Talarico et al., (2013) and Talarico et al., (2017). These parameters are extracted from ISO 31000:2018, Risk management – Guidelines. The parameter T_{ij} represents the threat level on route i and j. T_{ij} is defined for each route (r) and can be described as the likelihood, considering route characteristics. This Likelihood can be determined by using statistics obtained from past information provided by police regarding crimes and robberies committed at any street or route. If past statistical information is not available, the threat level of a route can be determined based on route characteristics like street width, degree of brightness, proximity to to police stations and etc. Consequently, due to its probabilistic nature, we consider the value of T_{ij} between zero and one. Q^v is the level of potential vulnerability in vehicle v. This parameter is defined for each vehicle and can be determined based on the characteristics of the vehicle as a level of vulnerability. The vulnerability level is specified according to the vehicle safety and technical and technological facilities. The risk index, presented in Equation (1), is an accumulative and growing measure of the risk encountered by the vehicle. Therefore, the "global route risk" R_e^v, associated with vehicle v, represents the risk incurred by the vehicle upon its return to the depot $e \epsilon E$.

B. Mathematical model

In this subsection, model notations, parameters, and decision variables of the proposed mixed-integer programming (MIP) model are presented.

Model notations:

i	Pickup location of customer i
$n+i$	Delivery location of customer i
v	Index of Vehicles
$N = P \cup D$	Customer nodes; $i = 1, 2, \ldots, 2n$
P	Pickup customers nodes; $i = 1, 2, \ldots, n$
D	Delivery to customers nodes; $i = n+1, n+2, \ldots, 2n$
S	Set of origin nodes (starting depots)
E	Set of destination nodes (ending depots)

Parameters:

V	Number of vehicles
Q^v	Level of vulnerability in vehicle v
d_i	Demand of customer i
CA	Capacity of each vehicle
t_{ij}	Travel time between nodes i and j
Th_{ij}	Threat Probability between nodes i and j
Vu^v	Vulnerability Level of vehicle v
d_i	Demand of customer i, which can be positive (for pickup) or negative (for delivery).
c_{ij}	Travel cost between nodes i and j

s_i	Service time at node i
$[a_i, b_i]$	Pickup time window for customer i
$[a_{n+i}, b_{n+i}]$	Delivery time window for customer i
$[a_0, b_0]$	Time window for leaving the origin
$[a_{2n+1}, b_{2n+1}]$	Time window for arriving to destination
bigM	A big constant number

Decision variables:

X_{ij}^v	Binary variable that equals 1 if arc $(i, j)\epsilon A$ is traversed by the vehicle v; otherwise, it equals 0.
T_i^v	Arrival time of vehicle v at node i
M_i^v	The amount ofcash transported by vehicle v when it leaves customer i
R_i^v	The cumulative risk index related to the vehicle v when it arrived at node i

MIP model of MO-RCVRP is presented as follows:

$$min \sum_{v\in V}\sum_{i\in N}\sum_{j\in N} c_{ij} \cdot X_{ij}^v \qquad (2)$$

$$min \sum_{j\in N}\sum_{v\in V} R_j^v \qquad (3)$$

s.t:

$$\sum_{v\in V}\sum_{j\in(N\cup E), i\neq j} X_{ij}^v = 1 \qquad \forall\ i \in (S \cup N \cup E) \qquad (4)$$

$$\sum_{i\in S}\sum_{j\in P} X_{ij}^v = 1 \qquad \forall\ v \in V \qquad (5)$$

$$\sum_{j\in(N\cup E), i\neq j} X_{ij}^v - \sum_{j\in(N\cup S), i\neq j} X_{ji}^v = 0 \qquad \forall\ i \in (S \cup N \cup E), v \in V \qquad (6)$$

$$\sum_{i\in N}\sum_{j\in E} X_{ij}^v = 1 \qquad \forall\ v \in V \qquad (7)$$

$$M_i^v \leq CA \qquad \forall\ i \in (S \cup N \cup E), v \in V \qquad (8)$$

$$T_i^v + s_i + t_{ij} \leq T_j^v + bigM \cdot (1 - X_{ij}^v) \qquad \forall\ i, j \in (S \cup N \cup E), v \in V \qquad (9)$$

$$T_i^v + t_{ij} \leq T_j^v + bigM \cdot (1 - X_{ij}^v) \qquad \forall\ i \in S, j \in P, v \in V \qquad (10)$$

$$T_i^v + s_i + t_{ij} \leq T_j^v + bigM \cdot (1 - X_{ij}^v) \qquad \forall\ i \in N, j \in E, v \in V \qquad (11)$$

$$a_i \leq T_i^v \leq b_i \qquad \forall\, i \in E, v \in V \tag{12}$$

$$M_i^v + d_j \leq M_j^v + bigM \cdot (1 - X_{ij}^v) \qquad \forall\, i \in (S \cup N), j \in (P \cup E), v \in V \tag{13}$$

$$M_i^v + d_j \geq M_j^v - bigM \cdot (1 - X_{ij}^v) \qquad \forall\, i \in (S \cup N), j \in (P \cup E), v \in V \tag{14}$$

$$R_i^v + M_i^v \cdot Vu^v \cdot Th_{ij} \cdot c_{ij} \leq R_j^v + bigM \cdot (1 - X_{ij}^v) \qquad \forall\, i \in (S \cup N \cup E), j \in (N \cup E)\ , v \in V \tag{15}$$

$$R_i^v + M_i^v \cdot Vu^v \cdot Th_{ij} \cdot c_{ij} \geq R_j^v + bigM \cdot (1 - X_{ij}^v) \qquad \forall\, i \in (S \cup N \cup E), j \in (N \cup E)\ , v \in V \tag{16}$$

$$T_s^v = 0; \quad M_s^v = 0; \quad R_s^v = 0 \qquad \forall\, s \in S, v \in V \tag{17}$$

$$T_i^v \geq 0; \quad M_i^v \geq 0; \quad R_i^v \geq 0 \qquad \forall\, i \in (S \cup N \cup E), v \in V \tag{18}$$

$$X_{ij}^v = \{\, 0,1 \,\} \qquad \forall\, i \in (S \cup N \cup E), v \in V \tag{19}$$

