Scientia Iranica (2024) 31(11), 847–865

SCIENTIA IRANICA

Sharif University of Technology
Scientia Iranica
Transactions E: Industrial Engineering
https://scientiairanica.sharif.edu

A stochastic-fuzzy multi-objective model for the last-mile delivery problem using drones and ground vehicles, a case study

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Received 12 March 2021; received in revised form 11 July 2021; accepted 9 May 2022

KEYWORDS
Drone delivery;
Last-mile delivery;
E-commerce;
AUGMECON2;
Multi-objective optimization.

Abstract. Drone delivery as a novel approach for parcel delivery has been under the focus of many scholars and practitioners. In this regard, this paper introduces a stochastic-fuzzy multi-objective optimization model for designing a last-mile delivery system with drones and ground vehicles. The first two objective functions aim to minimize the detrimental effects of the delivery system on the environment and the total costs. The last objective function maximized the system's reliability by considering the breakdown probability of both drones and ground vehicles. Then, AUGMECON2 is utilized as an exact method to solve the proposed model. Besides determining the number of required drones and ground vehicles, the model indicates locations and capacities of facilities where vehicles start their one-to-one trips to meet the customer demands. The proposed model is then validated by applying it to a real case study of an e-commerce company in Karaj, Iran. The findings suggest that the system's total cost rises when the reliability increases and the environmental impacts decrease. Furthermore, when both drones and ground vehicles are considered for meeting the customer demands, the delivery system functions better in terms of costs, environmental impacts and reliability than when only one mode of delivery is considered.

1. Introduction

The growing number of e-commerce companies and increased parcel volumes to be delivered to customers have resulted in the emergence of novel last-mile delivery concepts and tools. One of these novel concepts is the utilization of drones, which are also known as Unmanned Aerial Vehicles (UAVs) [1]. In addition to the commercial services and package deliveries, the applications of drones have also been investigated in emergency search and rescue operations [2], medical

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To cite this article:
K. Rahmani Mokarrari, Sh. Shirazian, A. Aghsami, and F. Jolai "A stochastic-fuzzy multi-objective model for the last-mile delivery problem using drones and ground vehicles, a case study", *Scientia Iranica* (2024), **31**(11), pp. 847-865
DOI: 10.24200/sci.2022.57891.5460

purposes [3], last-mile distribution of relief goods, and critical medical supplies for post-disaster emergencies [4,5].

Traffic jams and fuel costs are significant obstacles to delivery operations. UAVs are efficient tools to tackle this problem by reducing delivery time and costs [6]. Gong et al. [7] previously considered a transportation mode selection based on costs and carbon emissions to reduce environmental effects. Mohtashami [8] mentioned that transportation fleets are a significant factor leading to an increase in environmental impacts. However, in terms of energy efficiency and CO_2 emissions, UAVs proved to have a better performance than other ground vehicles and modes of delivery [9]. Park et al. [10] have also compared the environmental impacts of drone and motorcycle delivery. They concluded that the global warming potential per 1 km delivery by motorcycle is six times more than UAVs. Chiang et al. [11] also proposed a mixed-integer green routing model for drone delivery to investigate UAVs' impact on CO_2 emissions and cost. This study concluded that using UAVs for last-mile logistics is both cost-effective and environmentally friendly.

Considering these points, many companies worldwide, such as DHL, Google, and Amazon, have started to employ drones for their last-mile delivery [12]. The applications of drones in parcel delivery have mainly been investigated in developed countries and leading e-commerce businesses such as Amazon. However, in developing countries such as Iran, drones for package delivery purposes are gradually being brought into focus. Since 2016, Digikala, the largest e-commerce company in Iran, has been investigating the possibilities of using cargo drones for parcel delivery. This company has even held a competition and invited the academics and robotic teams to design and construct UAVs suitable for delivering 2 kg packages to customers. The National Post Company of Iran has recently unveiled its drones for postal package delivery [13,14].

It should also be noted that, like any other type of vehicle, drones are prone to failures and breakdowns. Internal technical problems or weather conditions can lead to a drone malfunction [12]. However, the breakdown probability of drones has been overlooked in most of the previous studies.

Regarding the discussed points, drones are expected to be widely used by e-commerce and postal companies as an efficient last-mile delivery means. Therefore, it is necessary to provide optimization models to propose the optimal way of utilizing drones for last-mile delivery that is efficient in terms of reliability, environmental and economic aspects. These three aspects have never been considered simultaneously in a drone delivery network design. We aim to fill this gap by proposing a multi-objective model to study the trade-off among these aspects.

In this paper, we design a last-mile delivery system network that utilizes a heterogeneous fleet of ground vehicles and drones for delivering parcels to a set of customers with stochastic demands. Other sources of uncertainties are also taken into account to make this study more consistent with real-world cases. These uncertainties include fuzzy parameters such as costs, drones' battery capacity, and breakdown rates of drones and ground vehicles. The proposed model is designed to determine the locations of launching facilities and their capacities, the number of required drones and vehicles, and the allocation of customers to each facility and vehicle by minimizing total costs, environmental impacts and maximizing the system's reliability. Moreover, a real case study in an Iranian e-commerce company is presented to investigate the proposed model's applicability.

The remainder of this paper proceeds as follows: Section 2 presents the literature review. Section 3 describes the problem and presents our proposed model. In Section 4, the solution methodology is presented. In Section 5, the case study is introduced, and in Section 6, the case study results are presented. Sensitivity analysis is carried out in Section 7, and managerial insights are presented in Section 8. Section 9 concludes the paper and proposes future directions to extend the current paper.

2. Literature review

Many scholars have reviewed the relevant literature on the utilization of drones in logistics and last-mile delivery. Chung et al. [12] studied the optimization problems related to the applications of drone and drone-truck operations in urban areas. Otto et al. [15] reviewed papers on the urban applications of UAVs. Rojas Viloria et al. [16] reviewed drone routing problems. Macrina et al. [17] is another recent survey that reviewed studies on transportation systems where deliveries are performed by trucks and drones.

A large body of literature on drone delivery has focused on studying novel variants of the traveling salesman and vehicle routing problems. Previous studies in this context can be divided into two major streams: papers that only investigate the drones' operations and those that consider drones working collaboratively with trucks or ground vehicles.

Sundar and Rathinam [18] developed an approximation algorithm and fast heuristics for a mixed-integer linear model for a single UAV routing problem with multiple depots that can also act as a refueling station for the drone. Kim et al. [19] also contributed to the literature by addressing the uncertainty of flight duration (i.e., battery capacity) in the form of a robust optimization model to indicate the number of drones and their flight routes. The authors concluded that taking the uncertainty into account minimizes drones' failure rate to return to their initial depot.

Murray and Chu [20] proposed a mixed-integer linear programming model for routing and scheduling a drone working collaboratively with a delivery truck to minimize the service time. They termed this problem the flying sidekick traveling salesman problem. Ha et al. [21] extended the previous paper by introducing a new variant of the traveling salesman problem in which the waiting time of both truck and drone is captured and minimized. Agatz et al. [22] modeled the Traveling Salesman Problem with a drone and a truck and demonstrated that the truck-drone delivery system is remarkably more cost-saving than truck-only delivery. Schermer et al. [23] introduced the Traveling Salesman Drone Station Location Problem (TSDSLP), which incorporated the Traveling Salesman, Facility Location, and Parallel Machine Scheduling problems. Murray and Raj [24] have also extended the original flying sidekicks traveling salesman problem by considering parcels be distributed via multiple heterogeneous UAVs with different travel speeds, payload capacities, service times, and flight endurance limitations. A detailed queue scheduling for UAV arrivals and departures is incorporated within the proposed MILP formulation.

Carlsson and Song [25] investigated the efficiency of a truck-UAV delivery system by real-time simulation and theoretical analysis in the Euclidean plane. They concluded that the system's efficiency improvement depends on the speed of the truck and UAV. Moshref-Javadi et al. [26] investigated a truck-drone routing problem, where a single truck stops at customer locations and launches drones multiple times to satisfy customer demands. The objective function of this problem minimizes the customers' waiting time. A hybrid metaheuristic algorithm based on Simulated Annealing and Tabu Search is developed to solve large-size problems. Moreover, several bound analyses were conducted to demonstrate the maximum customer waiting time reductions compared to the truck-only delivery system. Moshref-Javadi et al. [27] investigated a more complex problem, where the truck continues its route instead of waiting for the drones to return after dispatching. The truck then collects the drones at a different location.

