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Research Article

Investigating Greenhouse Gas (CO_2) Emission and Performance of Drone in Emergency Medical Services (EMS) Systems

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Abstract
The benefits of using eco-friendly technologies along with their efficiency for EMS systems have caused to address the importance of drones in terms of performance and environmental aspects. In this study, by considering the applications of drone capability such as fast delivery along with a focus on the energy consumption of drone, a new bi-objective mathematical model of location-allocation problem of EMS systems is presented. In the first objective function, the impact of drone to maximize the expected survival of patients is investigated and in the second one, the minimization of CO_2 emission of drone utilization in EMS systems is considered which is the most documented and well-known greenhouse gas often used to calculate pollution and energy impacts. The importance of patient's lives in comparison with the associated reduction of carbon emission has caused to be solved the model by a preemptive fuzzy goal programming approach to measure the achievement degree of objectives. By using data and obtained results from a similar study, the model is evaluated to show the applicability and benefits of drones in healthcare service and environmental aspects. The results show that drone utilization in comparison with regular ambulance vehicles can save more lives as well as emit less CO_2. The results strongly support the notion that using drones for EMS systems is not only efficient but also is environmentally friendly.
Keywords: Location-allocation problem, Greenhouse gas (CO_2) emission, EMS system, Drone energy, Preemptive fuzzy goal programming

Introduction

Emergency Medical Services are urgent services that treat illnesses and injuries which require an urgent medical response, providing out-of-hospital treatment and transport to definitive care. EMS plays a significant role in health systems. It can be said, efficiently respond to emergency calls can have a direct effect on patients' health. Therefore, this study concentrates on managing EMS systems aided with rapid-response vehicles to serve the patients. There are several strategic

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decisions to efficiently provide rapid response in order to save lives by an EMS system, so various aspects of EMS management have been studied by many researchers to find the best decisions. One of these decisions is reducing ambulance response time to arrive at the scene of reported incidents. In this regard, the location of ambulance stations, types, and the number of deployed ambulances are vital factors to save patient's lives. Indeed, one of the main strategic problems in EMS systems is the locating of ambulance stations that must be established and the vehicles as ambulances that must be deployed from the stations. Toregas et al. (1974) introduced the ambulance location problem for the first time and after that, various researches have been conducted to investigate this subject (Brotcorne et al., 2003; Li et al., 2011).

The weakness of early researches on the ambulance location problem is that technological advancement especially in vehicles used as ambulances has not been considered. Unmanned Aerial Vehicle, UAV, commonly referred to the drone that was first used in the 1990s by military organizations (Sharon Wulfovich et al., 2018), is one of those technological advancements that is being rapidly used in different fields of life. Today, the usage of drones is increasing exponentially, with new advantages and applications in our daily life. When it comes to healthcare, carrying emergency equipment or medication, collection of blood and tissue samples, conducting search and rescue operations, reaching remote patients and, responding to natural disasters are some powerful applications of drones that show excellent potential in health care. Furthermore, using drones as transportation vehicles in EMS systems affects the performance of health care services due to fast delivery to reduce the response time and also CO_2 emissions in comparison with regular types of vehicles like ground and air ambulances. Transport activities in EMS can be related to increasing levels of environmental externalities; for instance, fifteen percent of global carbon dioxide (CO_2) is associated with the transport sector (Rodrigue et al., 2016). Indeed, the drone is not only a new option in providing healthcare and EMS in a more effective manner, but also it provides benefits to reduce the carbon footprint and enhance environmental aspects. In other words, despite the efficiency aspects, we investigate the amount of CO_2 emissions of drones in EMS systems to show drones could be the main alternative instead of ground and air ambulances in terms of eco-friendly aspects too. Hence, based on the nature of emergency services to provide quick medical, incorporating new technology like drones as a special ambulance can guarantee the rapid response to patients and reduction of CO_2 emissions. This paper presents a location-allocation problem for EMS stations equipped with drones for patients whose survival is guaranteed by portable healthcare supplies carried by drones such as AED, blood bags, oxygen cylinder, drugs and etc. In this research, since the number of expected survivors and measuring the CO_2 emissions of drones are investigated therefore, a bi-objective mathematical model is presented such that the first objective maximizes the expected survival of patients and the second one minimizes the total amount of CO_2 emissions of drones. To solve the bi-objective linear programming model, a preemptive fuzzy goal programming (PFGP) approach is applied to determine the achievement degree of implementation EMS systems with presented objectives.

Literature Review

In order to review related researches with focus on EMS systems, ambulance location problems, and using drones in healthcare services, the related research can be classified and presented into two main categories with a concentration of EMS systems: ambulance location problems and using drones in healthcare that we discuss each section separately.