The objective function (2) specifies the minimization of total travel costs, while objective function (3) aims to minimize the total global route risk encountered by vehicles over all their collection routes. Constraint (4) ensures that each customer is visited by only one vehicle. Constraint (5) guarantees that each vehicle leaves the origin node only once. Constraint (6) represents that the vehicle v can leave node *j* only if it has previously entered it. Constraint (7) assures that each vehicle enters to destination node only once. Constraint (8) guarantees that maximum number of valuable items transported inside the vehicle must not exceed its capacity. Constraint (9) specifies that the arrival time of the vehicle v at node *j* equals the time to reach at node i plus the service time at node i and the interval time of the arc (*i*,*j*). Constraint (10) shows the sequence of origin nodes. Constraint (11) represents the sequence of destination nodes. Constraint (12) manages the time windows for service at the intermediary nodes, origin nodes and destination nodes (customers). Constraints (13) and (14) define the amount of money transported (shipped) in the vehicles when leaving customers. Constraints (15) and (16) represent the global route risk faced by the vehicle upon its return to the depot (the risk of transporting cash for each vehicle at each node). Constraints (17)-(19) define the domain constraints.

III. SOLUTION APPROACH

The proposed model to formulate the studied problem is a multi-objective mathematical model. To solve the model, the epsilon-constraint method is implemented as an exact solution approach. This method, developed by Chankong and Haimes (1983), is designed for general multi-objective problems and provides a representative subset of the Pareto set. In this method, high priority objective function is considered as the objective, while the remaining objective functions are transformed into constraints. Depending on whether the problem involves minimization or maximization, the objectives in the constraints are bounded by their upper or lower limits, respectively. For the bi-objective case, the mathematical formulation of the method is as follows:

$$Minimize\ F_1(x)$$

Subject to

$$F_2(x) \geq \varepsilon_2$$

In this study, the first objective function (minimization of traveled costs) is considered the high priority objective function and risk minimization objective function is transformed into a constraint.

The solution approach steps are also shown in Fig. 1.

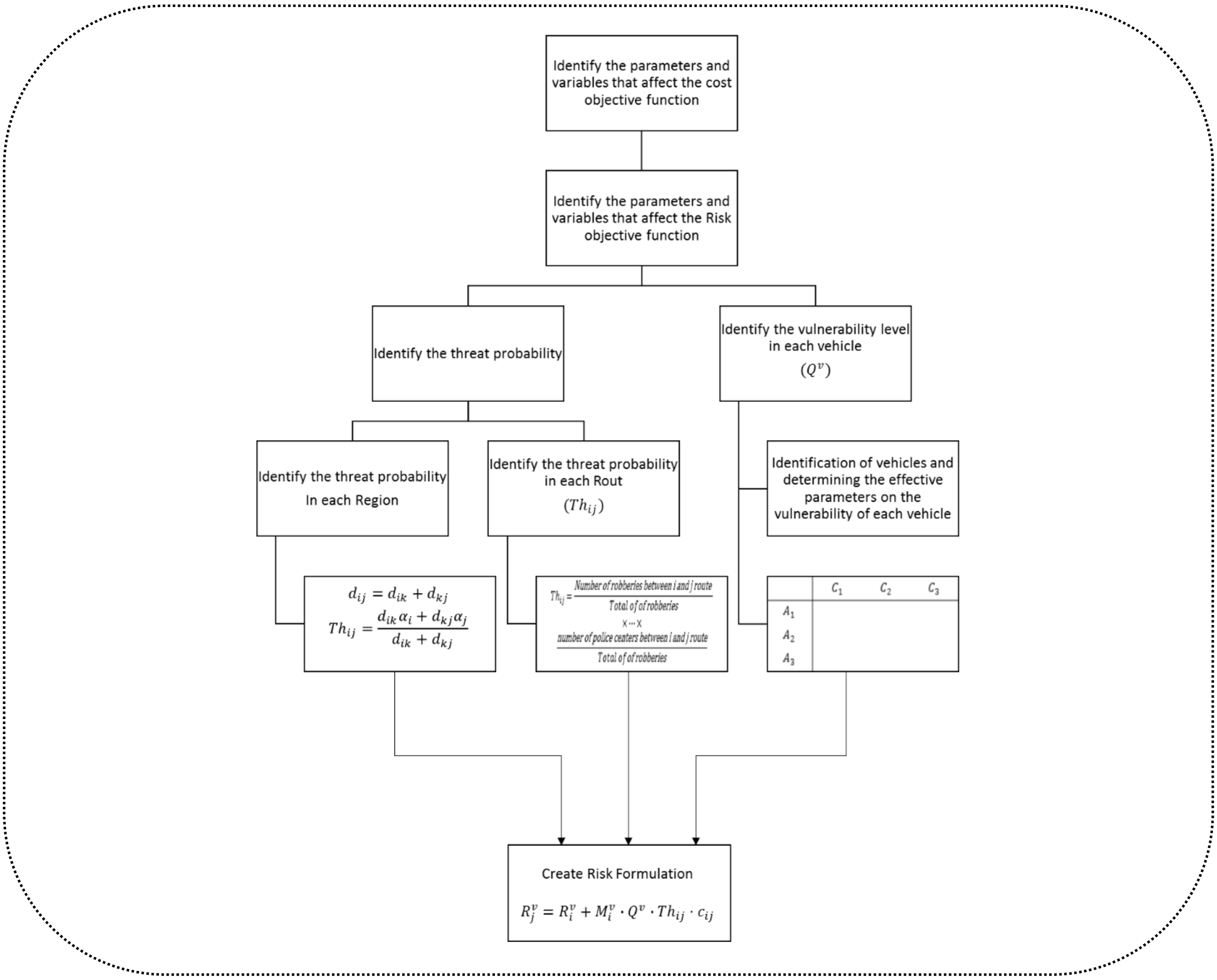

Fig. 1. Graphical abstract of solution approach

IV. COMPUTATIONAL EXPERIMENTS

A. Data generation for test problem

To evaluate the proposed model, ten test problems with random data were generated. The initial test problem included five customers, with parameters such as customer placement (within coordinates of 200 by 200 units), customer demand, the number of vehicles, vehicle capacity and the vulnerability level for the vehicle generated as random numbers between 0 and 100. The probability of threat for each route was generated using a normal distribution $(\mu = 0.5, \sigma = 0.2)$. Subsequent test problems were designed by increasing the size of the problem, adding five customers to each successive test problem. In accordance with Table 1, the final test problem included 50 customers. The proposed model and epsilon-constraint method were coded in GAMS software. All of the numerical experiments were performed on a PC with 2.67GHz CPU and 4 GB RAM.