Salama and Srinivas [28] proposed a new model for clustering delivery locations and routing decisions. A fleet of homogenous drones is carried with a single truck to focal points to satisfy customer demands. The authors considered two different policies for indicating focal points: (1) limiting the truck stop locations to customer locations and (2) allowing stop locations to be anywhere in the delivery region. The case of multiple drones and multiple trucks was furthered investigated by considering capacity limitations for both trucks and drones [29]. The proposed model seeks to cover two delivery levels consisting of truck routing from the main depot and drone routing. Also, two efficient heuristic algorithms are applied for large-size problems.

Recently, a growing number of studies have investigated facility location problems for drone delivery systems. The effectiveness of delivery systems is highly dependent on the location of distribution centers. In this regard, Shavarani et al. [30] proposed a bi-objective stochastic facility location problem that minimizes uncovered customers and facility establishment and drone's total cost procurement simultaneously. In this study, customers are uniformly distributed along the network edges, and their demand follows the Poisson distribution. A similar problem in the context of humanitarian relief logistics for the Tehran earthquake was studied by Golabi et al. [31] to minimize the aggregated traveling time of people to the relief facilities and drones from located facilities to the inaccessible demand points.

In addition to determining the location of launching facilities, Shavarani et al. [32] considered refueling station establishment for drones as a multi-level facility location problem. Moreover, customer demand, distance capacity, and network costs are fuzzy variables. The problem's objective function aims to minimize the customer waiting time, which is restricted to the M/G/K queueing system. Hong et al. [33] also proposed a MIP formulation and an efficient heuristic algorithm to locate recharging stations and construct a feasible drone delivery network in an area with obstacles. Kim et al. [34] proposed two planning models for strategic (location) and operational (routing) planning for a pick-up and delivery problem of medical supplies.

Dukkanci et al. [35] investigated the energy minimization problem of drone delivery with speed range constraints. Chauhan et al. [36] studied a maximum coverage facility location problem with drones where drone energy consumption was introduced as a function of distance and payload. As the short-term planning period was assumed, the recharging of drone batteries is not considered. A three-stage heuristic approach is applied, consisting of a facility location and allocation problem, multiple knapsack sub-problems, and a final local search stage. Chauhan et al. [37] then improved the previous paper by considering the uncertainty in initial battery availability and drones' battery consumption. To that end, a robust optimization framework is utilized, resulting in a more reliable estimation of the actual coverage of drones. Considering uncertainty, Kim et al. [38] proposed a stochastic facility location model applicable to emergency planning and humanitarian logistics. Chen et al. [39] have also considered uncertainty in demand to study revenue and capacity decisions of drone delivery operations.

Natural disasters, breakdowns, and failures can interrupt supply chains and delivery networks. Therefore, the reliability of these networks is one of the most important areas that has been studied in different parts of supply chains. The reliability of hub locations, supplying facilities, and communication paths have been addressed in multiple studies, such as [40–42]. However, the reliability of vehicles has rarely been investigated.

Vehicles are inevitably subjected to breakdowns causing economic losses and customer dissatisfaction [43]. Drones may experience breakdowns as well. In addition to internal problems, drones' functionality can be affected by weather conditions such as wind, extreme temperatures, and humidity [12]. However, taking these factors and the uncertainty involved in drones' operations has been neglected in most previous studies [12]. In general, five main strategies are introduced to alleviate vehicle breakdowns. (1) repair the vehicle to resume the operation, (2) employing another vehicle from the available ones, (3) rent a new vehicle temporarily, (4) quite the broken vehicle and employ the available ones, and (5) quite the broken vehicle and prepare a new one [44].

As discussed, drones are superior in terms of speed, flexibility in moving, and energy consumption. Moreover, they do not need human pilots, can avoid traffics, and are more environmentally friendly [12,20,21,26]. However, a significant challenge to drone delivery is their limited flying range and carrying capacity [36]. In other words, drones usually can only pick up one light package at a time, and their traveling range usually is shorter than that of trucks. Moreover, contrary to popular belief, drones are not entirely emission-free. The utilized electricity to recharge drones may be generated from fossil fuels, leading to more emissions compared to the ground vehicles for long-distance deliveries [12]. Therefore, to improve the efficiency and quality of last-mile delivery and reduce transportation costs, drones and ground vehicles can be utilized cooperatively to deliver goods to customers [12,21].

From the literature review, it can be concluded that the failures of drones have not been considered in almost any of previous drones' last-mile delivery problems. More importantly, three critical aspects of delivery systems, namely environmental, economic, and reliability, have not been taken into account simultaneously. The uncertain nature of some parameters of such a problem has also been overlooked in many studies. This paper aims to contribute to drone delivery literature by considering both fuzzy and stochastic uncertainties involved in a last-mile delivery problem of drones. Moreover, in order to have a reliable logistic network, it is necessary to take the breakdowns of drones into account, which has been overlooked in previous studies. Meanwhile, considering that utilizing drones is not always environmentally friendly and cost-effective, we construct a model capable of deciding between ground vehicles and drones to deliver customer parcels. The proposed model in this paper simultaneously captures facility location and allocation decisions in addition to the optimal number of vehicles required to meet the customer demands effectively. Due to the problem's multi-objective nature (environmental, economic, and reliability aspects), we employed the AUGMECON2 method to solve the model.

3. Problem description and formulation

A mixed-integer linear formulation of the last-mile delivery for drones and motorcycle delivery is proposed in this section. This model aims to determine the location of depots (i.e., launching facilities) and each facility's inventory. It is assumed that there are a given number of customers with specific locations and with stochastic demands based on the available historical data. The delivery of these demands takes place by either motorcycles or a heterogeneous fleet of drones. It is also assumed that demand cannot be split, and each customer should be visited only once by a drone or a motorcycle. To propose a more comprehensive decision-making framework, time period and changes of parameters from one period to another are also considered.

Drones considered in this study differ in travel time, launch time, recovery time, and endurance [24]. As in this study, only single package delivery is considered. One-to-one deliveries are modeled, which is consistent with previous studies and the initial application of drone deliveries by companies such as Amazon [36]. Moreover, the consistency between vehicles' capabilities and packages in terms of weight and delivery distance is considered. Recharging drones are not considered in this study as the batteries can be recharged overnight or between the planning periods [36]. The green aspect of the problem is considered by calculating the environmental impacts of both drones and vehicles introduced by Park et al. [10]. The schematic figure of the problem under study can be seen in Figure 1.

As discussed, vehicles may face breakdowns. This paper assumes that the number of breakdowns in one unit of distance for each type of vehicle (either drone or motorcycle) follows a Poisson distribution. This assumption is compatible with previous studies [43,44]. The following formula measures the probability of x breakdowns if X is the number of breakdowns per unit of distance and λ is the defect rate:

$$P(X=x)=\frac{e^{-\lambda}\lambda^{x}}{x!}. \tag{1}$$

The notation used in the formulation of this problem is shown in Table 1.

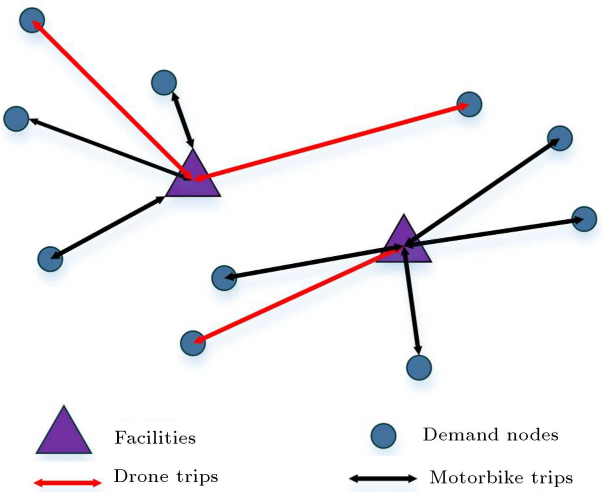


Figure 1. Schematic figure of the delivery system under study.

$$\min Z_1 = \sum_i \sum_s \widetilde{F}_s y_{is} + \sum_i \sum_u \widetilde{F'}_u z_{iu} + \sum_i \sum_v \tilde{F}_v z'_{iv} + \sum_t \sum_i \sum_k \sum_u \widetilde{f'}_u D_{ik} x_{ikut} + \sum_t \sum_i \sum_k \sum_v \tilde{f}_v D'_{ik} x'_{ikvt} + \pi \sum_i \sum_t ud_{it}, \quad (2)$$

$$\min Z_2 = \sum_t \sum_i \sum_k \sum_v \widetilde{\mu'}_v x'_{ikvt} D'_{ik} + \sum_t \sum_i \sum_k \sum_u \widetilde{\mu}_u D_{ik} x_{ikut}, \quad (3)$$

$$\min Z_3 = \sum_t \sum_u \sum_i \sum_k \tilde{\lambda}_u D_{ik} x_{ikut} + \sum_t \sum_v \sum_i \sum_k \widetilde{\lambda'}_v D'_{ik} x'_{ikvt}. \quad (4)$$