Ambulance location problem

EMS systems need given number of ambulances over the territory they serve and static ambulance location problem helps to choose the most appropriate sites to use, and the number of ambulances that should be assigned at each of them. Indeed, an ambulance location problem with a set of standby sites aims to locate one or more ambulances stations to complete a mission and return to its designated standby station. Several studies have been concentrated on the ambulance location problem as discussed in Brotcorne et al. (2003) and Aringhieri et al. (2017). Coverage deterministic, probabilistic, and stochastic models are the three main categories of ambulance location models. Deterministic single coverage model is one of those models was formulated by Toregas et al. (1971) to locate the emergency vehicle by using the notion of coverage. The location set covering problem (LSCP) was presented by Toregas et al. (1971) to minimize the number of ambulances such that all sites are covered.

Church and ReVelle (1974) formulated a maximal covering location problem (MCLP) in order to optimize costs by locating emergency centers to cover the maximum demographic demands. Daskin and Stern (1981) presented the hierarchical objective set covering problem (HOSC) for the first time to minimize the number of vehicles needed to ensure complete coverage and maximize the number of vehicles that can cover a zone. Indeed, the HOSC addresses reorganizing ambulances around sites that can be covered easily and leaving harder to those sites that are covered once because it doesn't consider each site's demand. The probabilistic and stochastic models were introduced to improve the previous coverage models. These models seek to determine the set of ambulance locations that maximize the expected coverage. Daskin (1982) was one of the first studies of the maximal coverage location model. The objective of the maximum expected covering location problem (MEXCLP) is to locate a given number of ambulances in order to maximize the expected coverage according to the unavailability of ambulances to respond to emergency calls. This model was developed by considering some assumptions in the busy fraction of vehicles (Bianchi and Church, 1988; Daskin et al., 1988). Two variants of the MEXCLP were proposed by Batta et al. (1989) to relax some assumptions in this type of research. The travel time of an ambulance or a vehicle can be varied and in this regard, Daskin (1987), and later and Goldberg et al. (1990), proposed the models to consider the stochastic travel time between locations. Finally, Mandell (1998) and McLay (2009) developed the coverage expected models by proposing two types of vehicles in their research. Recent models to provide a realistic EMS system tend to address the uncertainty in ambulance location that one of those models is maximal survival.

The performance of most EMS models is evaluated by some indicators such as the proportion of calls responded. The drawbacks of these models to capture the saving lives have caused to be introduced the maximal survival model. This model was presented by Erkut et al. (2008) for the first time to use survival functions. In their study function of response time into the existing covering model was incorporated and they showed the efficiency of the maximal survival location problem (MSLP) in comparison with the MCLP and the p-median location problems. The objective function of MSLP addressed to maximize the expected number of lives saved. Erkut et al. (2008) adopted other covering models such as the MEXCLP to demonstrate the benefits of MSLP in patient outcomes. As a developed version of MSLP, Knight et al. (2012) considered multiple survival functions of heterogeneous patients. Not only did the works of Erkut et al. (2008) and Knight et al. (2012) show the efficiency of using survivability in location models, but also proved response time is still the most important measure of evaluating EMS performances. Therefore, it can be said, these works and their results with considering technological advancements in transportation made the foundation of this study to address the importance of using drones as a new vehicle to transport in EMS systems and serve the patients. A glance at the recent researches in the ambulance location problems shows Mohri and Haghshenas (2021) studied the ambulance location problems in the field of covering road crashes. They proposed an edge maximal covering location problem with partial coverage of the facilities on the demand edges. Wang et al. (2021) provided a comprehensive overview of emergency facility location problems in logistics including mathematical models and their extensions and applications. The next subsection discusses using drones in healthcare and the most important studies in this field will be reviewed.

