Multi-Objective Two-Stage Stochastic Programming Model for a Proposed Casualty Transportation System in Large-Scale Disasters: A Case Study

Nadide Caglayan 1,2 and Sule Itir Satoglu 1,*

1 Industrial Engineering Department, Faculty of Management, Istanbul Technical University, 34367 Istanbul, Turkey; caglayan16@itu.edu.tr
2 Industrial Engineering Department, Faculty of Engineering and Architecture, Erzurum Technical University, 25050 Erzurum, Turkey
* Correspondence: onbaslis@itu.edu.tr

Abstract: Disaster management is a process that includes mitigation, preparedness, response and recovery stages. Operational strategies covering all stages must be developed in order to alleviate the negative effects of the disasters. In this study, we aimed at minimizing the number of casualties that could not be transported to the hospitals after the disaster, the number of additional ambulances required in the response stage, and the total transportation time. Besides, we assumed that a data-driven decision support tool is employed to track casualties and up-to-date hospital capacities, so as to direct the ambulances to the available hospitals. For this purpose, a multi-objective two-stage stochastic programming model was developed. The model was applied to a district in Istanbul city of Turkey, for a major earthquake. Accordingly, the model was developed with a holistic perspective with multiple objectives, periods and locations. The developed multi-objective stochastic programming model was solved using an improved version of the augmented ε-constraint (AUGMECON2) method. Hence, the Pareto optimal solutions set has been obtained and compared with the best solution achieved according to the objective of total transportation time, to see the effect of the ambulance direction decisions based on hospital capacity availability. All of the decisions examined in these comparisons were evaluated in terms of effectiveness and equity. Finally, managerial implication strategies were presented to contribute decision-makers according to the results obtained. Results showed that without implementing a data-driven decision support tool, equity in casualty transportation cannot be achieved among the demand points.

Keywords: casualty transportation; disaster management; mass casualty incidents; information system; multi-objective programming; stochastic programming

1. Introduction

In the disaster management process, the implementation decisions concerned with the mitigation, preparedness, response, and recovery stages must be made to alleviate these events’ negative effects, and to keep the situation under control. Disaster management operations include preparation, supply, transportation, location, distribution, tracking, and storage problems. These operations play an important role in preventing damages [1]. Although there are different definitions in the literature, the disaster management process is evaluated in four stages. Three main phases cover these processes. The three phases of disaster management are pre-disaster, disaster situation (disaster) and post-disaster. While pre-disaster management considers the period before the disaster occurs, the disaster situation is the aftermath of the event, and post-disaster is the period between the occurrence of the disaster and the return to the normal conditions [2]. Some studies divide the process into two phases as pre-disaster and post-disaster. According to Caunhye et al. [3], the main decisions are evaluated in pre-disaster operations (facility location, pre-positioning and
evacuation) and post-disaster operations (involving relief distribution and casualty transportation). In this study, pre-disaster and post-disaster stages were evaluated together to plan the casualty transportation process from triage points to the hospitals.

Planning of emergency activities can be made stronger with the implementation strategies determined before the event occurs. The disaster management studies model several decisions pertaining the temporary medical centers [1], needed equipment and materials [4], evacuation planning [5], and relief transportation processes [6]. These decisions will serve as an effective roadmap by facilitating the operational decisions in the response phase. Casualty transportation including multi-stage decisions is an important part of disaster management, with pre-disaster planning and post-disaster decisions. This transportation operation includes evacuation, and casualties transportation from the affected areas to the medical centers [7]. Effective transportation planning improves the survival rates of the casualties in disasters [8]. The timely and effective usage of resources is vital for the people affected by disasters [9]. One of the resources used in the casualty transportation process is ambulances. The response stage carried out by responsible organizations, after a disaster, must be designed to cope with the challenges of a dynamic planning situation, by considering limited ambulance resources [10]. In case of disaster response, the main duties of ambulances are to provide first aid to the casualties and to transport urgent casualties to the hospitals. Managing ambulance operations immediately after a disaster is complex, due to the dynamic nature of the problem and events’ uncertainties [11].

In ambulance planning, the number and location of the casualties, the availability of ambulances, the nearby hospitals’ capacity, the accessibility of the incident sites and the current traffic situation are necessary information [12]. According to Altay and Labonte [13], qualified information provides effective decision-making and coordination between humanitarian actors in complex systems. The information transfer between disaster coordination units also helps manage the chaotic process. It cannot be easy to access information in a large-scale disaster, unless an information system is developed beforehand. The use of information technologies and data analytics implications enhances disaster management and operation planning [14]. The information system may help mitigate the negative effects of disaster before the occurrence [15].

Planning of ambulances is the responsibility of emergency medical services (EMS). Bélanger et al. [16] classified EMS decisions according to the decision levels, the decisions taken for the problem, strategies and models. Ambulance location problems are divided into static location and relocation problems. Coverage, location-allocation problems are also evaluated under static location problems. In this study, the coverage problems are classified at the strategic level, ambulance location-relocation-allocation problems are considered on the operational decision level, and these problems are discussed. The coverage analysis of the EMSs includes emergency medical facility sites, demand locations, and road traffic conditions [17]. The static ambulance location problem aims to select the stations where the vehicles are available to await the emergency calls. The problems where the ambulance locations are changed according to the system’s changes over time are relocation problems [18]. Ambulance dispatching addresses the problem of assigning ambulances to the emergency calls. In this type of problem, the fast response of the ambulances to the call is a performance factor and rules are studied to improve the response time [19].