Subjected to:

$$\sum_i \sum_u x_{ikut} + \sum_i \sum_v x'_{ikvt} \leq 1, \quad (5)$$

$$\sum_k \tilde{b}_{ukt} x_{ikut} D_{ik} \leq \tilde{B}_u z_{iu}, \quad (6)$$

$$\sum_k x'_{ikvt} \leq M z'_{iv}, \quad (7)$$

$$x_{ikut} \leq \gamma_{ukt}, \quad (8)$$

$$\sum_i \sum_u \sum_v \widetilde{\widetilde{dem}}_{kt} (x_{ikut} + x'_{ikvt}) + ud_{it} \geq \widetilde{\widetilde{dem}}_{kt}, \quad (9)$$

$$\sum_k \sum_u \sum_v \widetilde{\widetilde{dem}}_{kt} (x_{ikut} + x'_{ikvt}) \leq M \sum_s Cap_s y_{is}, \quad (10)$$

$$\sum_s y_{is} \leq 1, \quad (11)$$

$$z_{iu} \leq \sum_s y_{is}, \quad (12)$$

$$z'_{iv} \leq \sum_s y_{is}, \quad (13)$$

$$\sum_i z_{iu} \leq 1, \quad (14)$$

$$\sum_i z'_{iv} \leq 1, \quad (15)$$

$$\gamma_{ukt} = \left\lceil \min \left(1, m_u / \widetilde{\widetilde{dem}}_{kt} \right) \right\rceil, \quad (16)$$

$$z_{iu}, z'_{iv}, x_{ikut}, x'_{ikvt}, y_{is} \in \{0, 1\}, Q_{it}, ud_{it}, I_{it} \geq 0. \quad (17)$$

The first objective function (2) calculates the total costs, including the establishment cost of facilities, the fixed costs, traveling costs of drones and fuel vehicles, and missed demands. The second objective function (3) determines the total emissions of the delivery system. The third objective function (4) maximizes the reliability of the system. Based on formula (1), the most reliable case is when there are no defects for vehicles ($X = 0$). According to the concept of a Poisson distribution function, if we want to maximize the reliability for the two means of delivery, we can write:

$$\max P(X=0) = \max e^{-\sum_u \sum_i \sum_k \tilde{\lambda}_u D_{ik} x_{iku} - \sum_u \sum_i \sum_k \widetilde{\lambda'}_v D'_{ik} x'_{ikv}} \sim \min \sum_u \sum_i \sum_k \tilde{\lambda}_u D_{ik} x_{iku} + \sum_u \sum_i \sum_k \widetilde{\lambda'}_v D'_{ik} x'_{ikv}. \quad (18)$$

Constraint (5) ensures that each customer can be visited by at most one compatible drone or one delivery vehicle. Constraint (6) enforces the energy consumption constraint on all the drones. To calculate the average energy requirement of drone u per distance ($\tilde{b}_u$), the one-to-one energy consumption formula introduced by Figliozzi [9] is used. Considering the customer and time period, we can write the change the proposed formula by Figliozzi [9] as follows:

$$b_{ukt} = \frac{g}{\vartheta(s)\, \eta_p \eta_r} \left(2m_u^{t'} + 2m_u^{b} + \widetilde{dem}_{kt} \right), \quad (19)$$

where s is the constant velocity travel speed; g the

Table 1. Description of notations.

Notations	
Indices and sets	
$k \in K$	Set of demand nodes
$i \in I$	Set of location for potential facilities
$u \in U$	Set of available drones
$v \in V$	Set of delivery vehicles
$s \in S$	Set of facility sizes
$t \in T$	Period of time
Parameters	
$\widetilde{F_s}$	Fuzzy establishment cost of a facility with size s
$\tilde{F}'_u$	Fuzzy fixed cost of employing drone u
$\tilde{F}_v$	Fuzzy fixed cost of employing vehicle v
$\tilde{f}'_u$	Fuzzy traveling cost of drone u per distance
$\tilde{f}_v$	Fuzzy traveling cost of vehicle v per distance
Cap_s	Supplying capacity of a facility with size s
$\widetilde{dem}_{kt}$	Stochastic demand of customer k in period t
γ_{ukt}	Compatibility of drone u with demand of customer k in period t
$\tilde{b}_{ukt}$	Energy requirement of drone u to carry the demand of customer k in period t, in Wh per distance
$\tilde{B}_u$	Battery capacity of drone u
m_u	Maximum mass that drone u can carry
$\tilde{\lambda}_u$	Break down probability of drone u in unit of distance
$\widetilde{\lambda}'_v$	Break down probability of vehicle v in unit of distance
$\widetilde{\mu_u}$	The environmental impact of 1 km drone delivery
$\widetilde{\mu'_v}$	The environmental impact of 1 km vehicle (i.e. motorbike) delivery
D_{ik}	Euclidean distance between facility i and customer k for drones
D'_{ik}	Rectilinear distance between facility i and customer k for vehicles
π	Penalty for missed demands
Decision variables	
y_{is}	1, if facility i with size s is established; 0 otherwise
x_{ikut}	1, if customer k is served by drone u from facility i in period t; 0 otherwise
x'_{ikvt}	1, if customer k is served by vehicle v from facility i in period t; 0 otherwise
z_{iu}	1, if drone u is assigned to facility i; 0 otherwise
z'_{iv}	1, if vehicle v is assigned to facility i; 0 otherwise
ud_{it}	Unmet demand of facility i in period t

gravity acceleration; $\vartheta(s)$ the lift-to-drag ratio; η_p the total power transfer efficiency; η_r the battery recharging efficiency; $m_u^{t'}$ the UAV mass tare, i.e. without battery and load; m_u^b the UAV battery mass.

Constraint (7) ensures that customers can receive service from a facility by a vehicle only if the vehicle is assigned to that facility. Constraint (8) ensures that a drone can visit a customer only if the drone is compatible with that customer's demand. Constraint (9) shows the balance between the missed demands, the amount of product that has been sent to the customers, and the demand of each customer in each period of time. The Constraint (10) shows that the number of products sent to the customers cannot surpass the facility's capacity. It also shows that the demand of customers can be met by a facility only if it had been established. The Constraint (11) ensures that each facility can be established with one size. Constraints (12) and (13) indicate that each vehicle or drone can be allocated to a facility only if the facility is established. The two Constraints (14) and (15) indicate that each drone or vehicle can be allocated to at most one facility. Constraint (16) shows how the compatibility of drones and customers' demands can be evaluated. The Constraint (17) shows the range and types of different variables.

4. Methodology

4.1. Possibilistic Chance-Constrained Programming (PCCP)

Some of the proposed problem's critical parameters must be estimated mostly by relying on experts' subjective opinions due to their fluctuating and uncertain nature and the unavailability of historical data in the phase of designing the last-mile network. Therefore, we formulate these imprecise parameters as possibilistic data in the form of trapezoidal fuzzy numbers as follows:

$$\tilde{F}_s = \left(F_s^p, F_s^m, F_s^m, F_s^o\right),$$

$$\tilde{F}'_u = \left({F'}_u^p, {F'}_u^m, {F'}_u^m, {F'}_u^o\right),$$

$$\tilde{F}_v = \left(F_v^p, F_v^m, F_v^m, F_v^o\right),$$

$$\tilde{F}'_u = \left({f'}_u^p, {f'}_u^m, {f'}_u^m, {f'}_u^o\right),$$

$$\tilde{f}_v = \left(f_v^p, f_v^m, f_v^m, f_v^o\right),$$

$$\tilde{\lambda}_u = \left(\lambda_u^p, \lambda_u^m, \lambda_u^m, \lambda_u^o\right),$$

$$\widetilde{\lambda'}_v = \left({\lambda'}_v^p, {\lambda'}_v^m, {\lambda'}_v^m, {\lambda'}_v^o\right),$$

$$\widetilde{\mu'}_v = \left({\mu'}_v^p, {\mu'}_v^m, {\mu'}_v^m, {\mu'}_v^o\right),$$

$$\widetilde{\mu_u} = \left(\mu_u^p, \mu_u^m, \mu_u^m, \mu_u^o\right),$$

$$\tilde{B}_u = \left(B_u^p, B_u^m, B_u^m, B_u^o\right).$$

It should be noted that cost-relevant parameters are normally treated as fuzzy parameters as we cannot get hold of the historical data in the designing phase when no previous data is available on the establishment costs and employment costs of drones and vehicles. Therefore, these parameters are treated as fuzzy numbers, which experts can estimate based on their judgments and knowledge. These parameters have also been considered uncertain and fuzzy in similar studies such as Ref. [32].