Drone in healthcare

There are several types of research that have been developed with considering various models for drone delivery. Generally, a majority of these researches that drone is used to deliver has focused on vehicles routing and traveling salesman problem. For example, Murray and Chu (2015) developed the traveling salesman problem by a combination of drone and truck delivery. Yurek and Ozmutlu (2018) solved a traveling salesman problem with drones by a combination of drone and truck in a two-stage iterative decomposition approach. Ha et al. (2018) developed the study of Murray and Chu (2015) by focusing on minimum cost. Carlsson and Song (2017) studied the efficiency of adding drones as a ratio of the drone and truck velocities. Wang et al. (2017), Daknama and Kraus (2017), Dayarian et al. (2017), Dorling et al. (2016) were the researchers that modeled and developed the drone delivery with traveling salesman problem, vehicle routing problem with drones too. Since in this paper we concentrate on using drones in healthcare especially on EMS systems therefore, we focus on recent research. Dorling et al. (2016) outlined the various benefits of using drones as reduction delivery cost, high speed in transportation, and using less labor. Delivery of blood and vaccines by drones was studied by Scott and Scott (2017). Haidari et al. (2016) investigated in using drones and their benefits too. Dorling et al. (2016) studied energy consumption in drones. They showed there is a relationship between the weight of battery of drones and their utilization and proposed a new cost function based on the consumption of energy of drones. This study addresses the necessity and efficiency of drone technology in health care to enhance the survival rate of patients who need emergency medical services in the shortest possible time. Considering drone technology has raised various types of applications in optimizing mathematical models. For instance, Vempati et al. (2017) presented a mathematical model using drones to maximize the profit of amazon cooperation. Hong et al. (2017) outlined a drone's delivery network by using the facility location problem to locate the recharge stations for drones. Troudi et al. (2017) studied on the logistic delivery system of drones. They investigated in immediate delivery of parcels in urban areas in order to propose a post-production logistic system by using drone technology. From the health care application of drones, Kim et al. (2017) presented research on drone-aided-delivery and pick up systems for medication and test kits to help the patients with chronic diseases who need medicine and routine health examination in rural areas. Pulver et al. (2016) researched on locating AED drones to enhance cardiac arrest response time by employing a maximum coverage location problem to increase service coverage by drones. Pulver and Wie (2018) developed a new spatial optimization model with backup coverage location to aid in designing a network delivery of AED by drones. Van de Voorde et al. (2017) discussed using AED-equipped drones as magic bullets in their paper. They surveyed the role of benefit's drones such as being fast and low operational cost and then stated the barriers of using drones to actual deployment in real life. One of the major issues in the health care is out-of-hospital cardiac arrest (OHCA). Kong et al. (2011) researched on OHCA and estimated between 180000 and 400000 death occur due to cardiac arrest out of hospital in the united states each year. The automated external defibrillator (AED) is one of the most important instruments able to enhance the survival rates of OHCA which as a part of this research, the delivery of this equipment for OHCA by drones is addressed. Finally, it is important to mention some recent work on this scope. Scott and Scott (2020) reviewed the applications of drones in healthcare as well as models for drone delivery in medical emergencies and also based on queuing theory, they presented the probability of using defibrillators that can be delivered by drones. Rashidzadeh et al. (2021) investigated drone utilization in a blood supply chain to measure sustainability. They showed that by using drones in the last-mile delivery stage, all three aspects of sustainability will be reached.

The studies reviewed so far demonstrate several gaps in the area of using technology such as drones in EMS systems. A clear gap is shown need to use the characteristics of drones as ambulances in location problems such as maximal survival location problem (MSLP) for specific diseases. As discussed previously, considering drones as ambulances enables the EMS system to serve more patients and save more lives by delivering medical supplies at the earliest time. Therefore, we consider the combination of using drones with MSLP in the considered types of patients. Moreover, despite the importance of addressing using drones in EMS systems and ambulance location problems, there is no study that addresses the CO_2 emissions of using drones simultaneously. Furthermore, the relevant literature does not sufficiently address the multi-objective functions, characteristics of drones such as energy consumption and CO_2 emissions to deliver the medical supplies, save lives and consider different survival functions for proposed patients. Hence, our study targets another gap in the existing literature. To overcome these shortcomings and fulfill these gaps, we propose a bi-objective mathematical model that can be used to investigate trade-offs between saving lives and CO_2 emissions in the EMS system.

Problem Description

In a medical emergency service, fast delivery of healthcare products or services could be a vital factor to save lives. In this section, we introduce a mathematical model including the optimized location of EMS systems equipped by drones to investigate the importance of drones in saving lives and deliver emergency medical supplies faster than ambulances. Furthermore, the CO_2 emissions of drone utilization is another goal of this research to investigate the application of drones in EMS systems from environmental prospects too. In this paper, a new location-allocation problem for EMS stations equipped with drones is presented. The purpose of this study is to locate stations and allocate drones to each station to deliver medical supplies such as Automated External Defibrillator (AED), blood bags, vaccines, and other portable medical supplies that could be carried by drones and guaranteed that receiving those medical supplies save the lives. The first objective is following the expected survival lives of multiple-classes of patients categorized by severity and needed response time that will be saved by delivering the required medical supply carried by drones. In the second objective, we minimize total amount of CO_2 emissions of drones in the EMS stations. Both objective functions are presented to be determined the optimal number of drones and the location of their stations such that the performance and environmental aspects of drone utilization in EMS systems to be investigated.

As presented in previous sections, Erkut et al. (2008) proposed new location models by considering a survival function of the response time for the first time. They proved that response time is the main parameter to define a survival functions. They presented Maximal Survival Location Problem (MSLP) and showed its efficiency in comparison with other traditional location models when the survival of patients would be considered. Considering the out-of-hospital cardiac arrest (OHCA) patients and only one survival function was the main limitation of their model.

According to importance of response time on survival of patients especially on OHCA, the role of drones to reduce the response time has been researched recently. Multiple studies show that AED can increase survival rates for patients suffering a cardiac arrest. (Marenco et al., 2001;Cummins et al., 1984; Caffrey et al., 2003).