Table I. Information of Testing Problems

Problem	Number of Customers	Number of Vehicles	Minimum Cost Value	Minimum Risk Value
1	5	2	554	387,434
2	10	2	754	811,257
3	15	3	1,049	1,565,696
4	20	3	1,194	2,377,790
5	25	4	1,462	3,095,787
6	30	4	---	---
7	35	5	---	---
8	40	5	---	---
9	45	6	---	---
10	50	6	---	---

The most important research gap is the lack of vulnerability and threat parameters existing in real world and standards analyzing and determining the probability of risk. The main advantages and significant contributions of this work include innovations in the risk assessment method and its evaluation through a real case study.

B. Results for test problems

Set of Pareto optimal solutions was obtained for all test problems. In Table I, the minimum cost and risk values are shown for test problems 6 to 10. As the size and complexity of the problems increased, solutions could not be obtained in a reasonable time. All Figures illustrate the results and the conflict between two objective functions is conspicuous. As the value of first objective function (travel cost) decreases, the values of second objective function (risk) increases. For example, Fig. 2 illustrates the Pareto frontiers for problem 2. Moreover, routing maps are shown in Fig. 3.

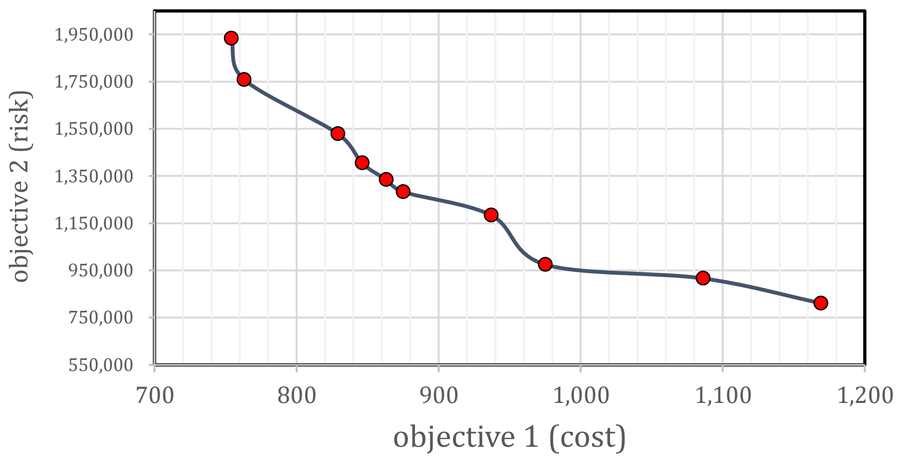

Fig. 2. The Pareto frontiers for test problem 2

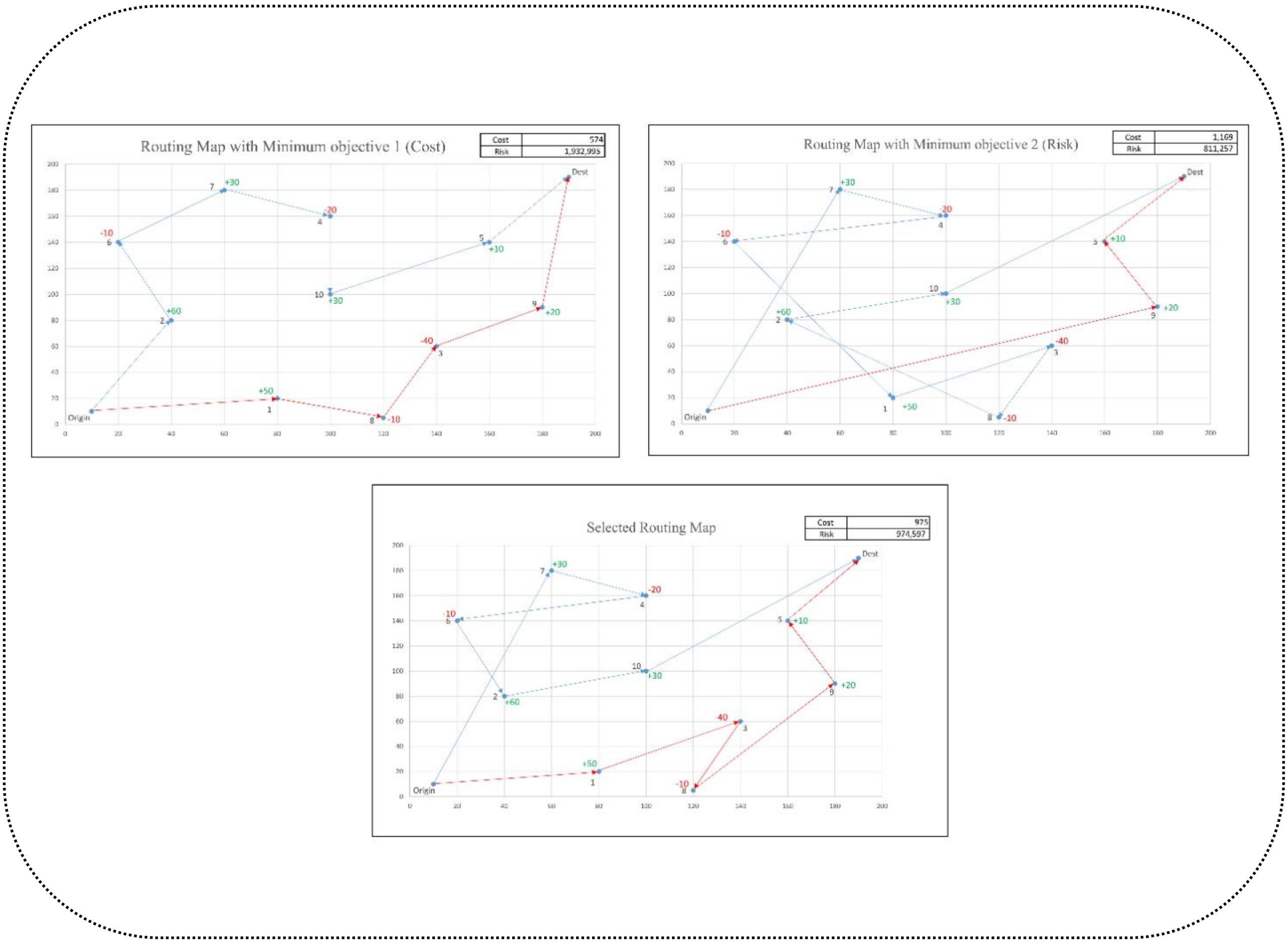

Fig. 3. Routing maps for test problem 2

As shown in Fig 3., we solved problem 2 considering only the minimum cost. The routing map indicates that the shortest path was taken to minimize the cost, resulting in a cost of 574. In contrast, it shows that when the problem was solved considering only the minimum risk, a long route was selected, leading to an increased cost of 1169. Finally, to select the optimal route from the Pareto solutions, we used the TOPSIS decision method.

C. Case Study

In this section, a model is developed and solved based on real data from an authentic bank located in Iran. This bank is located in a megacity with 235 active centers, which include the center, supervision, branches and Virtual Teller Machine (VTM). This problem involves moving from the bank's supervisory board office and then going/referring to the first branch which requires pickup, then selecting other branches that need picking up and delivering cash in a way that the selected route must have the lowest defined risk and transportation cost (travel cost). Supervisions are considered as depots, while VTMs and branches of bank are considered as pickup and delivery centers. In a real scenario, the transportation of cash problem by cash-in-transit vehicles will be addressed in this bank. For this purpose, a supervision of this bank and all subsidiaries' branches of this supervision, which all located in a specific geographical region of the city, have been selected. Due to the confidentiality of these information, the title of the branches is defined as an alias, and the required cash volumes are approximated without considering the actual unit. More information about supervision and branches is given in Table II.