Usually when dealing with the uncertain constraints involving possibilistic or fuzzy data in their left and/or right-hand sides, the Possibilistic Chance-Constrained Programming (PCCP) approach is utilized [45]. This method has been applied in a vast variety of studies (e.g., [45–47]). In this method, a minimum confidence level of satisfaction as a safety margin can be set by the Decision-Maker (DM) to control these uncertain constraints' confidence levels.

To that end, the two standard fuzzy measures, i.e., the possibility (Pos) and necessity (Nec) measures, are usually applied [45,48]. Utilizing possibility or necessity measures depend on the DM's optimistic or pessimistic attitude about the possible level of occurrence of an uncertain event involving possibilistic parameters. In other words, when the DM has a conservative attitude towards satisfying the possibilistic chance constraints, using the necessity measure is more meaningful [48]. Here, due to the nature of the problem, using necessity measures seems more rational so as to ensure the satisfaction of possibilistic chance constraints, at least in the pre-defined confidence levels.

The crisp equivalent of the proposed model can be formulated by using the expected value for the objective function and the necessary measure for the possibilistic chance constraints. For more convenience, the compact form of the model is proposed as follows [48]:

$$\begin{aligned}
&\min Z = \tilde{F}y + \tilde{C}x \\
&\text{s.t.:} \\
&Cx \leq \tilde{E}y \\
&y \in \{0,1\}, x \geq 0
\end{aligned} \tag{20}$$

Considering the imprecise parameters, the basic PCCP model can be written as follows:

$$\begin{aligned}
&\min Z = E\left[\tilde{F}\right]y + E\left[\tilde{C}\right]x \\
&\text{s.t.:} \\
&Nec\left\{Cx \leq \tilde{E}y\right\} \geq \beta \\
&y \in \{0,1\}, x \geq 0
\end{aligned} \tag{21}$$

The crisp counterpart of the above model is stated as follows:

$$\begin{aligned}
&\min Z = \left(\tfrac{F^p+2F^m+F^o}{4}\right)y + \left(\tfrac{C^p+2C^m+C^o}{4}\right)x \\
&\text{s.t.:} \\
&Cx \leq \left[(1-\beta)E^m + \beta E^p\right]y \\
&y \in \{0,1\}, x \geq 0
\end{aligned} \tag{22}$$

In this approach, DM decides several values for confidence levels, and the final value is chosen based on a subjective manner and based on the DM's choice. Thus, there is no guarantee that each confidence level's selected value is the best possible choice [48].

In the proposed model, the objective functions (2)–(4) and Constraint (6) deal with fuzzy parameters. With regard to the mentioned approach, the crisp equivalent of these equations can be written as below, where β is considered as the confidence level of Constraint (6):

$$\min Z_1=\sum_i\sum_s \frac{F_s^p+2F_s^m+F_s^o}{4}y_{is}+\sum_i\sum_u \frac{F'^p_u+2F'^m_u+F'^o_u}{4}z_{iu}+\sum_i\sum_v \frac{F_v^p+2F_v^m+F_v^o}{4}z'_{iv}+\sum_t\sum_i\sum_k\sum_u \frac{f'^p_u+2f'^m_u+f'^o_u}{4}D_{ik}x_{ikut}+\sum_t\sum_i\sum_k\sum_v \frac{f_v^p+2f_v^m+f_v^o}{4}D'_{ik}x'_{ikvt}+\pi\sum_i\sum_t ud_{it}+\pi'\sum_i\sum_t I_{it}, \tag{23}$$

$$\min Z_2=\sum_t\sum_i\sum_k\sum_v \frac{\mu'^p_v+2\mu'^m_v+\mu'^o_v}{4}x'_{ikvt}D'_{ik}+\sum_t\sum_i\sum_k\sum_u \frac{\mu_u^p+2\mu_u^m+\mu_u^o}{4}D_{ik}x_{ikut}, \tag{24}$$

$$\min Z_3=\sum_t\sum_u\sum_i\sum_k \frac{\lambda_u^p+2\lambda_u^m+\lambda_u^o}{4}D_{ik}x_{ikut}+\sum_t\sum_v\sum_i\sum_k \frac{\lambda'^p_v+2\lambda'^m_v+\lambda'^o_v}{4}D'_{ik}x'_{ikvt}, \tag{25}$$

$$\sum_k b_{ukt}x_{ikut}D_{ik}\le\left[(1-\beta)B_u^m+\beta B_u^p\right]z_{iu}. \tag{26}$$

4.2. Stochastic programming

To solve our model with stochastic demand, chance-constrained programming is applied as a stochastic programming approach [49]. Chance-constrained programming was proposed to describe constraints with some probability levels. Chance-constrained programming is commonly used when the probability distributions of the uncertain parameters are known for DMs. The deterministic equivalent formulation can be obtained by defining a predetermined confidence level θ to satisfy constraints with stochastic parameters. We can refer to Refs. [50–52] as examples of utilizing chance-constrained programming in hub location, e-commerce facility location, and a green supply chain network design problem. A general form of the method can be proposed as follows, in which B_i and A_i are stochastic variables:

$$\begin{aligned}&\min Z=Cx\\&\text{s.t.:}\\&Pr(A_ix\le B_i)\ge\theta_i\\&x\ge 0\end{aligned} \tag{27}$$

Note that the following constraint has the confidence probability of θ_i, where $0<\theta_i<1$.

The equivalent deterministic formulation of the stochastic model can be obtained as below, where μ_{B_i} and μ_{A_i} indicate the means of B_i and A_i, and σ_{B_i} and σ_{A_i} show the standard deviations of B_i and A_i. As we considered that the stochastic parameters follow a normal distribution, $\phi^{-1}(1-\theta_i)$ demonstrates the inverse of cumulative standard normal distributions:

$$\begin{aligned}&\min Z=Cx\\&\text{s.t.:}\\&\left(\mu_{A_i}-\phi^{-1}(1-\theta_i).\sigma_{A_i}\right)x\le\mu_{B_i}\\&\qquad+\phi^{-1}(1-\theta_i).\sigma_{B_i}\ge\theta_i\\&x\ge 0\end{aligned} \tag{28}$$

Constraints (9) and (10) deal with customers' demand as a stochastic variable following a normal distribution in the proposed last-mile delivery problem with drones and motorcycles.

The confidence level of Constraints (9) and (10) are α, θ, respectively. Using representing μ_{kt} as the mean of customer demands and σ_{kt} as the standard deviation of demands in period t, Constraints (9) and (10) can be written as below:

$$\sum_i\sum_u\sum_v(\mu_{kt}+\phi^{-1}(1-\alpha).\sigma_{kt})(x_{ikut}\gamma_{uk}+x'_{ikvt})+ud_{it}\ge(\mu_{kt}-\phi^{-1}(1-\alpha).\sigma_{kt}), \tag{29}$$

$$\sum_k\sum_u\sum_v(\mu_{kt}-\phi^{-1}(1-\theta).\sigma_{kt})(x_{ikut}\gamma_{uk}+x'_{ikvt})\le M\sum_s Cap_s y_{is}. \tag{30}$$

4.3. Deterministic equivalent of the model

Considering the points above, we can write the final deterministic equivalent of the model as below:

$$\min Z_1=\sum_i\sum_s \frac{F_s^p+2F_s^m+F_s^o}{4}y_{is}+\sum_i\sum_u \frac{F'^p_u+2F'^m_u+F'^o_u}{4}z_{iu}+\sum_i\sum_v \frac{F_v^p+2F_v^m+F_v^o}{4}z'_{iv}+\sum_t\sum_i\sum_k\sum_u \frac{f'^p_u+2f'^m_u+f'^o_u}{4}D_{ik}x_{ikut}+\sum_t\sum_i\sum_k\sum_v \frac{f_v^p+2f_v^m+f_v^o}{4}D'_{ik}x'_{ikvt}$$

$$+\pi \sum_i \sum_t ud_{it}, \tag{31}$$

$$\min Z_2 = \sum_t \sum_i \sum_k \sum_v \frac{\mu'^p_v + 2\mu'^m_v + \mu'^o_v}{4} x'_{ikvt} D'_{ik} + \sum_t \sum_i \sum_k \sum_u \frac{\mu^p_u + 2\mu^m_u + \mu^o_u}{4} D_{ik} x_{ikut}, \tag{32}$$

$$\min Z_3 = \sum_t \sum_u \sum_i \sum_k \frac{\lambda^p_u + 2\lambda^m_u + \lambda^o_u}{4} D_{ik} x_{ikut} + \sum_t \sum_v \sum_i \sum_k \frac{\lambda'^p_v + 2\lambda'^m_v + \lambda'^o_v}{4} D'_{ik} x'_{ikvt}, \tag{33}$$