In this study, we aim to minimize the number of unserved casualties, the number of ambulances as well as the total transportation time by creating scenarios based on uncertain factors. Besides, a decision support tool is proposed to monitor hospitals’ available capacities, coordinate the ambulances, and track casualties. Hence, we developed a multi-objective, two-stage stochastic programming model for multiple periods to evaluate the problem related to ambulance management as a whole, based on the proposed decision support tool. In the aftermath of the disaster, the success of operations depends on the scenarios created in the pre-disaster phase and the implementation decisions made according to these scenarios. Therefore, different scenarios are created based on the number of casualties, the triage percentage of the casualties, the damage proportion of the roads and
hospitals in the model. In the study, the locations of triage points, existing hospitals and emergency medical services, the health scores of the casualty, hospital capacities, the population of the regions and some standards in the literature were taken into consideration. To the best of our knowledge, for large-scale emergency incidents such as disasters, there are no other study that assigned triage points to the emergency stations before the event and decided on the number of ambulances that may be required, by minimizing the number of unserved casualties and the time spent in transportation, based on their health status. This is the unique aspect of our study. The study presents the decisions to be taken before the disaster to carry out a fast and effective casualty transportation operation, by solving three different objectives at the same time. In this respect, this is an important study that can help decision-makers. The real case application also revealed the utility of our model.

The paper is organized as follows. In Section 2, the literature is reviewed. Section 3 includes two parts, where the problem definition and the proposed stochastic models are explained, and the methodology and the solution strategies are presented. Section 4 applies the model to a case of the earthquake. The results of the study are discussed in Section 5. Finally, conclusions and directions for future research are discussed in Section 6.

2. Literature Review

The operational planning of emergency aid is crucial in disasters. The effectiveness of tactical decisions to be taken during the response phase will be increased with strategic decisions taken during the preparedness phase. There exist several streams of research such as ambulance locating, dispatching, and routing studies in disaster response stage [11]. There are several studies that estimated the number of ambulances for the cases except the disaster. Because ambulance management problems are dynamic, these problems’ conditions become different, especially in case of large-scale disasters, compared with those of the normal conditions.

Decisions of ambulance location and allocation that minimizes the number of ambulances is difficult due to the limited number of ambulances to cover all of the demand points, and these are critical for EMS management [20]. While location planning decisions are strategic, redeployment problems are operational, and these problems are solved dynamically in real-time, and emergency medical service managers often need to make spontaneous decisions for allocation and redeployment [21]. Gong and Batta [22] developed two models for the assignment of ambulances to the injured areas and the relocation of ambulances. Models were evaluated according to make-span and weighted total flow time. Knight et al. [23] developed an ambulance location model to maximize the probability of survival by dividing patients according to their health status and expected response time. Salman and Gul [24] proposed a multi-period deterministic optimization model that minimizes the setup costs of new facilities and the total waiting and transportation times of the injured people. Na and Banerjee [25] evaluated triage assignment and transportation problems together. They developed a casualty assignment model by considering the priority of the injured, multi-type vehicles and different types of resources in their studies. They optimized the number of survivors and total evacuation costs. Flores et al. [5] proposed a lexicographic goal programming for evacuation planning by considering hospitals, medical centers, different types of vehicles and health conditions in their study. In the study, the objective function consists of four deviation variables considering critical population evacuated, non-critical population evacuated, total evacuation time and operation cost. Zhang et al. [26] proposed a casualty transportation model based on a real case application. They formulated the problem as a multi-trip dial-a-ride problem, and they solved it with a modified memetic algorithm. Schneeberger et al. [27] studied the location and allocation problem before a disaster and relocation of the ambulances after a disaster. However, the study does not consider the casualty transportation between the locations. Fancello et al. [28] studied the location and allocation problem of vehicles participating in relief operations in large-scale industrial disasters. The aim is to maximize the number of injured patients treated. Dean and Nair [29] developed a mixed integer programming model to
maximize the number of expected survivals. The developed model includes ambulances, multiple hospitals and victim score levels, but different purposes and damage ratios of road and hospitals does not consider. Jacobson et al. [30] developed a stochastic dynamic model for priority assignment problem by considering the ambulances and medical rooms, disaster level and casualties according to the probability distribution of survival time. Paul and Batta [31] studied ambulance allocation in the preparedness phase. The study aims to minimize the cost of unserved casualty in a survivability time, and the travel times, the shortest path is determined in the study. Mills et al. [32] studied on ambulance assignment to the injured peoples’ demand points and hospital selection for transportation. In the study, they established two heuristic models according to the Markov decision process. Shin and Lee [33] developed a Markov decision process model for casualty transportation. The model determines transport priority and hospital selection decisions to maximize the expected number of survivors. As a result, the number of studies aiming at the ambulance location-allocation and the minimum number of ambulances in case of disasters is very few. For a detailed review of the literature, readers can refer to the work of Farahani et al. [34].

Unlike previous studies, this study integrates the information system and the casualty transportation process. Firstly, a decision support tool is proposed for casualty tracking and monitoring the system elements. Secondly, a mathematical model is developed for the problem. The problem is considered as an ambulance location problem according to the population of the region before a disaster, and it is optimized to provide maximum service to the casualties after the disaster. The paper combines the actual situations and the disaster-relief operations by considering the population and the expected number of casualties according to their health score. This study can be classified according to the decisions, such that we consider the coverage problem in the first stage, the relocation problem in the second stage, and ambulance allocation in all stages, based on casualty prioritization for disaster events. These three problem types are solved in an integrated way in a multi-objective and two-stage stochastic programming model. To the best of our knowledge, this is the first study that integrates these coverage, ambulance allocation and reallocation problems simultaneously for disaster preparedness and response, in a multi-objective and stochastic setting. Besides, our study explains the role of information systems in disaster relief by the proposed data-driven decision support tool. Hence, it establishes a bridge between many study subjects.