The AED is a vital device to enhance survival rates for OHCA. However, one of the important factors to enhance the survival rates of cardiac arrest is EMS response time therefore using drones to carry AEDs to patients who are experiencing cardiac arrest could be dramatically curtail time of between cardiac arrest and the first shock by an AED. Moreover, as we discussed in literature review section, Knight et al. (2012) proposed a new model for allocating ambulances by incorporating survival functions for the heterogeneous patients to maximize the overall expected survival probability of patients. They investigated on demands for ambulances in Wales and based on the response time of each category to survive, three categories of patients were defined. Therefore, according to the above explanation about OHCA and importance of AED for it, study of Valenzuela et al. (1997) about cardiac arrest and classification of EMS calls in Fire and EMS Department (FEMS) in the U.S, we consider four categories of functions as survival probabilities for heterogeneous patients. Table 1 shows a summary of survival probabilities for heterogeneous patients based on the response time.

Table 1. Survival functions for heterogeneous patients

Type of patient	Survival function based on travel time (t) between EMS station *j* and patient location *i*
OHCA	$S(t_{ij}) = \dfrac{1}{1+e^{0.679+0.262t}}$
A	$S(t_{ij}) = \begin{cases} 1 & for\ 0 \le t \le 8 \\ 0 & for\ \quad t > 8 \end{cases}$
B	$S(t_{ij}) = \begin{cases} 1 & for\ 0 \le t \le 14 \\ 0 & for\ \quad t > 14 \end{cases}$
C	$S(t_{ij}) = \begin{cases} 1 & for\ 0 \le t \le 21 \\ 0 & for\ \quad t > 21 \end{cases}$

CO_2 emission of drone

Before proposing the mathematical model and how CO_2 emissions of drones can be measured, we need to define the energy consumption of drones to be considered in our model. Since we assume that one type of drone is used and we know that each drone has just one-to-one trips with considering the battery capacity and a drone travels toward patient and drops its medical supply and then returns empty to EMS station, therefore the consumed energy of drone according to Figliozzi (2017) to reach a location of patient and travel back empty to EMS station is defined by equation (1).

$$e = \frac{(m_t + m_l + m_b)g}{\vartheta(s).\eta_p.\eta_r} d + \frac{(m_t + m_b)g}{\vartheta(s).\eta_p.\eta_r} d \tag{1}$$

Where: g =gravity acceleration, $\vartheta(s)$=lift-to-drag ratio of drones, m_t=drone mass tare, i.e. without battery and load, m_b=drone battery mass (kg), m_l =drone load mass (kg), η_p = total power transfer efficiency, η_r=battery recharging efficiency, d= travel distance (meter)

Since the weight of the battery (m_t)does not change as a function of distance traveled so the recharging efficiency of batteries (η_r) is not considered. The summation of drone mass tare (m_t) and drone battery mass (m_b) is defined as drone total mass $(m = m_t + m_b)$. The equation (3) is defined as energy consumption of each drone between each EMS station i and patient location j.

$$e_{ij} = \frac{\left(m + m_l^i\right)}{\vartheta(s).\eta_p} g.d_{ij} + \frac{(m)}{\vartheta(s).\eta_p} g.d_{ji} \quad \forall i,j,l \tag{2}$$

$$e_{ij} = \frac{\left(2m + m_l^i\right)}{\vartheta(s).\eta_p} g.d_{ij} \quad \forall i,j,l \tag{3}$$

Considering the heterogeneous patients leads the loaded mass of each drones from stations to patient locations be varied, therefore we need to use an estimation of consumed energy of drones between each patient location and station. Equation 4 shows the expected value of energy consumption of drones in joule.

$$E(e_{ij}) = \frac{g.d_{ij}}{\vartheta(s).\eta_p}(2m + \sum_{l \in L} m_l^i.P(m_l^i)) \quad \forall i,j \tag{4}$$

In order to investigate on the environmental aspect of using drones, we need to measure the amount of CO_2 emissions of drones. It is true that drones in comparison with conventional ambulance vehicles, would not emit a great amount of CO_2 and most real-world delivery drones do not have tailpipe emissions, however, what is considered as the CO_2 emissions of drone, is the amount of CO_2 that would be emitted at power generation facilities due to drone electricity demand. Indeed, the amount of electricity that needs to be generated at the source in order for a drone's batteries to receive 1W-hour (Wh) of charge, should be considered to determine the CO_2 emissions. In this regard, Goodchild and toy (2018) found that for every kWh used by a drone, 0.3773 kg of CO_2 is emitted at power generation facilities. To better understand, we compare the conventional ambulance vehicles and drones in terms of considering the CO_2 emission. For conventional ambulance vehicles, the carbon footprint of the vehicle utilization phase includes Well-to-Tank (WTT) – emissions that take place along the fuel/energy supply chain – and Tank-to-wheel (TTW) – emissions associated to the combustion of the fuel. For a drone, the carbon footprint includes Generation-to-Battery (GTB) emissions associated to the electricity supply chain and Battery-to-Propeller (BTP) emissions that for electric drones, the BTP component is zero. The Emissions & Generation Resource Integrated Database (eGRID), published by the U.S. Environmental Protection Agency, is utilized to estimate GTB emissions. The eGRID values include the generation of electricity at the power plants as well as electricity transmission and distribution losses (Figliozzi, 2017). Therefore, according to the research of (Figliozzi, 2017), the CO_2 emissions of drone just considers the Generation-to-Battery (GTB) emissions associated to the electricity supply chain. Hence, based on the above explanations, the expected value of CO_2 emissions of each drone are obtained in equation (5).