Subjected to:

$$\sum_i \sum_u x_{ikut} + \sum_i \sum_v x'_{ikvt} \le 1, \tag{34}$$

$$\sum_k b_{ukt} x_{ikut} D_{ik} \le \left[(1-\beta) B^m_u + \beta B^p_u\right] z_{iu}, \tag{35}$$

$$\sum_k x'_{ikvt} \le M z'_{iv}, \tag{36}$$

$$x_{ikut} \le \gamma_{ukt}, \tag{37}$$

$$\sum_i \sum_u \sum_v (\mu_{kt} + \phi^{-1}(1-\alpha).\sigma_{kt})(x_{ikut}\gamma_{uk} + x'_{ikvt}) + ud_{it} \ge (\mu_{kt} - \phi^{-1}(1-\alpha).\sigma_{kt}), \tag{38}$$

$$\sum_k \sum_u \sum_v (\mu_{kt} - \phi^{-1}(1-\theta).\sigma_{kt})(x_{ikut} + x'_{ikvt}) \le M \sum_s Cap_s y_{is}, \tag{39}$$

$$\sum_s y_{is} \le 1, \tag{40}$$

$$z_{iu} \le \sum_s y_{is}, \tag{41}$$

$$z_{iu} \le \sum_s y_{is}, \tag{42}$$

$$\sum_i z_{iu} \le 1, \tag{43}$$

$$\sum_i z'_{iv} \le 1, \tag{44}$$

$$\gamma_{ukt} = \left[0, \min\left(1, m_u / \left(\mu_{kt} - \phi^{-1}(1-\aleph).\sigma_{kt}\right)\right)\right], \tag{45}$$

$$z_{iu}, z'_{iv}, x_{ikut}, x'_{ikvt}, y_{is} \in \{0,1\}, Q_{it}, ud_{it}, I_{it} \ge 0. \tag{46}$$

4.4. Multi-objective programming

The ϵ-constraint method is one of the most popular approaches to solve multi-objective models. This method shows the trade-offs between the objective functions by generating a set of exact Pareto optimal solutions. In this method, the problem is reformulated as a single objective problem where one of the objective functions is selected as the primary objective function. The other objective functions are transformed into additional constraints. The ϵ-constraint method has various advantages over other Pareto-generating methods, such as the weighted sum method. However, there are also some drawbacks, such as generating weakly Pareto-optimal solutions. To overcome this shortcoming, Mavrotas [53] proposed the augmented ϵ-constraint method (AUGMECON). Later, Mavrotas and Florios [54] proposed an improved version of the augmented ϵ-constraint method (AUGMECON2). AUGMECON2 is a general-purpose method; however, Mavrotas and Florios [54] noted that this method is particularly suitable for multiple-objective integer programming models.

To use this method, first, the range of each objective function needs to be determined through lexicographic optimization. A lexicographic optimization method is a sequential approach in which a priority is considered for the objective functions based on the DM's opinion. The lexicographic method gives a particular kind of Pareto-optimal solution that considers an order for the importance of the objectives. In the lexicographic optimization method, a sequence of single-objective constrained optimization problems is solved. To put it differently, the highest priority objective function is first minimized concerning the problem's constraints. The second objective function is then minimized while adding a new constraint binding the first objective function to its optimal value obtained from the previous step. This procedure is continued until the last objective function [55].

After indicating the ranges of objective functions, the following model should be constructed:

$$\begin{array}{l} \min \left(f_1(x) - eps_1 \times \left({}^{s_2}/_{r_2} + eps_2 \times {}^{s_3}/_{r_3}\right)\right) \\ \text{s.t.:} \\ f_2(x) = e_2 - s_2 \\ f_3(x) = e_3 - s_3 \\ x \in S \text{ and } s_2.s_3 \in R^+ \end{array} \tag{47}$$

In addition, $e_k = lb_k + \frac{i_k \times r_k}{g_k}$, where is the lb_k lower bound of objective function k; i_k the iterations; g_k the total number of intervals; r_k the range of objective functions.

5. Case study

Digikala is an Iranian e-commerce company that was

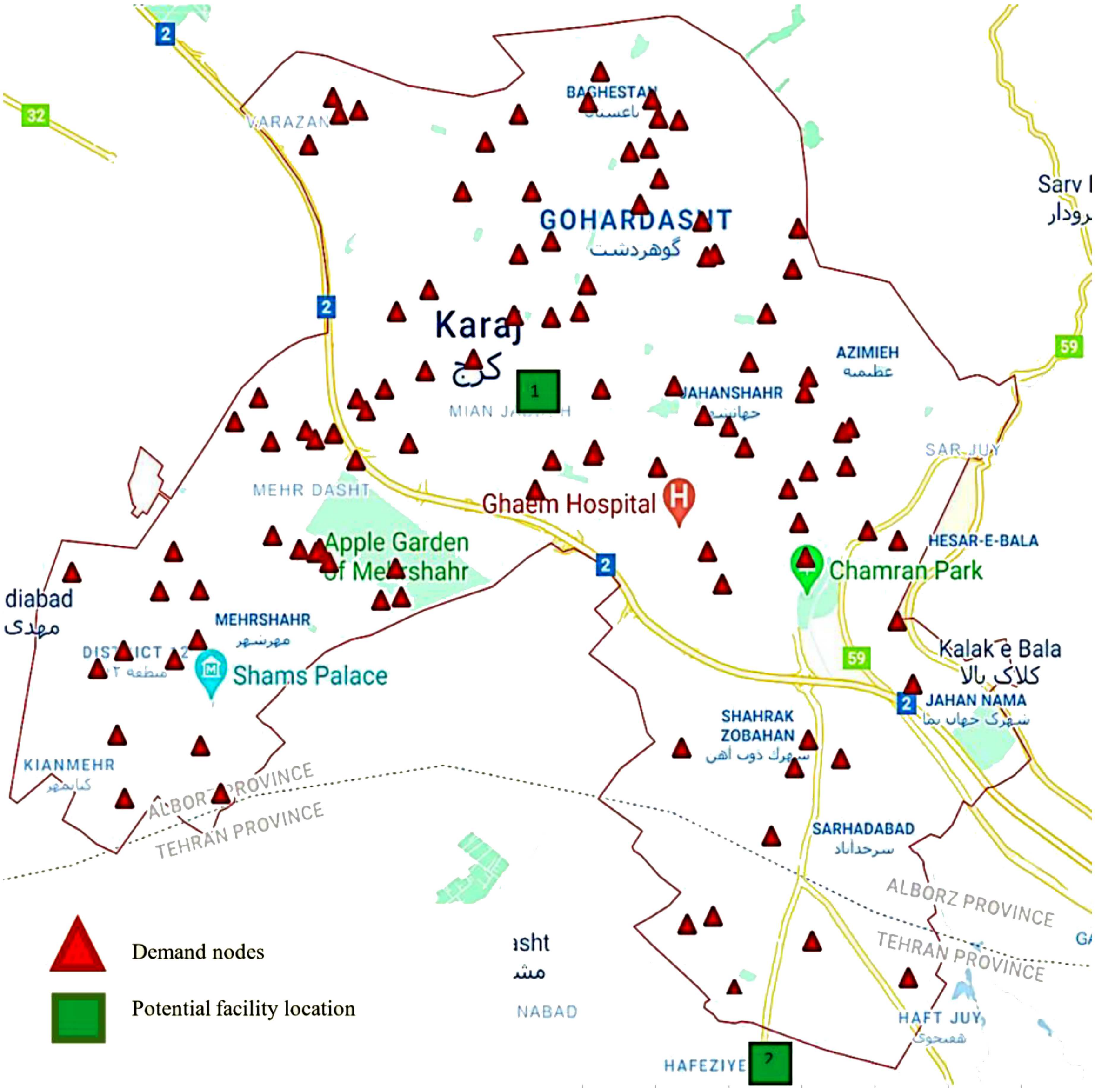


Figure 2. Demand nodes and potential facility locations in Karaj.

founded in July 2006. The company initially aimed to sell digital products but gradually expanded its business to various categories of products such as cosmetics, clothing, home appliances, books, toys, art pieces, sports equipment, fresh vegetables, meat and poultry, beverages, etc. We limit the scope of products to fresh foods and beverages as these types of orders need to be delivered promptly for delivering which the drones and motorbikes are suitable. This category of product encompasses 19% of orders [56].

It is noteworthy that supply chain and delivery network design plays a key role in e-commerce business management. Thus, problems comprised of location, routing, and inventory have received much attention [57]. To validate the proposed model, we apply the model to a real case study in Karaj, using the available data of Digikala's sales [58]. Karaj is the capital of Alborz province, and it is one of the largest urban areas of Iran.