TABLE II. Information related to the depot, delivery and pick-up customers

No	Title of centers	District number	Type of center	Required cash volume
1	A	7	Depot	-
2	B	6	Pickup	+1200
3	C	11	Delivery	-300
4	D	11	Delivery	-200
5	E	6	Pickup	+600
6	F	6	Delivery	-400
7	G	6	Delivery	-500
8	H	6	Delivery	-200
9	I	12	Pickup	+700
10	J	12	Delivery	-300
11	K	12	Pickup	+600
12	L	7	Delivery	-500
13	M	7	Delivery	-300
14	N	2	Delivery	-400
15	O	2	Pickup	+200
16	P	2	Depot	-

Furthermore, the intervals (distances) between nodes are calculated in Table III.

TABLE III. Distance between nodes (km)

Title of centers	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P
A	-	4.5	7.5	6.5	6.9	9.4	7.7	8.5	5.9	3.5	7.2	6.8	6.5	12.6	14.2	21.9
B	-	-	2.9	2.3	2.6	3.6	3.5	4.1	2.6	2.5	4.4	6.6	4.5	7.3	6.5	13.7
C	-	-	-	0.5	1.8	2.7	2.7	3.2	2.6	3.5	3.3	8.9	5.7	6.3	5.5	12
D	-	-	-	-	1.8	2.7	2.6	3.2	1.9	2.8	2.6	7.4	5.7	6.2	5.5	9.4
E	-	-	-	-	-	1	1	1.7	3.6	4.5	4.3	9.6	6.3	4.6	3.7	9.4
F	-	-	-	-	-	-	1	1.5	4.7	5.6	5.4	9.4	6.1	4.8	3.1	9.7
G	-	-	-	-	-	-	-	1	4.2	5.1	4.9	8.9	5.7	5.8	3.6	9.2
H	-	-	-	-	-	-	-	-	5.1	6	5.8	8.2	5.2	6.7	5	8.2
I	-	-	-	-	-	-	-	-	-	3.8	2.1	10.7	7.4	7.7	6.9	14.4
J	-	-	-	-	-	-	-	-	-	-	1.9	7.1	5.3	9.7	9	16.8
K	-	-	-	-	-	-	-	-	-	-	-	9.7	6.6	9	8.2	15.7
L	-	-	-	-	-	-	-	-	-	-	-	-	2.1	15.3	12.4	12
M	-	-	-	-	-	-	-	-	-	-	-	-	-	15.7	11.8	10.7
N	-	-	-	-	-	-	-	-	-	-	-	-	-	-	4.7	9.9
O	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	6.4
P	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-

he threat level for each route between two nodes should then be calculated. For this purpose, each node (either a branch or a bank supervision) is located in one of the urban areas, which is based on the statistics provided by the Social Security Department of the Islamic Republic of Iran, which are shown in Table IV. According to the provided statistics on the robbery incidents in each region (district), the probability of a threat for each route can be calculated. It should be noted that, in addition to robbery incidents, other factors such as road lighting, width of a road, average speed of vehicles, vicinity to main streets, etc., can be applied to calculate the threat more precisely.

TABLE IV. The number of urban crimes committed in Tehran with 22 districts

Crime / Region (District)	Murder	Individual and group conflicts	Robbery	Crimes related to vandalization	Social corruption
1	3	994	2182	143	465
2	5	1586	2566	319	451
3	6	1791	3796	387	666
4	10	3481	3143	277	962
5	5	1365	1926	161	544
6	2	805	1405	170	981
7	2	1414	2593	282	390
8	4	966	1328	113	326
9	4	1260	987	120	654
10	2	651	411	135	520
11	5	798	1078	166	580
12	7	1555	2979	403	752
13	3	548	1139	42	275
14	6	1222	1933	136	797
15	3	1351	759	150	556
16	5	1709	935	170	755
17	10	714	436	48	473
18	2	578	335	63	228
19	4	1960	265	69	328
20	1	652	748	157	204
21	1	134	193	9	56
22	2	139	217	26	39

The threat probability for each city district where the branches are located is shown in Table V.