$$E(Co_2e_{ij}) = \frac{g.d_{ij}}{\vartheta(s).\eta_p}(2m + \sum_{l \in L} m_l^i.P(m_l^i)f_{kwh}e_{gtb} \quad \forall i, j \tag{5}$$

Where: f_{kwh}=factor to convert Joules to kWh, e_{gtb}= Emissions of the GTB phase

Mathematical Model

Let *J* denote a set of EMS station, *I* denote a set of patient location and *L* denote a set of patient types. We also assume D_i^l defines the demand of type $l \in [L]$ from the patient location $i \in [I]$ and set of fully-charged drones by *K* and j_c indicates the set of EMS stations that covers a patient. Every patient type of *L* has a survival function. Our goal is to locate EMS stations to maximize survival of patients by using drones to deliver medical supplies and allocate drones to each EMS station and simultaneously we focus on minimizing the CO_2 emissions of drone utilization. The EMS stations allocate drones to each open EMS location. These EMS stations, as drone lunching sites equipped by EMS facilities, serve the patients. Several one-to-one trips are made by drones so the vehicle routing is not required in this research. The recharging of drone batteries is not considered and is assumed they are recharged when there are no demands for EMS during planning period.

The notation used in the formulation is given below:

Nomenclature

Sets

I	Set of patient location.
J	Set of potential EMS station location.
$J_c = \{j \mid E(e_{ij}) < B\}$	Set of EMS stations covering a patient.
K	Set of available drones.
L	Set of patient types.
Indices	
$i \in I$	-
$j \in J, J_c$	-
$k \in K$	-
$l \in L$	-
Parameters	
D_i^l	Demand of type *l* patient from patient location *i*.
d_{ij}	The travel distance of drone between EMS station *j* and patient location *i*.
$S_l(t_{ij})$	The probability of survival for a patient of type *l* in travel time t_{ij}.
W_l	A weighting parameter for patient type *l*.
P	Maximum number of EMS station.
$E(e_{ij})$	Expected energy consumed during one trip between patient location $i \in I$ and EMS station $j \in J$.
B	Battery capacity of drone [Wh].
f_{kwh}	Factor to convert Joules to kWh :1/3.6 * 10^6 [kWh/Joule].
e_{gtb}	Emissions of the GTB phase [kg CO_2e/kWh)].
m_l^i	The loaded mass of drone for patient type *l* in patient location *i* [kg].
$P(m_l^i)$	The probability of the loaded mass of drone for patient type *l* in patient location *i*.
M	Maximum mass capacity of *k*th located drone.

Decision Variable

X_{ijk} 1, If patient in patient location i is served by kth drone from EMS station $j \in J$,and 0, otherwise.

Z_{jk} 1, If the kth drone is assigned to EMS station $j \in J$, and 0, otherwise.

Y_j 1, If EMS station is located at $j \in J$, and 0, otherwise.

$$\max \sum_{i \in I} \sum_{j \in J} \sum_{k \in K} \sum_{l \in L} W_l \, D_i^l S_l(t_{ij}) X_{ijk} \tag{6}$$

$$\min \sum_{i \in I} \sum_{j \in J} \sum_{k \in K} \sum_{l \in L} \frac{g.d_{ij}}{\vartheta(s).\eta_p} (2m + \sum_{l \in L} m_l^i . P(m_l^i)) f_{kwh} e_{gtb} X_{ijk} \tag{7}$$

$St.$

$$\sum_{j \in J_c} Y_j \le P \tag{8}$$

$$\sum_{j \in J_c} \sum_{k \in K} X_{ijk} \le 1 \quad \forall i \in I \tag{9}$$

$$\sum_{i \in I} E(e_{ij}) X_{ijk} \le B Z_{jk} \quad j \in J_c, k \in K \tag{10}$$

$$\sum_{l \in L} m_l^i P(m_l^i) X_{ijk} \le M \quad \forall i \in I, j \in J_c, k \in K \tag{11}$$

$$\sum_{j \in J_c} Z_{jk} \le 1 \quad k \in K \tag{12}$$

$$Y_j \ge Z_{jk} \quad j \in J_c, k \in K \tag{13}$$

$$X_{ijk} \le Z_{jk} \quad i \in I, j \in J_c, k \in K \tag{14}$$

$$X_{ijk}, Y_j, Z_{jk} \in \{0,1\} \forall i \in I, j \in J_c, k \in K \tag{15}$$