According to the available Digikala open data, during nine days, 2136 orders were placed in Karaj in August 2018. Therefore, on average, 237 orders are placed daily. Considering that approximately 19% of orders are in the fresh food category, 45 orders should be delivered daily. We also took the average 2.2% annual increase in the sales volume from 2018 to 2019 [56]. Subsequently, 100 demand nodes have been randomly selected, as shown in Figure 2. Digikala has one warehouse located southeast of Karaj to process and send the orders. The location of this warehouse and another potential location are considered the potential locations for establishing launching facilities (i.e., warehouse).

Facility locations with their capacities, the allo-

Table 2. Data for the case study.

Case study's data	
Indices and sets	
$k \in K$	100
$i \in I$	2
$u \in U$	50
$v \in V$	12
$s \in S$	2
$t \in T$	1
Parameters	
$\widetilde{F_s} = (0.8F_s^m, F_s^m, 1.2F_s^m)$	$F_s^m \sim$ Uniform (100000,150000) USD
$\widetilde{F'_u} = \left(0.8F'^m_u, F'^m_u, 1.2F'^m_u\right)$	$F'^m_u \sim$ Uniform (3000,5000) USD [32]
$\tilde{F}_v = (0.8F_v^m, F_v^m, 1.2F_v^m)$	$F_v^m \sim$ Uniform (4000,6000) USD [59]
$\widetilde{f'}_u = \left(0.8f'^m_u, f'^m_u, 1.2f'^m_u\right)$	$f'^m_u \sim$ Uniform (0.006,0.014) USD [32]
$\tilde{f}_v = (0.8f_v^m, f_v^m, 1.2f_v^m)$	$f_v^m \sim$ Uniform (0.3,0.7) USD [32]
$\widetilde{\widetilde{dem}}_{kt}$	$\sim$ Normal $(2.5,1^2)$
$\tilde{B}_u = (0.8B_u^m, B_u^m, 1.2B_u^m)$	$B_u^m \sim$ Uniform (666,888) [36]
m_u	$\sim$ Uniform (4.5,5.5) kg [9,36]
$\tilde{\lambda}_u = (0.8\lambda_u^m, \lambda_u^m, 1.2\lambda_u^m)$	$\lambda_u^m \sim$ Uniform (0.01,0.03)
$\tilde{\lambda'}_v = (0.8\lambda'^m_v, \lambda'^m_v, 1.2\lambda'^m_v)$	$\lambda'^m_v \sim$ Uniform (0.04,0.06)
$\widetilde{\mu_u} = (0.8\mu_u^m, \mu_u^m, 1.2\mu_u^m)$	$\mu_u^m \sim$ Uniform $(3.4 \times 10^{-7}, 5.2 \times 10^{-7})$ [11]
$\widetilde{\mu'}_v = (0.8\mu'^m_v, \mu'^m_v, 1.2\mu'^m_v)$	$\mu'^m_v \sim$ Uniform $(4.36 \times 10^{-6}, 6.5 \times 10^{-6})$ [11]
Cap_s	2500, 4000 kg
$\eta_p \eta_r$	$\sim$ Uniform (0.66,1) [9]
$\vartheta(s)$	$\sim$ Uniform (2.5,4.5) [9,36]
m_u^t	$\sim$ Uniform (10,10.2) kg [9,36]
m_u^b	$\sim$ Uniform (0.04,0.06) kg [9,36]

cation of 100 demand nodes, the amount of unmet demand, and the required number of motorbikes and drones will be determined for this case by employing the proposed model.

The values of other parameters are extracted as shown in Table 2. It should be noted that drones or vehicles with more costs have higher technologies and consequently have fewer environmental impacts and breakdown rates.

6. Results

The results of the mentioned case study are depicted in Figures 3 and 4.

In order to investigate the performance of the model, we assumed that the DM sets both the confidence level of stochastic constraints and the confidence level of fuzzy constraint 0.8. One of the Pareto solutions is selected to demonstrate the results of the case study under investigation.

For $\varepsilon_2 = 53.9536$, $\varepsilon_3 = 0.0048$, the values of 1641965.793, 0.005, and 53.365 are obtained for Z_1, Z_2, and Z_3, respectively. Both potential facility points are established from which drones and motorcycles delivered customers' demands. The result shows that

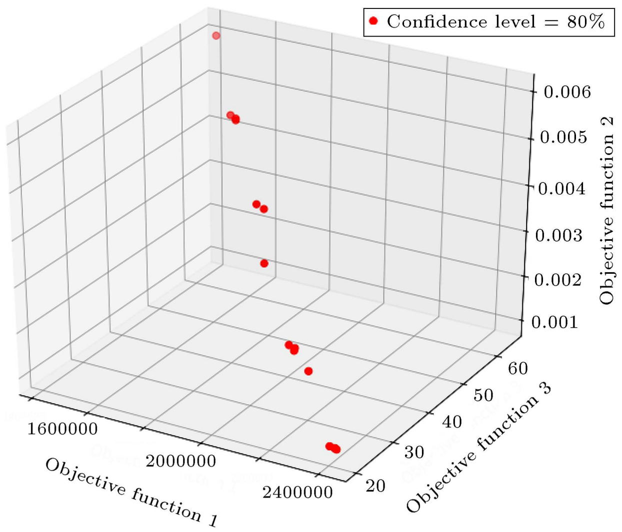


Figure 3. 3D Pareto front for confidence level of 80%.

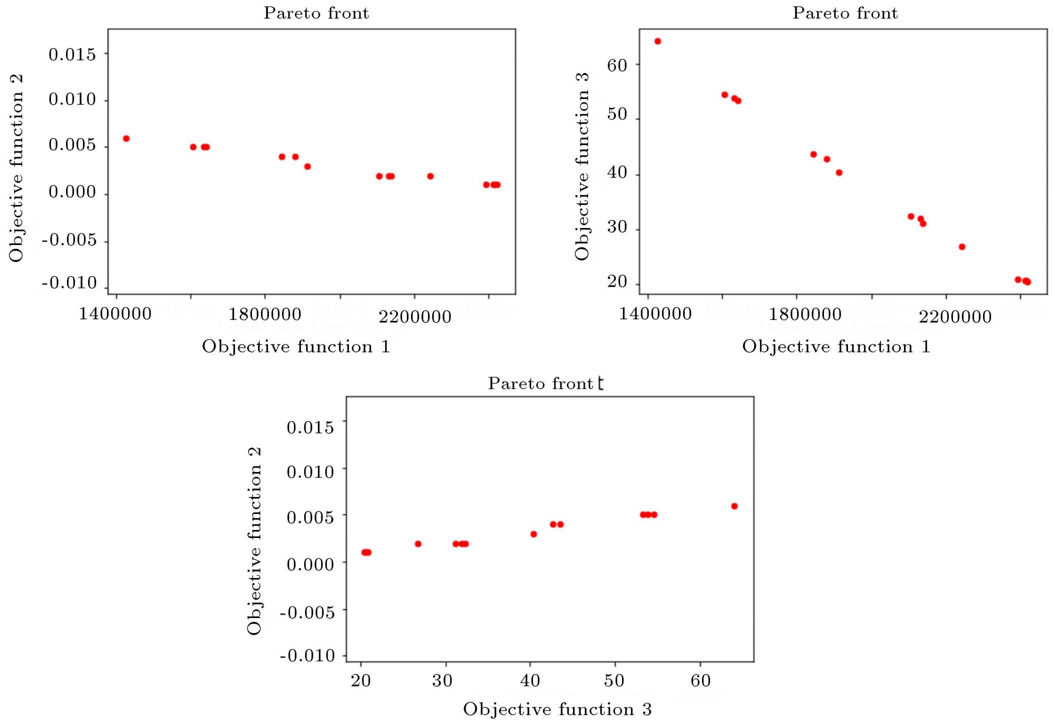


Figure 4. 2D Pareto fronts for confidence level of 80%.

15 drones and eight motorcycles are assigned to facility point 1 to deliver customer orders. Drones satisfy the orders of 27 customers, and motorcycles cover the orders of 31 customers. Facility point 2 launched a fleet of 22 heterogeneous drones to deliver the demand of 37 customers. Besides, two motorcycles are employed to meet five customer orders. The results are summarized in Table 3.

In this illustrative example, 50 drones and 12 motorcycles can be used for delivery; however, the solution indicates that 37 drones and ten motorcycles are allocated to the established facilities. As mentioned earlier, γ_{ukt} is the parameter which presents the compatibility of drone u with the demand of customer k. Customer orders that are not compatible with drones' features, such as the maximum carrying load, are assigned to motorcycles. In order to ensure that the model reflects this assumption, the results were investigated. For instance, γ_{141} gets a value of zero, while x'_{1431} equals 1, which means customer four is assigned to motorcycle number 3 since it is not compatible with the available drones. Besides, no unmet demands are observed in the selected solution.