3. Methodology

In this section, firstly, the problem is defined, and the casualty transportation system is proposed. Later, the mathematical formulation of the proposed stochastic programming model is presented and explained. The aim of the study is to determine the optimum implication strategy to minimize the number of unserved casualties, transportation time and planning the number of needed ambulances. As shown in Figure 1, the research approach followed involves three phases: problem definition, model development, and evaluation of the results. Problem definition concerns the type of the casualty transportation system, collection of the necessary data, and creation of the scenarios on the basis of the uncertain parameters and their values. Stage 2, which is model development, includes the formulation of the objective functions based on the key factors affecting the casualty transportation system in case of disasters, as well as the constraints’ definition. Here, some vital parameters are pre-determined and considered. At the last stage, we solve our multi-objective stochastic two-stage stochastic model for a case using the improved version of the augmented $\varepsilon$-constraint (AUGMECON2) algorithm. Further details of the phases are described in the following sub-sections.
3.1. Problem Definition

In large-scale disasters, it is important to be able to transport the casualty to the hospitals in a short time to prevent loss of life. In order to respond quickly, the number of ambulances that the regions may need should be planned in advance. Accordingly, in the disaster preparedness stage, determining the location and number of ambulances by considering the population and the number of expected casualties is a strategic decision for emergency management. In this study, casualties are classified based on their health score, which is a sum of Respiratory rate, Pulse rate, and Motor response values (RPM score) [35]. It is assumed that the RPM scores are 1–4 for unstable urgent casualties (T1), 5–8 for stable urgent (T2), and 9–12 for non-urgent (T3). The real-time monitoring of the casualty number, their RPM scores, hospitals’ available capacities and ambulance dispatching will provide information that affects the casualty transportation decisions. If the RPM scores given according to the triage are tracked, the ambulances can select the one at the nearest demand point among the casualties with the lowest RPM score. Therefore, the priority patient can be transferred to the hospital earlier. The general framework of the proposed casualty transportation system and ambulance movements in the process are presented in Figure 2. The first left block explains the general data stream, and other blocks

![Research Methodology Flow Diagram](image)

**Figure 1.** Research methodology flow diagram.

**3.1. Problem Definition**

In large-scale disasters, it is important to be able to transport the casualty to the hospitals in a short time to prevent loss of life. In order to respond quickly, the number of ambulances that the regions may need should be planned in advance. Accordingly, in the disaster preparedness stage, determining the location and number of ambulances by considering the population and the number of expected casualties is a strategic decision for emergency management. In this study, casualties are classified based on their health score, which is a sum of Respiratory rate, Pulse rate, and Motor response values (RPM score) [35]. It is assumed that the RPM scores are 1–4 for unstable urgent casualties (T1), 5–8 for stable urgent (T2), and 9–12 for non-urgent (T3). The real-time monitoring of the casualty number, their RPM scores, hospitals’ available capacities and ambulance dispatching will provide information that affects the casualty transportation decisions. If the RPM scores given according to the triage are tracked, the ambulances can select the one at the nearest demand point among the casualties with the lowest RPM score. Therefore, the priority patient can be transferred to the hospital earlier. The general framework of the proposed casualty transportation system and ambulance movements in the process are presented in Figure 2. The first left block explains the general data stream, and other blocks
show the selection of the hospital, demand points and ambulance movements between the locations. In the study, it is assumed that the infrastructure of the proposed system is ready for information flow. With this system, descriptive information of casualties, RPM score after triage, location and time information, current capacity information of hospitals, locations and descriptive information of ambulances are transferred to the EMS coordination center. Ambulance drivers in the surrounding locations can view the available capacity of hospitals and the casualties based on RPM score. According to this study, a mathematical model with three different objective functions is proposed considering the crucial factors. The general purpose of the mathematical model is to transport the highest number of casualties to the hospitals according to the RPM (urgency) score with the least resource usage. With the proposed mathematical model, it is possible to determine the demand points assigned to the EMSs before the disaster (first stage decision), the minimum number of ambulances required at these stations according to the number of ambulances available, and the assignment of the casualty to ambulances and hospitals after the disaster (second stage decision). The proposed model is a multi-objective two-stage stochastic programming model, which includes multi-facility and multi-period.

![Figure 2. The casualty transportation system design.](image)

### 3.2. A Multi-Objective Two-Stage Stochastic Programming Formulation

The proposed stochastic model finds an optimal solution while minimizing the number of unserved casualties, needed ambulances and transportation time by considering casualty RPM score, demand, the possibility of damage to the hospitals, and distance between the disaster areas and the hospitals and emergency coordination stations. In the first stage of the model for all objective functions, the demand points are assigned to the existing emergency coordination stations, and it is decided to locate the minimum number of ambulances to these stations. The first-stage decision variables of the model consist of whether the demand point-j is assigned to the emergency medical service station-i, and how many ambulances should be in the emergency medical service station-i, denoted by \( y_{ij} \) and \( x_{ij} \), respectively. The uncertainty of the expected number of casualties in the demand points is considered by a set of scenarios that represent the second stage of the stochastic model. Second stage decisions determine the required number of ambulances to minimize the unserved number of casualties and transportation time from demand points to the hospitals, after the disaster. For these purposes, a multi-objective two-stage stochastic programming model is developed. A mathematical model with three different objective functions is proposed considering the crucial factors.
functions is proposed. The general purpose of the mathematical model is to transport the casualties to the hospitals by considering their health conditions, by using the least amount of resource. With the proposed model, it is possible to determine the demand points assigned to the emergency stations before the disaster, the minimum number of ambulances required at these stations according to the number of ambulances available, and the appointment of the injured people to the ambulances and hospitals after the disaster. The proposed model includes assignments to three location groups: hospital, emergency medical service coordination stations, and triage points. In addition to this, the model has some assumptions. These assumptions are:

- In the first stage, the ambulances are assigned to the EMS according to the existing number of ambulances.
- Before the disaster, ambulances are only available at emergency stations.
- Ambulances may leave EMS, but casualties are not transported to the EMS, but to the hospitals.
- At the beginning of the first period, while emergency stations send ambulances only to the triage points assigned to the station, ambulances can serve to each point within the period and in the following periods.
- Additional ambulances can come in every period, and the arriving ambulance will serve in the next period.
- Ambulances can work throughout the periods.
- RPM scores of the patients do not change.