TABLE V. Threat likelihood in each urban district

No	Districts	Robbery statistics	Threat likelihood
1	2	2566	24%
2	6	1405	13%
3	7	2593	24%
4	11	1078	10%
5	12	2979	28%
Total		10621	100%

To calculate the threat level for each route between the nodes *i* and *j*, the percentage of the distance which is covered within each of the mentioned districts is considered. By using a balanced average of the probabilities between the two urban districts, the threat level is calculated as follows and illustrated in Fig 4.

$$d_{ij} = d_{ik} + d_{kj} \tag{20}$$

$$Th_{ij} = \frac{d_{ik}\alpha_i + d_{kj}\alpha_j}{d_{ik} + d_{kj}} \tag{21}$$

d_{ij} : Distance between the nodes i and *j*

d_{ik} : Distance between the nodes *i* and *k* (boundary of the area *i* and *j*)

d_{kj} : Distance between the nodes *j* and *k* (boundary of the area *i* and *j*)

α_i : Threat in area of *i*

α_j : Threat in area of *j*

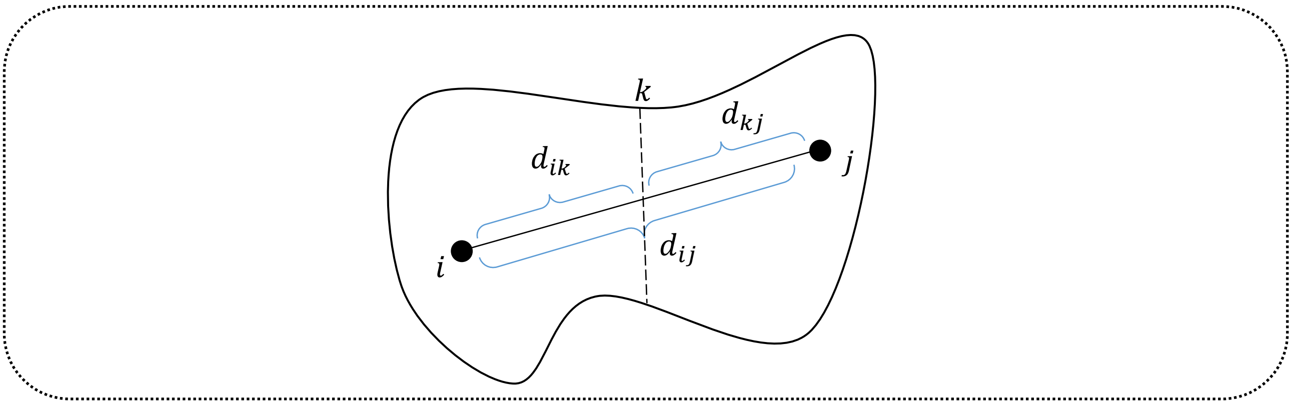

Fig. 4. Balanced average for calculated threat probability

For the sake of simplicity, the Simple Average Method was used. Eventually, the calculated threat probability (T_{ij}) for each route is given in Table VI.

The next parameter considered is the level of potential vulnerability for each vehicle. For this purpose, three criteria among most important criteria were selected as follows:

1. Armor Level: The level of armor resistance of the vehicle's body.
2. Seating Capacity: The capacity of the vehicle for security forces.
3. Engine: The vehicle's maneuvering capability while driving.

By examining various products offered by reputable companies, four types of vehicles were selected. In the next step, the decision matrix and the Analytic Hierarchy Process (AHP) method were employed to evaluate the resistance level of each vehicle, which is inversely related to the vulnerability level. It should be noted that any common method in decision analysis techniques can be used to calculate the weights. Table shows the vulnerability levels of the three selected vehicles in the case study.

TABLE VI. Threat probability in each route

Title of centers	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P
A	-	19%	17%	17%	19%	19%	19%	19%	26%	26%	26%	24%	24%	24%	24%	24%
B	-	-	12%	12%	13%	13%	13%	13%	21%	21%	21%	19%	19%	19%	19%	19%
C	-	-	-	10%	12%	12%	12%	12%	19%	19%	19%	17%	17%	17%	17%	17%
D	-	-	-	-	12%	12%	12%	12%	19%	19%	19%	17%	17%	17%	17%	17%
E	-	-	-	-	-	13%	13%	13%	21%	21%	21%	19%	19%	19%	19%	19%
F	-	-	-	-	-	-	13%	13%	21%	21%	21%	19%	19%	19%	19%	19%
G	-	-	-	-	-	-	-	13%	21%	21%	21%	19%	19%	19%	19%	19%
H	-	-	-	-	-	-	-	-	21%	21%	21%	19%	19%	19%	19%	19%
I	-	-	-	-	-	-	-	-	-	28%	28%	26%	26%	26%	26%	26%
J	-	-	-	-	-	-	-	-	-	-	28%	26%	26%	26%	26%	26%
K	-	-	-	-	-	-	-	-	-	-	-	26%	26%	26%	26%	26%
L	-	-	-	-	-	-	-	-	-	-	-	-	24%	24%	24%	24%
M	-	-	-	-	-	-	-	-	-	-	-	-	-	24%	24%	24%
N	-	-	-	-	-	-	-	-	-	-	-	-	-	-	24%	24%
O	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	24%
P	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-

TABLE VII. Weight of resistance level for each vehicle

Model-make	Armor level	Seating capacity	Engine	Weight
Iveco-Euro Daily (6)	3	3	3	0.1059
Toyota-Land Cruiser 79	3	4	4	0.1466
Ford-F-650	4	5	6.7	0.3916
Ford TRANSIT 350HD	2	2	3.2	0.0397
Hino-338	4	3	8	0.3312

Table VIII.Vulnerability levels of each vehicle in the case study

Vehicle	1 Ford-F-650	2 Toyota-Land Cruiser 79	3 Iveco-Euro Daily (6)
Vehicle Vulnerability	60	85	89

After solving the case study, a set of Pareto solutions is presented in Fig. 5. This Figure illustrates the results, and the conflict between the two objective functions is conspicuous; as the value of first objective function (travel cost) decreases, the values of the second objective function (risk) increase.