The first objective function shown in equation (6) maximizes the overall expected patient survival of defined types of patients. To minimize the total CO_2 emissions of drones, equation (7), is presented. Equation (8) states the maximum number of EMS stations that must be located. Equation (9) ensures that each patient receives medical supply at most by one drone from one EMS station. Equation (10) enforces that the consumed energy of drone to deliver the medical supplies must be less than the battery capacity of drone. Equation (11) defines that the required mass of all types of patients carried by each drone must be less than or equal to the capacity of the drone. Equation (12) forces that each drone must be assigned to at most one EMS station. Equation (13) ensures that each drone must be assigned to an EMS station which has been already covered by it. Equation (14) forces that patient i is served by kth drone from EMS station j if the kth drone has been already assigned to EMS station j. Equation (15) corresponds to decision variable definition constraints and forces all of them to be binary.

Solution method

The goal of multi-objective programming models is to find efficient solutions. An efficient solution has the property that it is impossible to improve anyone objective values without sacrificing at least

one other objective. The proposed model in this paper is a bi-objective integer (0-1) linear programming with objective functions that are in conflict with each other that a feasible solution cannot optimize them simultaneously.
Multi-objective optimization can be solved in two ways: classic methods and evolutionary algorithms. One of the most powerful approaches of classic methods in real-world decision-making to solve multi-objective mathematical models is Goal Programming (GP) firstly introduced by Charnes and Cooper (1957). In GP, decision-makers should determine an expectation level for each objective and the purpose is to minimize the total deviations of each objective value from its goal (Shahnazari-Shahrezaei et al., 2013) but due to uncertainty in the supply chain especially in the last stage for delivery, it is almost impossible for decision-makers to define a goal for each objective precisely. To incorporate this uncertainty into the decision-making process a fuzzy set theory as an effective approach has been introduced by Kim et al. (2000).
A novel extension of FGP is preemptive version that has been developed recently by Tsai et al. (2008). In the preemptive FGP (PFGP) the goals should be prioritized. Chen and Tsai (2001) and Tsai et al. (2008) applied this approach to the allocation problem successfully. Mirzaee et al. (2018) solved a problem of supplier selection by a novel PFGP approach and evaluated performance of this approach. They showed the superiority of their approach against weighted fuzzy goal programming, max-min programming, and classical goal programming approaches. Therefore, according to this and the presented objectives in the model which don't have the same priority since the patients' lives are more important that the environmental issues, the maximization of expected survival patients and minimization of CO_2 emissions of drone will be had the first, and second priority respectively. The PFGP model for goals is presented as below based on Mirzaee et al. (2018):

$$Max \sum_{h=1}^{2} \mu_h \tag{16}$$

$$St.$$

$$\mu_1 + \frac{1}{g_1 - L_1}.\delta_1^- \leq 1 \tag{17}$$

$$f_1 + \delta_1^- \geq g_1 \tag{18}$$

$$\mu_2 + \frac{1}{U_2 - g_2}.\delta_2^+ \leq 1 \tag{19}$$

$$f_2 - \delta_2^+ \leq g_2 \tag{20}$$

$$\mu_1 \geq \mu_2 \tag{21}$$

$$\mu_1, \mu_2, \in [0,1] \tag{22}$$

Where: λ_1, λ_2 are the achievement degrees for the first and second fuzzy goals, f_1, f_2 are objective function values for the first and second objective, U_1, L_1 are the upper and lower bounds of the first objective, U_2, L_2 are the upper and lower bounds of the second objective, g_1, g_2 are the determined goals for the first and second objective, δ_1^-, δ_1^+ are the deviations of the first and second objective from their goals.

The linear membership function for each goal is defined as follows:

For minimization:

$$\mu_{f_i}(x)=\begin{cases}1\,,f_i\le g_i\\ \dfrac{U_i-f_l}{U_i-g_i},g_i\le f_i\le U_i\\ 0,g_i\ge U_i\end{cases}$$

For maximization:

$$\mu_{f_i}(x)=\begin{cases}1\,,f_i\ge g_i\\ \dfrac{f_i-l_i}{g_i-l_i},l_i\le f_i\le g_i\\ 0,g_i\le l_i\end{cases}$$