The formulation is represented by two main location sets \((I, J)\), where \(I\) is the set of ambulance locations presenting the location-allocation areas of the ambulances, and \(J\) is the set of triage areas, which are the centers of sub-districts. Set of ambulance locations consists of EMSs and hospital locations. EMSs shown with the set \(E\) are ambulance locations in the first stage (before the disaster) and second stage. Hospitals shown with the set \(H\) are also ambulance locations, since ambulances wait in each hospital. In the second stage (after the disaster), the ambulances leaving the EMSs or the hospitals take the casualty from the triage point and transfer to the hospitals and repeat the cycle by leaving this new location (hospital). The indices, parameters and the model formulation are explained below.

**Index and sets:**
- \(S\) Set of scenarios \(s \in S\)
- \(R\) Set of RPM scores \(r \in R\)
- \(I\) Set of ambulance locations \(i, i' \in I : I = E \cup H\)
- \(E\) Set of emergency medical services \(E \subset I\)
- \(H\) Set of hospital locations \(h \in H : H \subset I\)
- \(J\) Set of triage areas \(j \in J\)
- \(T\) Discretized time periods \(t, n \in \{0, \ldots, T\}\)

**Parameters**
- \(N_{\text{A}_{\text{max}}}\) Maximum number of ambulances that can be sent to the disaster area
- \(N_{\text{A}_{\text{actual}}}\) The existing number of ambulances
- \(N_{\text{pop}}\) The maximum population can be covered by one ambulance
- \(p_{\text{pop}}\) The population of demand point-\(j\)
- \(\lambda_r\) RPM score-\(r\) of casualty \((r = 0, 0; r = 1, 1 \ldots)\)
- \(t_{ij}\) Transportation time between \(i\)-ambulance location and \(j\)-demand point
- \(t_{\text{standard}}\) The time limit between the demand points and EMSs for transportation
- \(t_{\text{prep}}\) The preparation time for ambulances
- \(T_{\text{period}}\) Length of period
- \(M\) A very big number
- \(z_{sr}^j\) The number of RPM score-\(r\) casualties at demand point-\(j\) in period-\(t\) according to scenario-\(s\)
- \(t_i^j\) Transportation time between ambulance location-\(i\) and demand point-\(j\) in scenario-\(s\)
- \(C_h^j\) The capacity of hospital-\(h\) in the scenario-\(s\)
- \(\tau_{\text{casualty}}^s\) The sum of expected casualties in the scenario-\(s\)
\[ \tau_s^{\text{capacity}} \text{ The total capacity of hospitals in the scenario-} \]

First Stage Decision Variables:
\[
x_i \text{ The number of ambulances in ambulance location-} \]
\[
y_{ij} = \begin{cases} 1 & \text{If demand point-} j \text{ is assigned to ambulance location-} i, \\
0 & \text{otherwise.} \end{cases}
\]

Second Stage Decision Variables:
\[
dx_{it}^s \text{ The number of additional ambulances required at the ambulance location-} i \text{ in period-} t \text{ according to scenario-} \]
\[
d_{it}^s = \begin{cases} 0 & \text{otherwise.} \end{cases}
\]

\[
y_{it}^s \text{ The number of ambulances in ambulance location-} i \text{ at the beginning of period-} t \text{ according to scenario-} \]
\[
\omega_{it}^s \text{ The number of RPM score-} r \text{ casualties transported from demand point-} j \text{ to hospital-} h \text{ in period-} t \text{ according to scenario-} \]
\[
v_{ij}^s \text{ The number of RPM score-} r \text{ casualties unserved in demand point-} j \text{ at period-} t \text{ according to scenario-} \]
\[
lx_{ijt}^s \text{ The number of ambulances arriving from ambulance location-} i \text{ to demand point-} j \text{ and transporting the casualty from demand point-} j \text{ to hospital-} h \text{ in period-} t \text{ according to scenario-} \]
\[
AC_{h}^s \text{ The available capacity of hospital-} h \text{ in period-} t \text{ according to scenario-} \]
\[
\beta_s = \begin{cases} 1 & \text{if } \tau_s^{\text{casualty}} \geq \tau_s^{\text{capacity}} \text{ in period-} t, \\
0 & \text{otherwise.} \end{cases}
\]

Objectives
\[
\text{First Objective (f1) : Minimize } E_x^s[Q(x, y, \xi)], \tag{1}
\]
\[
\text{Second Objective (f2) : Minimize } \sum_{i \in E} x_i + E_z[\mathcal{W}(x, y, \nu)], \tag{2}
\]
\[
\text{Third objective (f3) : Minimize } \sum_{i \in E, j \in J} t_{ij}y_{ij} + E_z[\mathcal{G}(x, y, \zeta)], \tag{3}
\]

where,
\[
E_x^s[Q(x, y, \xi)] = \min \sum_{s \in \mathcal{S}} p_s \left[ \sum_{r \in \mathcal{R}} \sum_{j \in J} \sum_{t \in T} (13 - \lambda_r)\omega_{ij}^s \right] \tag{4}
\]
\[
E_z[\mathcal{W}(x, y, \nu)] = \min \sum_{s \in \mathcal{S}} p_s \left[ \sum_{i \in I} \sum_{t \in T} dx_{it}^s \right] \tag{5}
\]
\[
E_z[\mathcal{G}(x, y, \zeta)] = \min \sum_{s \in \mathcal{S}} p_s \left[ \sum_{i \in I} \sum_{j \in J} \sum_{h \in H} lx_{ijh}^s \left( t_{ij}^s + t_{jh}^s \right) \right] \tag{6}
\]