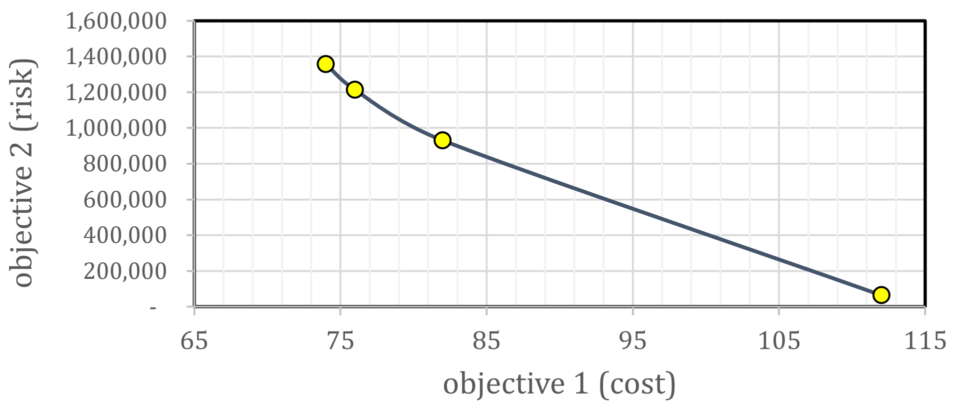

Fig. 5. The Pareto frontiers for the case study

As observed in Fig. 6, we solved the case study by considering only the minimum cost; the routing map indicates that the shortest route was taken, resulting in a total cost of 74. However, in Fig. 7, the problem was solved considering the minimum risk (total risk = 64.600). It can be seen that a longer route was taken, leading to an increased cost of 112. Other information on the rate of risk reduction and, on the other hand, the increase in the amount of costs is shown in Table IX. Finally, to select the optimal route from the Pareto solutions, we used the TOPSIS decision method. In employing this method for route selection, we first normalized the criteria, followed by determining both positive and negative ideal solutions. Subsequently, we calculated the distances from each option to these ideal solutions. the alternatives were finally ranked based on their proximity to the ideal solutions. In our case study, with four routes evaluated based on cost and risk, sol_4 emerged as the optimal choice, demonstrating the best balance between these criteria.

Table IX. Pareto table for the case study

	Cost value	Risk value
sol_1	74	1,357,412
sol_2	76	1,213,766
sol_3	82	930,274
sol_4*	112	64,600

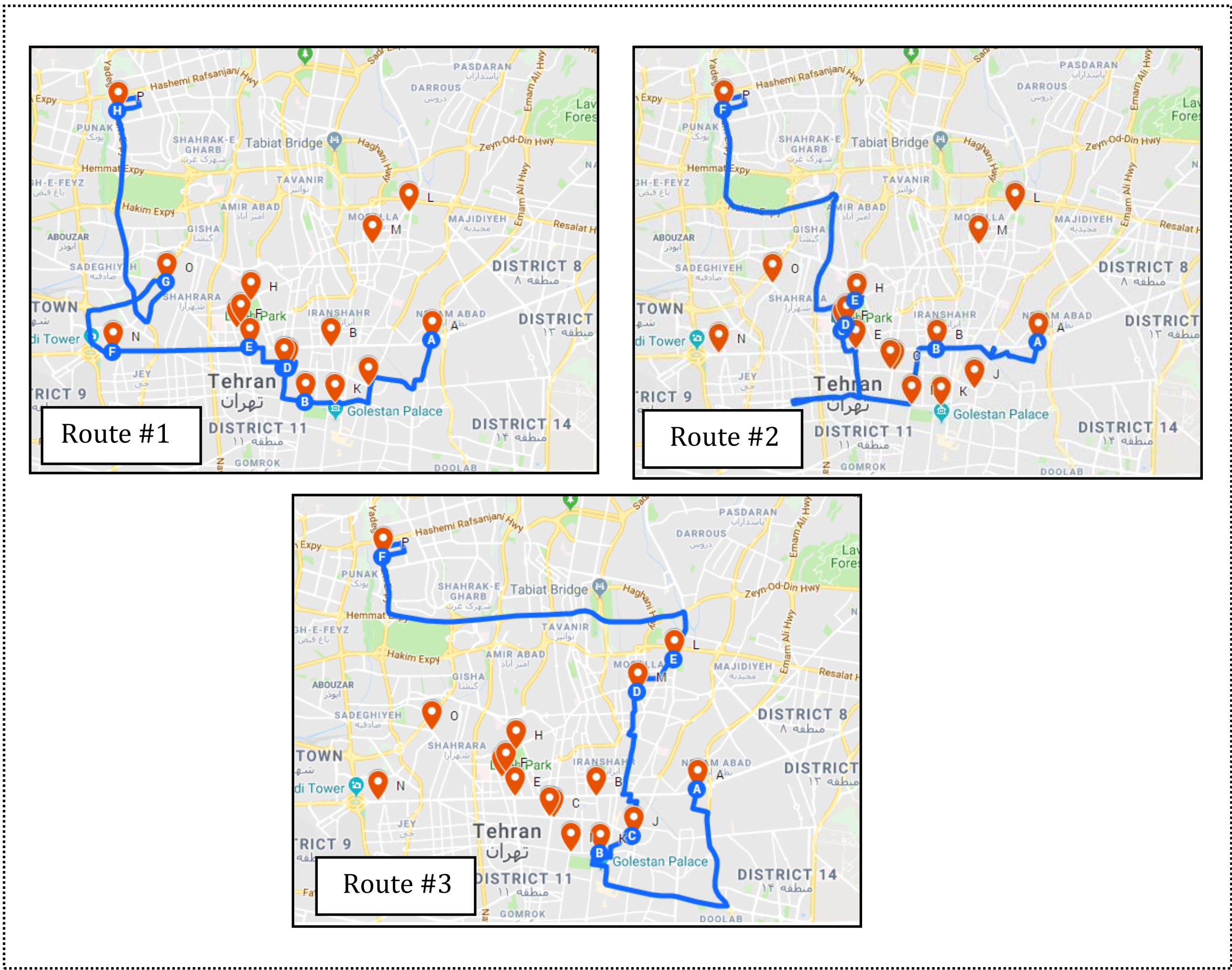

Fig. 6. Routing map with minimum cost for the case study (total cost=74)