Therefore, the proposed model of this paper based on PFGP is described as follows:

$$Max\sum_{h=1}^{2}\mu_h \tag{23}$$

$$St.$$

$$\mu_1+\frac{1}{g_1-L_1}.\delta_1^-\le 1 \tag{24}$$

$$\sum_{i\in I}\sum_{j\in J}\sum_{k\in K}\sum_{l\in L}W_l\,D_i^lS_l(t_{ij})X_{ijk}+\delta_1^-\ge g_1 \tag{25}$$

$$\mu_2+\frac{1}{U_2-g_2}.\delta_2^+\le 1 \tag{26}$$

$$\sum_{i\in I}\sum_{j\in J}\sum_{k\in K}\sum_{l\in L}\ \frac{g.d_{ij}}{\vartheta(s).\eta_p}(2m+\sum_{l\in L}m_l^i.P(m_l^i)f_{kwh}e_{gtb}X_{ijk}-\delta_2^+\le g_2 \tag{27}$$

$$\mu_1\ge\mu_2 \tag{28}$$

$$\sum_{j\in J_c}Y_j\le P \tag{29}$$

$$\sum_{j\in J_c}\sum_{k\in K}X_{ijk}\le 1\qquad\forall i\in I \tag{30}$$

$$\sum_{i\in I}E(e_{ij})X_{ijk}\le BZ_{jk}\qquad j\in J_c,k\in K \tag{31}$$

$$\sum_{l\in L}m_l^iP(m_l^i)X_{ijk}\le M\quad\forall i\in I,j\in J_c,k\in K \tag{32}$$

$$\sum_{j\in J_c}Z_{jk}\le 1\quad k\in K \tag{33}$$

$$Y_j\ge Z_{jk}\qquad j\in J_c,k\in K \tag{34}$$

$$X_{ijk}\le Z_{jk}\quad i\in I,j\in J,k\in K \tag{35}$$

$$X_{ijk}\le Z_{jk}\quad i\in I,j\in J_c,k\in K \tag{36}$$

$$\mu_1,\mu_2\in[0,1] \tag{37}$$

$$\delta_1^-,\delta_2^+\ge 0 \tag{38}$$

Equation (23) maximizes the total achievement degree of objectives. Equations (24)–(27) determine achievement degrees of goals related to each objective function. Equation (28) shows the priory of goals. Equations (29)–(36) are the same constraints of presented model in Section 3. Equations (37) and (38) correspond to variable definition constraints.

Numerical Experiments

In this study, the feasibility and efficiency of using drones for deliveries of medical supplies will be tested. To approve the efficiency of this research, it is appropriate to be examined the presented model with the real data of related researches. According to the literature review, there is an appropriate paper in this area of research that can be utilized. The research of Knight et al. (2012) implied the data of emergency calls of Welsh Ambulance Services NHS Trust (WAST) in the region of South East Wales with 18 demand locations $i\epsilon\{1.2.\ldots.18\}$ corresponding to postcode districts, and 11 EMS stations $j\epsilon\{\mathrm{A.B.}\ldots.\mathrm{K}\}$ along with four types of patient (Knight et al., 2012). In their research, 36 ambulances have been assigned to 11 EMS stations such that they are able to save 216.7 patients on average. The result of the proposed model can be evaluated with the related results of Knight et al. (2012) especially in terms of expected survival patients to investigate the advantages of using drones compared with ordinary ambulances. As we know, the energy consumption of drones is defined by the travel distance, so, we need to indicate the energy consumption between each demand and EMS station. In this regard, we assume that the specific type of drone (The MD4-3000 is used for specification parameters of drone in the mathematical model) will be used by EMS stations to serve the patients. The specification parameters of drones to calculate the energy consumption and all other parameters such as the required medical supply for each type of patient are shown in Table 2 and Table 3. (Figliozzi, 2017; Knight et al., 2012).

Table 2. Parameters values

Parameter	Value	Parameter	Value
η_p	0.66	e_{gtb}	0.562[kg CO2e/kWh]
$\vartheta(s)$	3.5	M	5[kg]
m	10.1[kg]	g	9.8(m/s^2)
B	777[Wh]	f_{kwh}	$1/3.6 \times 10^6$ [kWh/Joule]

Table 3. Parameters values

l:Patient type	Required medical supply	m_l^i: drone load mass (kg) $\forall i$	W_l: weighting parameter $\forall i$
OHCA	AED	1.1(kg)	16
A	Medical oxygen cylinder	1.67(kg)	8
B	Blood bag with container	5(kg)	4
C	Drugs	3(kg)	2

In this research, the number of EMS stations to be located and the total number of drones to be assigned have been considered equal to the number of ambulance stations and the total number of ambulances respectively, in the study of Knight et al. (2012). Therefore, we assume that there are 11 EMS stations along with 36 drones that should be assigned to them. After carefully converting the data (To convert the data for this research, the average speed of ordinary ambulance and drones in rural area have been considered 30km/h (8.4m/s) and 80.5 km/h (22.37m/s) respectively) of study of Knight et al. (2012) including travel distance, travel time, energy consumption and, etc. to be utilizable for this research, the proposed model is carried out by the PFGP approach. It should be noticed that the patient category of each demand location determines the load mass of drones and this affects the energy consumption of drones and CO_2 emissions subsequently. Hence, the probability of loaded mass based on patient category for each demand location, $\boldsymbol{P(m_l^i)}$ should be calculated. All proposed models are implemented in GAMS ver25.1.2 and made on a Windows 10 desktop with Intel Core i5-6100 CPU 3.7 GHz, 4 Core(s), and 8 GB of RAM.