7. Sensitivity analysis

This section investigates the impact of some of the critical parameters on the objective functions and the model's outputs.

7.1. Impact of the number of available vehicles

One of our study's main purposes was to compare two modes of transportation (i.e., motorbikes and drones) in a last-mile delivery system in Karaj. Therefore, a different number of drones and motorbikes and the Lex-

Table 3. Results of the case study.

Established facilities	Drone	Motorbike	Number of recovered customers	Unmet demand
Facility 1	15		27	0
		8	31	0
Facility 1	22		37	0
		2	5	0
Sum	37	10	100	0

Table 4. Sensitivity analysis on the number of available vehicles.

Number of available |motorbikes| |drones|	Objective 1	Objective 2	Objective 3
|50| |12|	220397.3	0.015	138.421
|12| |50|	1360919	0.006	66.845
|50| |0|	4.71E+13	0.014	132.604
|0| |50|	1.09E+14	3.88E-04	3.58

icographic optimization method's corresponding results are shown in Table 4. The certainty level $(\beta, \alpha, \theta, \aleph)$ is fixed on 80% in the following results.

As shown, a combination of drone/motorbike in Karaj's last-mile delivery system leads to a lower level of the total cost. When both drones and motorbikes are utilized, and the proportion of drones in the vehicles' fleet is higher, the total costs are approximately six times more than when there are more motorbikes. The system's adverse environmental effects are remarkably lower on the plus side, and the delivery system is more reliable. Therefore, the number of drones and motorbikes in the delivery system can be determined concerning the relative importance level of objective functions for the DM of the last-mile delivery project of Karaj.

When only one type of delivery mode is considered, total costs increase notably. However, when only drones are utilized, the environmental impacts are at their lowest level, and the system's reliability is higher. This is consistent with the previous studies emphasizing the superiority of drones in lower CO_2 emissions and environmental impacts [10,11].

7.2. Impact of drones' efficiency

The efficiency of drones can be related to the weather, battery usage during take-off and landing, and the drones' initial conditions. To take the uncertainties involved in the mentioned factors, we investigate the impact of the drones' efficiencies on the required drones and the objective functions. To that end, the value of $\eta_p \eta_r$ has been changed from 60% to 100%. However, it should be noted that 100% of efficiency is not likely to occur in reality. The value of $\eta_p \eta_r$ shows the power transfer efficiency from the battery to the propellers and the energy that is lost when batteries are recharged [9]. The results of the Lexicographic optimization are demonstrated in Figure 5.

It should be noted that the certainty level (i.e., confidence level) is fixed at 80%, as depicted, total costs (green line) decrease as the efficiency of drones increases. That is, the number of required drones decreases when higher efficiencies are considered for drones as more efficient batteries can help drones fly for longer hours, and consequently, each drone can meet the demands of more customers. The results can be observed in Figure 6.

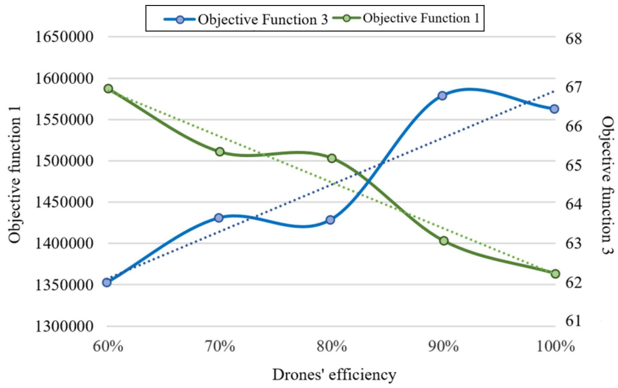
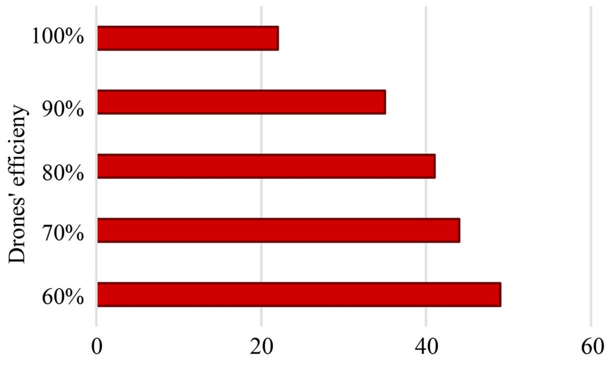


Figure 5. Sensitivity analysis on the efficiency of drones.



	60%	70%	80%	90%	100%
Series1	49	44	41	35	22

Figure 6. Sensitivity analysis on the efficiency of drones.

Interestingly, the delivery system of Karaj is more reliable when the efficiency of drones is lower. This stems from the fact that less efficient drones travel shorter distances, and as a result, they experience fewer breakdowns. However, when drones' efficiency is higher, fewer drones are utilized, and consequently, they have to travel long distances, which exposes them to more breakdowns and failures.

7.3. Impact of the confidence level of uncertain constraints

In this section, the effect of confidence level $(\beta, \alpha, \theta, \aleph)$

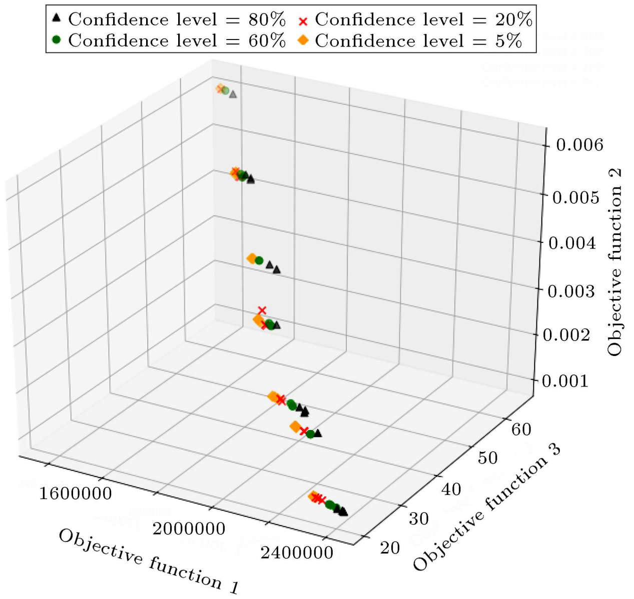


Figure 7. 3D Pareto fronts for different confidence levels.

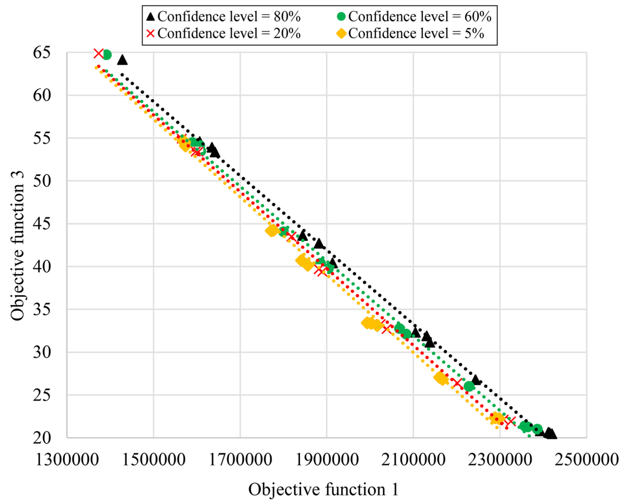


Figure 8. 2D Pareto fronts of different confidence levels.

of uncertain constraints is investigated on the objective functions of the problem.

As demonstrated in Figures 7 and 8, the confidence level remarkably affects Karaj's parcel delivery system's first objective function (total costs). Therefore, it can be concluded that if the DM wants to have higher levels of uncertainty for the uncertain constraints and variables, they should expect more total costs for the delivery system. Confidence level; however, does not seem to have a notable effect on the other two objective functions.

7.4. Impact of the number of potential facilities

We have also investigated the impact of increasing the number of Karaj potential locations for launching the drones. The results summarized in Table 5 demonstrate that, in general, considering more potential locations in Karaj leads to a decrease in the delivery system's total costs. Moreover, fewer drones are employed as the distance from launching facilities to the customers becomes shorter.

Also, it is understood that the system's reliability decreases when more potential facility locations are considered. This is also consistent with the results of the sensitivity analysis on the drones' efficiency.