According to the results obtained from the test problems and the case study, it can be concluded that the approach used in the assessment and calculation of risk is strikingly effective in selecting the optimal route. In the aforementioned case study, two parameters-vulnerability and threat level-have been added to the problem. It is observed that the first vehicle with a lower vulnerability level has taken a longer route than other vehicles with higher vulnerability levels, even though there is not much difference between their vulnerability levels. On the other hand, among the routes selected by the vehicles, the priority was to select routes with a lower threat level. Therefore, employing these parameters in the real world can significantly impact the determination of solution types and obtained results. Additionally, the problem analyst's perspective can be very influential in determining the type of risk formula. In this approach, we use the same paradigm for risk parameters and allocate them equal weights. Hence, based on the decision maker's preferences, an exponential approach can be used for the risk formula or risk objective function. Also, weights can be allocated to parameters.

Threat probability is schematically represented in Fig. 8.

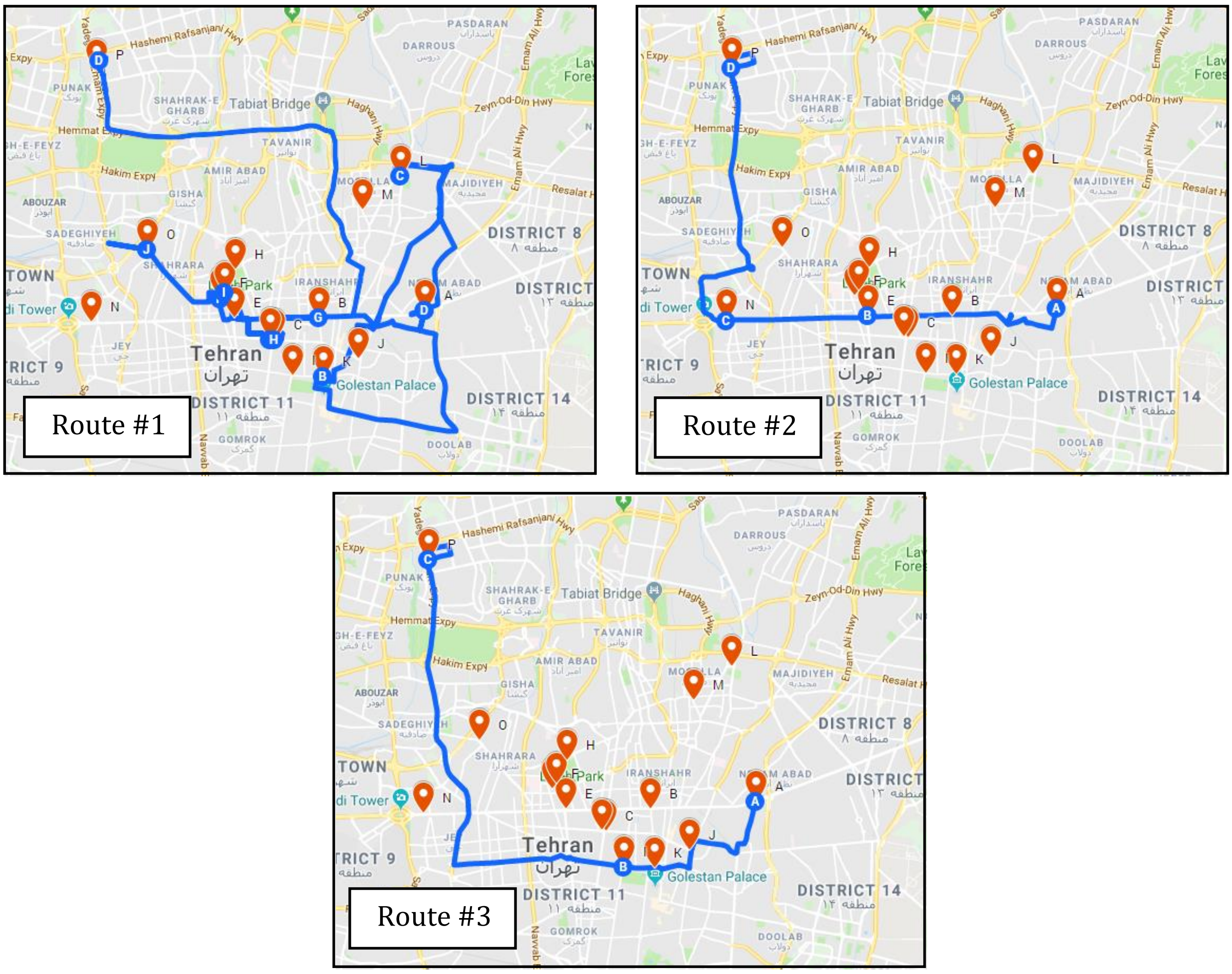

Fig. 7. Routing map with minimum risk for the case study (total risk=64.600)

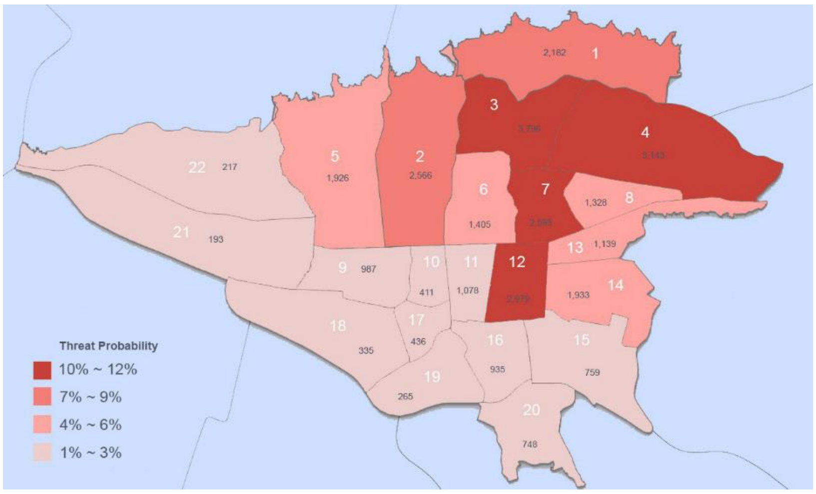

Fig. 8. Threat probability for each district

Moreover, we concluded that if we consider the problem as a pickup and delivery vehicle routing problem without considering risk, a vehicle will aim to carry a maximum amount of cash if it does not exceed its capacity. Considering the risk approach in the problem, the vehicle tries to carry the minimum amount of cash. After picking up the cash, it will be delivered to the first person in need, provided that it is in accord with its supplied cash, in order to minimize the risk.