Table 4. Results of numerical example

L_1	U_2	μ_1	μ_2	$\sum_{h=1}^{2} \mu_h$	f_1^*	f_2^*
188.61	22.57	0.841	0.388	1.229	205.7	9.51

Table 5. Results of decision variables of numerical example

$Y_j = 1$	$Z_{jk} = 1$	$X_{ijk} = 1$
1[a]	1-2[b]	1-1-2[c], ,3-1-2
	1-8	18-1-8
	1-9	2-1-9,11-1-9
	1-17	9-1-17
2	2-19	14-2-19
	2-21	16-2-21
4	4-30	5-14-30
7	7-31	6-7-31,15-7-31
	7-32	17-7-32
	7-29	7-7-29
8	8-3	8-8-3
	8-14	13-8-14
9	9-10	4-9-10,10-9-10
	9-33	12-9-33

[a] $Y_1 = 1$, [b] $Z_{12} = 1$, [c] $X_{112} = 1$

Table 4 shows that based on the PFGP approach, the maximum total value of achievement degree is 1.229 that states the optimal solution based on humanitarian and environmental views. Moreover, the results of Table 5 show that 14 drones and 6 EMS stations are applied such that they save 205.7 patients and emit 9.51 kg CO_2. In order to show the efficiency of using drones in EMS systems, we compare our results with the results of Knight et al. (2012). In Table 6, the obtained results from the first objective function show that drone utilization in EMS stations in comparison with the utilization of regular ambulance vehicles are able to save more patients' lives. Furthermore, to prove the impact of drone utilization on the environmental aspect, we calculate the CO_2 emissions of regular ambulance vehicles and compare the results of drones together. It should be noted that each drone based on the battery range could make several one-to-one trips but the regular ambulances are able to make one-to-many trips that require considering a vehicle routing problem. Furthermore, the formulation of consumed energy and CO_2 emissions for diesel vehicles such as regular ambulance vehicles will change the main mathematical model. Therefore, to prevent the conflict in predefined assumptions and follow the main mathematical model, and also to explore the structural finding by drone utilization in comparison with regular ambulance vehicles, the ratio indicator of CO_2 emissions per unit distance is defined for the environmental aspect. By determining this indicator, we can estimate the total amount of emitted CO_2 of regular ambulances in the study of Knight et al. (2012). In this regard, the optimal value of CO_2 emissions obtained from drone utilization is multiplied by the defined indicator, to acquire the results of regular ambulance utilization. It is worth noting that, based on Figliozzi (2017), the data of MD4-3000 drone and diesel cargo van RAM ProMaster 2500 have been used to determine the ratio indicator. The results state that drone is preferred if one-to-one service performance is considered. Besides, this comparison proves the superiority of drone technology against the conventional vehicles of ambulances in achieving environmental aspects. Based on Table 6 and Table 7, it is obvious that drone utilization in EMS stations is more efficient in comparison with regular ambulance vehicles from performance and environmental aspects since they save more patient's lives and emit less CO_2 emissions.

Table 6. Comparing the obtained results of this study with Knight et al. (2012)

Research	Optimal number of drone/Regular ambulance vehicle	Optimal number of EMS station	Number of saved patients
Knight et al. (2012)	36	11	198.57
This study	14	6	205.7

Table 7. Comparing the expected value of CO_2 emissions

Items	Emissions per unit distance(kgCO2e/km)
Regular ambulance vehicle (1)	6.79
Drone (2)	2.42
Ratio: (1)/(2)	2.80
CO_2 emissions (drone)	9.51
Estimation CO_2 emissions (Regular ambulance vehicle)	26.63

Conclusion

This paper presented a novel bi-objective mathematical model for EMS systems to maximize the survival of heterogeneous patients and minimize the CO_2 emissions which in, drone as an EMS vehicle to deliver the portable medical supplies was introduced. In other words, a new mathematical model of location-allocation problem of EMS stations with drone-aided delivery by incorporating survival functions for heterogeneous patients was presented to maximize the expected survivor of heterogeneous patients and minimize the CO_2 emission of utilization drones. Since the objective functions in the proposed model didn't have the same priority, it was solved by the preemptive fuzzy goal programming approach in order to measure the achievement degree of objective functions. To prove the impact of drones in EMS systems, we used the real data of research of Knight et al. (2012) to be able to compare the results of drone utilization with the regular ambulance. The results showed that drone utilization in EMS stations is more efficient in comparison with regular ambulance vehicles from performance and environmental aspects since they can save more patient's lives and emit less CO_2 emissions. Future research should focus on alternative power sources for drones, such as fuel cells and real-life constraints such as strict regulation to fly drones. Tracking the location of the drone and recovering them from a lost location in case of any power failure, combining various transportation means such as trucks and drones, considering limitations of drones such as flight time, and applying another method to solve the mathematical model instead of the fuzzy goal programming approach can be considered as some interesting subjects for future studies.

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