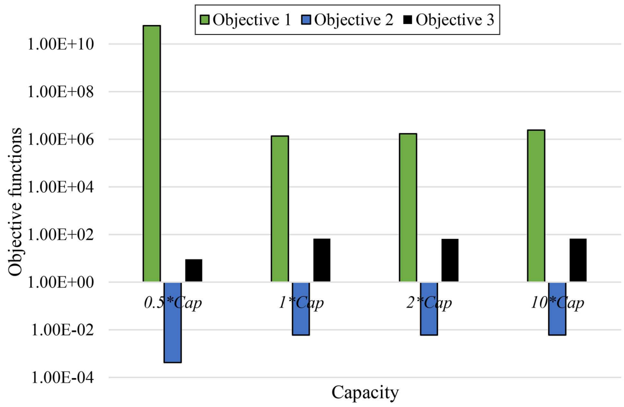


Figure 9. Impact of capacity sizes on objective functions.

7.5. Impact of the capacity size of facilities

In this section, we investigated the effect of capacity sizes on the objective functions and critical variables. Two supplying capacities (2500 and 4000) had been considered for the case study that facilities could be established with either of these sizes. It is obvious that the establishment cost of facilities also rises as capacity sizes increase. As shown in Figure 9, when half of the capacity sizes are considered, total costs rise considerably. Also, one of the facilities faces unmet demand. Moreover, the environmental effect is lower. The system is pretty reliable, which stems from the fact that fewer deliveries have been carried out due to the supply shortage of facilities. When increasing the capacity sizes, total costs increase slightly, and other objective functions have relatively static values. The capacity sizes also affect the number of established facilities. According to the results shown in Table 6, when capacity sizes increase tenfold, only one facility is established. However, in other cases, both of the potential facilities in Karaj are established.

8. Discussion and managerial insights

This study explores a last-mile delivery problem in an Iranian e-commerce company to locate the capacitated facilities and allocate the available drones and motorbikes to the established facilities to satisfy given demands. The mathematical formulation seeks to optimize three objectives comprised of the system's total cost, the environmental impact of ground and air

Table 5. Sensitivity analysis on the number of potential facility locations.

Number of potential facilities	Objective 1	Objective 3	Number of established facilities	Number of employed drones
1	1531512	67.995	1	38
2	1360919	66.845	2	28
4	1277807	67.247	3	24
6	1284640	67.503	4	23
8	1252052	68.321	3	24
10	1249576	68.414	3	23

Table 6. Sensitivity analysis on the capacity sizes.

Capacity sizes	$0.5Cap$	Cap	$2Cap$	$10Cap$
Number of established facilities	2	2	2	1

transportation vehicles, and their reliability considering the breakdown probabilities of vehicles.

As mentioned in Section 2, drone delivery has been under the focus of both practitioners and academics. Many well-known companies, such as DHL, Google, and Amazon, have been investing in employing drones in their last-mile parcel delivery processes. Also, there is a large body of literature on optimizing drone delivery processes. However, most of the case studies in this area of research belong to developed countries. Therefore, it is required to propose proper mathematical models for designing drone delivery networks in developing countries. Using drones for package delivery purposes is gradually being brought into focus in such countries. For example, in Iran, Digikala, one of the largest Iranian e-commerce companies, has shown interest in using cargo drones for package delivery. In this regard, we proposed a multi-objective mathematical model to present a last-mile package delivery network using both ground vehicles and drones for Digikala in Karaj.

The study of Chauhan et al. [34] is the closest paper to this paper. However, we extended the model to consider the possibility of assigning both drones and ground vehicles to facilities with respect to the compatibility of drones and customer demand. Moreover, Chauhan et al. [36] considered drone energy consumption as a function of distance and payload without investigating drones' environmental impacts and their energy consumption. This has also been covered in our proposed model by adding an objective function associated with environmental impacts. The environmental aspect of delivery plays a pivotal role in managerial decisions.

Additionally, considering breakdown probabilities for both delivery vehicle types has not been investigated in last-mile delivery literature. Shavarani et al. [32] set the customer demand, distance capacity, and network costs as fuzzy variables in the facility location problem of a refueling station for drones. Kim et al. [38] presented a facility location model of humanitarian logistics using drones with stochastic flight distance. However, in our study, a comprehensive model is proposed to account for both the fuzzy and stochastic nature of critical parameters.

In Section 7, the impact of some parameters such as the number of available vehicles, the drones' efficiency, the confidence level of uncertain constraints and the number of potential facilities on the values of objective functions and variables were examined. Based on the results yielded by the sensitivity analysis, managerial perspectives can be discussed as follows.

According to Table 4, it is suggested to the managers of the drone delivery project of Karaj to only use drones instead of ground vehicles if the environmental objective has a higher priority and an adequate budget is available to satisfy higher costs. In other words, as the environmental impact of the system is at its lowest level when only drones are utilized, concerning this objective and regardless of the costs, utilizing a drone fleet is suggested to be considered. Suppose the management faces budget limitations and budget shortages, which is normally the case. In that case, it is recommended to reduce the number of drones and used the ground vehicle instead until they meet their budget level. As a result, the costs of the delivery system of Karaj decrease; however, it leads to an increase in the system's environmental impacts. Moreover, it is suggested to have more drones than motorbikes in the delivery as the system's reliability is also in a better condition when the transportation fleet consists of more drones.

Figures 5 and 6 suggest that the management should take drones' efficiency into account when planning for a drone delivery system as it significantly affects the system's reliability and total costs. Suppose the management wants to reduce the total costs. In that case, they should use drones with more efficient batteries and consider serious plans for periodic maintenance to keep drones' efficiency high. Moreover, they should realize that inevitable factors can affect drones' efficiency. Hence, they should consider their drones' efficiency lower than they expect to be prepared for possibly higher costs. Interestingly, when drones with higher battery efficiency are considered, the management should expect more breakdowns as fewer drones are utilized and each travel longer distances which prone them to more failures. Again, this shows the importance of considering proper maintenance plans to the management, which is out of this study's scope but can be an interesting research area for future studies.

According to Figure 8, when there is a higher level of uncertainty involved in the project and critical parameters of the problem, the management of the drone delivery project of Karaj should assign more budget for the costs to implement the project feasibly.

According to Table 5, the management should consider a trade-off between the number of potential facilities and the number of utilized drones to achieve the preferred level of reliability for the delivery system in Karaj. If the management decides to establish more facilities, the number of used drones decrease. As a result, there will be a decrease in the system's reliability observed in Table 5. The same result is achieved in a reverse manner. Additionally, if it is not possible for the management to increase the number of drones, the issue could be resolved by increasing the number of potential facilities. Moreover, even when ten possible locations for facilities are considered, only three have been established for the particular case study. Therefore, it can be concluded that three established facilities can meet customers' demand in the best possible way as the costs are lower and the reliability level is relatively acceptable.

Sensitivity analysis on the capacity sizes shows that the capacities considered are the most suitable for the case under study. So, it is suggested to the management to consider 2500 units as the supplying capacities for establishing potential facilities as it leads to fewer costs and all the demand can be satisfied with these supplying capacities. Moreover, according to Figure 9, increasing the capacity to a certain level leads to an improvement in total costs, environmental aspects, and system reliability. However, the DMs in Karaj should be aware that increasing capacities has no noticeable effect on improving the objective functions given the current conditions and assumptions.

9. Conclusion

In this paper, a stochastic-fuzzy multi-objective optimization framework was developed to design a last-mile delivery system. The proposed model is capable of indicating the following variables: location and capacity of launching facilities, the number and types of required vehicles, the allocations of customers to each facility, and the amount of unmet demand in each time period. Moreover, this model considers the trade-offs between three objective functions as a novel feature, including total cost, reliability, and environmental impacts. To check the applicability of the proposed model, it is applied to a case study in an Iranian e-commerce company. Furthermore, several sensitivity analyses are carried out to study the impacts of critical parameters on the objective functions and decision variables' values. Results demonstrate that the confidence level of uncertain parameters impacts the total cost of the system considerably. Findings suggest that the best delivery system includes drones and ground vehicles (i.e., motorbikes). Moreover, drones' efficiency and the number of potential facility locations play an important role in determining the optimal number of required drones.

For future research, metaheuristic algorithms can be used to solve this model and compare the results to those of the current study obtained by AUGMECON2 as an exact method. Considering the breakdowns of facilities can also be studied as another extension of the proposed model. Moreover, proposing a model for preventive or corrective maintenance of drones and other types of delivery vehicles can be an interesting area for future research. Also, the vehicles may face by a partial breakdown, which causes the vehicle to provide the service (delivering parcels) at a lower rate instead of stopping service completely [60]. Therefore, considering the partial breakdowns could be an interesting problem for future research.

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