Subject to
First stage constraints:
\[
t_{ij}y_{ij} \leq t_{\text{standard}}, \forall i \in E, \forall j \in J \tag{7}
\]
\[
\sum_{i \in E} y_{ij} = 1, \forall j \in J \tag{8}
\]
\[
\sum_{j \in J} y_{ij} \geq 1, \forall i \in E \tag{9}
\]
\[
\sum_{j \in J} p_{ij}y_{ij} \leq N_{\text{pop}}x_i, \forall i \in E \tag{10}
\]
\[
\sum_{i \in E} x_i \leq N_{\text{actual}} \tag{11}
\]

Second stage constraints:
Casualty assignment constraints:

\[ v_{ij}^s = z_{ij}^s + v_{ij}^{s(t-1)} - \sum_{h \in H} w_{hij}, \forall s \in S, \forall r \in R, \forall j \in J, t = 1, \ldots, T \] (12)

\[ \tau_{casualty}^s \geq \tau_{capacity}^s \beta^s, \forall s \in S \] (13)

\[ \tau_{casualty}^s \leq \tau_{capacity}^s + M \beta^s, \forall s \in S \] (14)

\[ \sum_{r \in R} \sum_{h \in H} \sum_{j \in J} w_{hij} = \sum_{h \in H} C_h^s \beta^s + \sum_{r \in R} \sum_{j \in J} \sum_{t \in T} z_{ij}^s (1 - \beta^s), \forall s \in S \] (15)

Ambulance assignment constraints:

\[ \sum_{r \in R} w_{hij}^s = \sum_{i \in I} I_{x_i}^s, \forall s \in S, \forall h \in H, \forall j \in J, t = 1, \ldots, T \] (16)

\[ \sum_{h \in H} I_{x_{ij}}^s \geq y_{ij}, \forall s \in S, \forall i \in E, \forall j \in J \] (17)

The number of ambulances constraints:

\[ by_{x_{i1}}^s = x_i, \forall s \in S, \forall i \in I \] (18)

\[ by_{x_{i2}}^s = y_{x_{i1}}^s, \forall s \in S, \forall i \in I, t = 2, \ldots, T \] (19)

\[ \sum_{i \in I} by_{x_{it}}^s = \sum_{i \in I} x_i + \sum_{i \in I} \sum_{n=1}^{t} dx_{i(t-n)}^s, \forall s \in S, t = 1, \ldots, T \] (20)

\[ yx_{it}^s = by_{x_{it}}^s + dx_{it}^s - \sum_{j \in J} \sum_{h \in H} I_{x_{ijh}}^s + \sum_{r \in R} \sum_{j \in J} I_{x_{ijr}}^s, \forall s \in S, \forall i \in H, t = 1, \ldots, (T - 1) \] (21)

\[ yx_{it}^s = by_{x_{it}}^s + dx_{it}^s - \sum_{j \in J} \sum_{h \in H} I_{x_{ijh}}^s, \forall s \in S, \forall i \in E, t = 1, \ldots, (T - 1) \] (22)

\[ \sum_{j \in J} \sum_{h \in H} I_{x_{ijh}}^s = by_{x_{it}}^s + dx_{it}^s, \forall s \in S, \forall i \in E, \forall t \in T \] (23)

\[ \sum_{i \in I} \sum_{t \in T} dx_{it}^s \leq NA_{max}, \forall s \in S \] (24)

Time and capacity constraints:

\[ \sum_{i \in I} \sum_{j \in J} \sum_{h \in H} I_{x_{ijh}}^s (t_{ij}^s + t_{ij}^{s(t-1)} + t_{prep}) \leq T_{period} * \sum_{i \in I} (by_{x_{i1}}^s + dx_{i1}^s), \forall s \in S, t = 1, \ldots, T \] (25)

\[ \sum_{r \in R} \sum_{h \in H} w_{hij}^s \leq AC_{ij}^s, \forall s \in S, \forall h \in H, \forall t \in T \] (26)

\[ AC_{ij}^s = AC_{ij}^{s(t-1)} - \sum_{r \in R} \sum_{j \in J} w_{hij}^s, \forall s \in S, \forall h \in H, t = 1, \ldots, T \] (27)

\[ C_h^s = AC_{0h}^s, \forall s \in S, \forall h \in H \] (28)

\[ I_{x_{i0}}^s = 0, \forall s \in S, \forall i \in I, \forall j \in J, \forall h \in H \] (29)

\[ by_{x_{i0}}^s = 0, \forall s \in S, \forall i \in I \] (30)

\[ dx_{i0}^s = 0, \forall s \in S, \forall i \in E \] (31)

\[ w_{0j}^s = 0, \forall s \in S, \forall r \in R, \forall j \in J \] (32)

\[ v_{0j}^s = 0, \forall s \in S, \forall r \in R, \forall j \in J \] (33)

\[ x_r, dx_{i0}^s, by_{x_{i0}}^s, l_{x_{i0}}^s, w_{rj}^s, v_{rj}^s, AC_{ij}^s \geq 0 \text{ and integer}, \forall s \in S, \forall r \in R, \forall h \in H, \forall i \in I, \forall j \in J, \forall t \in T \] (34)
\[ y_{ij}, \beta^s \in \{0, 1\}, \forall s \in S \forall i \in I, \forall j \in J \] (36)

The stochastic model has three objective Functions (1)–(3), and they minimize the RPM-weighted unserved number of casualties, the number of additional ambulances required in the response stage, and the total time of casualty transportation to the hospital, respectively. The model finds an optimal number of ambulances while minimizing unserved casualties, the expected number of ambulances required and the total transportation time by considering casualty RPM scores, population, expected demand, the hospitals’ capacity, and distances between EMSs, the disaster areas and the hospitals.