V. CONCLUSION

In this paper, a bi-objective mixed-integer non-linear programming model with practical applications in the CIT sector was offered; the first objective is to minimize total travel cost and the second objective aims to minimize the risk exposure to robberies. To calculate the risk related to a robbery, two new and critical parameters have been employed. In the proposed formula, the vulnerability level and threat probability are two effective parameters in risk evaluation. To solve the model, the Epsilon-constraint method using the GAMS solver has been implemented. The Solution approach has been tested on a set of small, medium, and large instances, resulting in producing a limited set of Pareto front points. To illustrate our method, a case study is presented.

Some suggestions for future work are as follows: Recently, risk assessment in optimization models has received increasing attention, and still, many contributions to optimization problems can be considered. For example, in this particular issue, as discussed above, the risk-based formulation can be improved by adding other parameters, weight allocation, and formula modification. Furthermore, methods for calculating the parameters of the problem can be developed and enhanced. Also, due to the probabilistic nature of certain parameters, such as the threat parameter (T), uncertainty methods can be used in optimization solutions, including stochastic programming, dynamic programming, fuzzy programming, or robust optimization. The model can be developed and extended to other types of transportation, considering the real-world needs, such as: heterogeneous VRP, split delivery VRP, and hub-and-location VRP.

REFERENCES

Bozkaya, B., Salman, F. S., & Telciler, K. (2017). An adaptive and diversified vehicle routing approach to reducing the security risk of cash-in-transit operations. Networks, 69(3), 256-269.

Calvo, R. W., & Cordone, R. (2003). A heuristic approach to the overnight security service problem. Computers & Operations Research, 30(9), 1269-1287.

Chankong, V., & Haimes, Y. Y. (1983). Multiobjective decision making theory and methodology. North Holland, New York.

Ge, X., Jin, Y., & Zhang, L. (2023). Genetic-based algorithms for cash-in-transit multi depot vehicle routing problems: economic and environmental optimization. Environment, Development and Sustainability, 25(1), 557-586.

Ghannadpour, S. F., & Zandiyeh, F. (2020). An adapted multi-objective genetic algorithm for solving the cash in transit vehicle routing problem with vulnerability estimation for risk quantification. Engineering Applications of Artificial Intelligence, 96, 103964.

Krarup, J. (1995). The peripatetic salesman and some related unsolved problems. In Combinatorial programming: methods and applications (pp. 173-178). Springer, Dordrecht.

Meiyi, W., Xiang, L., & Lean, Y. (2015). Time-dependent fuzzy random location-scheduling programming for hazardous materials transportation. Transportation Research Part C: Emerging Technologies, 57, 146-165.

Momeni, M., Soleimani, H., & Mirzapour Al-e-Hashem, S. M. J. (2022). A nonlinear mathematical model for autonomous vehicle routing problem by considering traffic congestion for each route. Journal of Quality Engineering and Production Optimization, 7(2), 14-33.

Ngueveu, S. U., Prins, C., & Calvo, R. W. (2009). A hybrid tabu search for the m-peripatetic vehicle routing problem. In Matheuristics (pp. 253-266). Springer, Boston, MA.

Radojičić, N., Marić, M., & Takači, A. (2018). A new fuzzy version of the risk-constrained cash-in-transit vehicle routing problem. Information Technology and Control, 47(2), 321-337.

Rezaeipanah, A., Ahmadi, G., Hajiani, M., & Darzi, M. R. (2019). An improved hybrid cuckoo search algorithm for vehicle routing problem with time windows. Journal of Quality Engineering and Production Optimization, 4(2), 189-208.

Smith, L., & Louis, E. (2010). Cash in transit armed robbery in Australia. Trends and Issues in Crime and Criminal Justice, (397), 1-6.

Soltanzadeh, S., Mardan, E., & Kamran Rad, R. (2020). An electric vehicle routing problem with battery swap and battery recharge approach. Journal of Quality Engineering and Production Optimization, 5(2), 1-20.

Talarico, L., Sörensen, K., & Springael, J. (2013). The risk-constrained cash-in-transit vehicle routing problem with time window constraints. In 14th Workshop of the EURO Working Group (pp. 104-109).

Talarico, L., Sörensen, K., & Springael, J. (2015). Metaheuristics for the risk-constrained cash-in-transit vehicle routing problem. European Journal of Operational Research, 244(2), 457-470.

Talarico, L., Sörensen, K., & Springael, J. (2017). A biobjective decision model to increase security and reduce travel costs in the cash-in-transit sector. International Transactions in Operational Research, 24(1-2), 59-76.

Tikani, H., Setak, M., & Demir, E. (2021). A risk-constrained time-dependent cash-in-transit routing problem in multigraph under uncertainty. European Journal of Operational Research, 293(2), 703-730.

Van Raemdonck, K., Macharis, C., & Mairesse, O. (2013). Risk analysis system for the transport of hazardous materials. Journal of Safety Research, 45, 55-63.

Vahdat Zad, M. A. (2018). A mathematical programming for a special case of 2E-LRP in cash-in-transit sector having rich variants. International Journal of Industrial Engineering & Production Research, 29(2), 159-174.

Xu, G., Li, Y., Szeto, W. Y., & Li, J. (2019). A cash transportation vehicle routing problem with combinations of different cash denominations. International Transactions in Operational Research.

Yildiz, A., Guneri, A. F., Ozkan, C., Ayyildiz, E., & Taskin, A. (2022). An integrated interval-valued intuitionistic fuzzy AHP-TOPSIS methodology to determine the safest route for cash in transit operations: a real case in Istanbul. Neural Computing and Applications, 34(18), 15673-15688.