In the first stage of the objective functions, regardless of the scenarios, before the disaster, the assignment of the demand points to the emergency medical stations (EMSs) is made where the ambulances are located, as well as the number of ambulances to be located at each EMS is decided, on the basis of the international coverage standards for the emergency services.

In the objective functions, \( E_Q, E_Y \) and \( E_Z \) are the mathematical expectation of random vectors. These functions denote the expected RPM-weighted number of unserved casualties, the expected additional number of ambulances and total transportation time of ambulances, as shown in Equations (4)–(6), respectively. We assume here that random vectors contain the data based on the scenarios. In the objective functions, \( p_i \) shows the scenario probabilities and its total value is equal to 1.

This model is a two-stage stochastic programming model. The first objective function \((f1)\) minimizes the total RPM weighted number of unserved casualties that arise after the disaster, and this depends on the first stage decisions of the location-allocation of the demand points to the EMSs \( (y_{ij}) \) and the number of ambulances located in these EMS \( (x_i) \) before the disaster. In the second objective function \((f2)\), the summation of total number of ambulances allocated in advance (before the disaster) and the expected number of additional ambulances after the disaster is minimized. Therefore, by this summation in the second objective function, the first stage decision affects the second stage decision and vice versa. Hence, the model can be interpreted as a two-stage stochastic programming model. The third objective function \((f3)\) is the sum of total casualty transportation time determined before the disaster (based on demand point-EMS allocation decisions) by considering the standards and the total expected casualty transportation time including the ambulance departing from the EMSs to the demand points and from demand points to the hospitals. The casualty transportation time after disaster increases compared to the before-disaster time due to road damage varying based on different scenarios.

The limitations of the first-stage decisions are presented in Constraints (7)–(11). Constraint (7) ensures that the casualty transportation time between the EMS and its assigned demand point is within the time standards. Constraints (8) and (9) imply that the demand points must be assigned to the EMSs. These constraints provide that each demand point is assigned to one EMS when one or more demand points are assigned to each station. Constraint (10) ensure that the number of ambulances is determined to cover the total population at the demand points assigned to each EMS. Constraint (11) ensures that the total number of ambulances assigned to the EMSs cannot exceed the existing number of ambulances.

Constraint (12) is a kind of the flow balance constraint that shows the numbers of new arrivals, transported casualties in each period and non-transported casualties in the previous period. Constraints (13)–(15) together denote whether casualties’ assignment is below the available hospital capacities or not. To be more specific, if the total number of casualties is less than the available capacity, it ensures that all casualties are assigned to the hospitals. If it is more than the capacity, it ensures that the casualties are transferred to the hospitals with the total available capacity, as shown in Constraint (15). Constraint (16) implies the number of casualties transported within ambulance cycles, because ambulances transport one casualty per cycle. Constraint (17) ensures that the ambulances at the EMS determined in the first stage serve the demand points assigned to the relevant EMS at the beginning
of the first period. Constraint (18) implies that the number of ambulances assigned at
the ambulance locations in the first stage is equal to the number of ambulances at
the beginning of the first period. Constraint (19) updates the number of ambulances located
at the beginning of periods according to their number and location at the end of the previous
period. Constraint (20) determines the number of ambulances in locations at the beginning
of each period according to the total number of existing ambulances and additional ambu-
lances assigned in the previous period. Here, ambulances added in the previous periods
also work in the following periods. Constraints (21) and (22) ensure that the number of
ambulances in locations at the end of the period is determined by considering trips of the
ambulances. Constraint (23) ensures that the number of deported ambulances from the
EMS is equal to the number of ambulances at these locations, because the casualties cannot
be transported to the EMS. Constraint (24) limits the number of additional ambulances that
can be assigned. Constraint (25) prevents casualty transportation times from being greater
than the working hours of ambulances for each period and limits the number of casualties
that can be transported within each period. This constraint also limits the number of trips
of an ambulance depending on the duration. Constraint (26) ensures that the number of
casualties to be transported to the relevant hospital is less than the capacity of that hospital.
Constraints (27) and (28) are the constraints that dynamically update the hospital capacities
in each period. Constraints (29)–(34) refer to variable values before the disaster. Finally,
Constraints (35) and (36) are nonnegativity and integer constraints.

3.3. Solution Methodology

The proposed multi-objective mathematical model is solved by using Mavrotas and
Florios’s algorithm [36], which is called improved version of the augmented ε-constraint
method (AUGMECON2). AUGMECON2 is the improved version of AUGMECON [37].
The algorithm has been demonstrated to be very efficient for providing the set of Pareto
optimal solutions in multi-objective mixed-integer problems compared to the alternative
methods in the literature. The AUGMECON2 method lexicographically optimizes each of
the objective functions; then the payoff table is demonstrated. The values of the objective
functions based on payoff table are divided into equal intervals for each of the kth objec-
tive function, and the methodology steps are processed iteratively. The general form of
the multi-objective model reformulated according to the AUGMECON2 method [36] is
presented below:

$$\min f_1(x) + \varepsilon \times \left( \frac{s_2}{(f_{2,\max} - f_{2,\min})} + 10^{-1} \times \frac{s_3}{(f_{3,\max} - f_{3,\min})} + \ldots + 10^{(2-p)} \times \frac{s_p}{(f_{p,\max} - f_{p,\min})} \right)$$ (37)

Subject to:

Equations (7)–(36)

$$f_2(x) + s_2 = f_{2,\min} + i_2 \times (f_{2,\max} - f_{2,\min}) / s_2$$ (38)

$$f_3(x) + s_3 = f_{3,\min} + i_3 \times (f_{3,\max} - f_{3,\min}) / s_3$$ (39)

$$\ldots$$

$$f_p(x) + s_p = f_{p,\min} + i_p \times (f_{p,\max} - f_{p,\min}) / s_3$$ (40)

$$x \in F \text{ and } s_p \in \mathbb{R}^+$$ (41)

In this mathematical model that is the converted version according to the AUGME-
CON2 algorithm, $f_k(x)$ refers to the kth objective function of $x$ for $p$ objectives, and $x$
is included in the feasible region set $F$. $k$ is the index of the set of objective functions
($k = 1, \ldots, p$). Surplus variables of the constraints are represented by $s_k$, and defined for
each (k-1) objectives except the first one. The maximum and minimum value of the
kth objective functions defined with $f_{k,max}, f_{k,min}$, respectively. The maximum and min-
imum value of objective functions are taken from the payoff table. The range of $f_k$ is
\((f_k_{\text{max}} - f_k_{\text{min}})\) is denoted with \(r_k\). \(i_k\) is the counter of the interval for each of \(k\)th objective function, and \(g_k\) is the length of the equal intervals of the objective function \(f_k\). \(\text{eps}\) refers to a very small number between \(10^{-6}\) and \(10^{-3}\) [36].

According to this notation, the steps of the AUGMECON2 Algorithm 1 are explained below. In addition to the notations used in the formulation, \(lb_k\) shows the lower bounds (smallest value) of each objective function in the payoff table. The number of Pareto optimal solutions is denoted by \(n_p\). Finally, \(b\) is bypass coefficient, \(\text{step}_k\) is step for objective function \(k\), and it is calculated by \(r_k / g_k\).

\textbf{Algorithm 1}. Definitions of algorithm steps

\begin{itemize}
  \item \textbf{Step 1.} Create the payoff table \(f_k(x) \quad k = 1, 2, \ldots, p\)
  \item \textbf{Step 2.} Determine the minimum and maximum values for \(f_k(x) \quad k = 1, 2, \ldots, p\)
  \item \textbf{Step 3.} Set lower bounds \(lb_k \quad k = 1, 2, \ldots, p\)
  \item \textbf{Step 4.} Calculate ranges \(r_k = \max f_k - \min f_k \quad k = 2, \ldots, p\)
  \item \textbf{Step 5.} Define \(g_k\) = number of intervals
  \item \textbf{Step 6.} Divide \(r_k\) into \(g_k\) intervals
  \item \textbf{Step 7.} Initialize counter \(i_k = 0 \quad k = 1, 2, \ldots, p\)
  \item \textbf{Step 8.} Do (Until reach to \(i_p = g_p\))
  \item \textbf{Step 9.} \(i_p = i_p + 1\)
  \item \textbf{Step 10.} \(i_{p-1} = i_{p-1} + 1\)
  \item \textbf{Step 11.} \(i_2 = i_2 + 1k = 1, 2, \ldots, p\)
  \item \textbf{Step 12.} Update and solve the Problem P for equations (37)-(41)
  \item \textbf{Step 13.} If the solution is feasible then:
  \item \textbf{Step 14.} \(n_p = n_p + 1\), calculate \(b\), \(i_2 = i_2 + b\); \(b = \text{int}(s_2 / \text{step}_k)\)
  \item \textbf{Step 15.} If \(i_2 < g_2\) then,
    \item \textbf{Step 16.} repeat to \textbf{Step 12}
  \item \textbf{Step 17.} else,
    \item \textbf{Step 18.} \(i_2 = 0\) then,
    \item \textbf{Step 19.} if \(i_{p-1} < g_{p-1}\) then,
      \item \textbf{Step 20.} repeat to \textbf{Step 11}
  \item \textbf{Step 21.} else,
    \item \textbf{Step 22.} \(i_{p-1} = 0\) then,
    \item \textbf{Step 23.} if \(i_{p-1} < g_{p-1}\) then,
      \item \textbf{Step 24.} repeat to \textbf{Step 10}
    \item \textbf{Step 25.} else,
      \item \textbf{Step 26.} \textit{Algorithm is ended}
        \item \textbf{Step 27.} End if
          \item \textbf{Step 28.} End if
            \item \textbf{Step 29.} End if
              \item \textbf{Step 30.} End if
                \item \textbf{Step 31.} The algorithm is completed, and the results obtained by creating the Pareto optimal solution table are evaluated.

The AUGMECON2 algorithm starts with the pay-off table built by solving the (original) model according to each objective function, separately. Based on this, the range, the minimum and maximum values of each objective are determined. The decision-maker decides the number of solutions hence the number of intervals. The mathematical model is reformulated as depicted above. Therefore, the right hand side of each constraint related with the \(k\)th objective function is increased as much as the length of the interval of each \(k\)th objective at each iteration, and the model is solved, and a Pareto optimal solution is found. This procedure is repeated until the intended number of solutions is reached. A more detailed explanation of the AUGMECON2 is presented in [36].

According to this solution methodology, we order objectives based on the sequence of the unserved number of casualties, the number of ambulances, and transportation time.
The proposed multi-objective mathematical model was solved to create the payoff table in IBM ILOG CPLEX® solver. Therefore, CPLEX® solver was employed for the solution.

4. Computational Study

Case Study and Data Collection

Istanbul has a population of 15.8 million and a surface area of 5.461 km² according to 2018 data. In this study, Kartal district of Istanbul is the case area, considered. Kartal is a big district with a population of 470,678 people [38]. The study was performed using population, distance and capacity data, including six emergency medical services (EMSs), 20 triage (demand) points and 11 hospitals for Kartal district. The scenarios were created by considering the Japan International Cooperation Agency (JICA) [39] and Directorate of Earthquake and Geotechnical Investigation (DEZIM) [40] reports. The first 12 h are important during the discharge and transportation of the casualties to the hospitals. In the first 12 h periods, half of all victims want to get access to an emergency health service [41]. It is the first period of the disaster response phase yet, and a time is needed to establish field hospitals. Therefore, according to the existing hospitals, it was studied for the first 12 h. The distance matrix was created for six EMSs, 11 hospitals and 20 triage points by using Google Maps® application. It is assumed that the triage points are at the center of the sub-districts. The structure of the proposed stochastic model is explained in Figure 3, according to the disaster stage and objectives for case district.

![Figure 3](image-url)  
Figure 3. The structure of the proposed stochastic programming model on Kartal map.

The scenarios were created by considering JICA [39] and DEZIM [40] reports. Based on the reports, we developed nine scenarios for the expected magnitude of the earthquake. Scenarios 1–3 was created considering the worst-case scenarios expected in the reports.
The aim was to consider extraordinary scenarios outside of expected situations and include them in the model. Here, we prepared the triage distributions among the expected number of casualties according to the expectation of the JICA [39] report. We added road and hospital damage rates to the scenarios in a way that exceeded the expectations of the reports. Scenarios 4–7 were prepared according to the JICA report [39], while Scenarios 7 and 8 were prepared based on DEZIM [40] report. There are big differences between the expectations of the two reports. There is a directly proportional relationship between the expected building damage rates and the number of injured people, and it is known that the buildings in the area preferred for the case study have been strengthened over the years. The purpose of created scenarios from two different reports is to analyze the worse, expected and optimistic scenarios. Stochastic programming also provides to evaluate all scenarios together. According to the reports, the scenarios are optimistic, expected and pessimistic by considering the triage groups. The estimated proportion of casualties was determined for each scenario based on the reports. The population in demand points is obtained from the Turkish Statistical Institute [38]. In addition to these parameters, we simulated the number of expected casualties and their RPM scores based on three periods and districts. After the locations are determined, the distances and arrival time matrices are obtained by using Google Maps®. The capacity of the hospitals was taken from the web sites of the hospitals, and it was assumed that hospitals have occupancy 40%, before the disaster. Besides, we considered that the time limit between the demand points and EMS is 10 min, at maximum [42], and an ambulance can cover the population of 50,000 people [43]. Finally, it is assumed that 12 ambulances are serving in the district, and the number of additional ambulances cannot exceed 200 ambulances. Scenario-based parameters are presented in Table 1.

### Table 1. The parameters based on the scenario in the case study.

| Scenario | Occurrence Probability of Scenarios | Magnitude of Earthquake | Proportion of Expected Type-T1 Casualty (%) | Proportion of Expected Type-T2 Casualty (%) | Proportion of Expected Type-T3 Casualty (%) | Expected Damage of Road | Expected Damage of Hospital |
|----------|------------------------------------|--------------------------|---------------------------------------------|---------------------------------------------|---------------------------------------------|--------------------------|----------------------------|
| Scenario 1 | 0.06 | 7.7 | 2 | 2.7 | 3.3 | 65% | 35% |
| Scenario 2 | 0.08 | 7.7 | 1.8 | 2.4 | 3 | 62% | 33% |
| Scenario 3 | 0.09 | 7.7 | 1.7 | 2.3 | 2.8 | 60% | 32% |
| Scenario 4 | 0.1 | 7.7 | 1.5 | 2 | 2.5 | 60% | 30% |
| Scenario 5 | 0.16 | 7.5 | 1.3 | 1.7 | 2.2 | 55% | 27% |
| Scenario 6 | 0.11 | 7.4 | 1.1 | 1.4 | 1.9 | 45% | 25% |
| Scenario 7 | 0.1 | 6.9 | 0.9 | 1.1 | 1.6 | 30% | 7% |
| Scenario 8 | 0.16 | 7.5 | 0.09 | 0.42 | 0.74 | 25% | 18% |
| Scenario 9 | 0.14 | 7.5 | 0.054 | 0.264 | 0.502 | 20% | 10% |

The expected proportion of the triage types was prepared based on the data published in the reports. The proportion of casualties for Scenarios 4 and 5 was obtained from Model-A and Model-C presented in the JICA report [39]. The proportions in Scenario 6 and 7 scenarios are assumed by considering the magnitudes of the earthquake and these models. The expected disaster should also be evaluated with the scenarios. The magnitudes of the earthquake are the same in Scenarios 5, 8 and 9. However, their data set are different other key parameters. Scenarios 8 and 9 were calculated according to the population considered in the DEZIM report [40]. We used the expected road damages, according to JICA report [39] (pp. 9–136). We calculated transportation time between locations by assuming an increase at the same proportion as the road damage. Hospital capacities are obtained from the hospitals’ websites. Besides, it assumed that the proportions of hospital damage are between 6–32% according to the JICA report [39] and 1–26% according to the DEZIM report [40]. This means the hospital capacities are decreased at these ratios, due to the disaster. Scenario probabilities were randomly generated by considering the expected magnitude (7.5) according to the reports.
5. Results and Discussion

The model was coded and run using IBM ILOG CPLEX 12.9 solver, and the experiments were conducted on an Intel Core i7 2.8 GHz computer with 16 GB RAM, for the Kartal case. The multi-objective stochastic mixed-integer programming model includes 53,785 constraints and 240,515 integer variables. The number of binary variables is 129. When the model was solved for the first objective, the time to reach the result was 58.19 s. According to the AUGMECON2 method, the necessary constraints and variables were added by converting into the $\varepsilon$-constrained model. The Pareto optimal table experiments took computational time between 1.2 and 53 min, and the average computing time for the experiments was found to be 524.61 s. Table 2 shows the payoff table achieved when the model was optimized according to the three objectives, separately.

Table 2. Payoff table obtained.

| The Minimized Objective Function                  | $f_1$  | $f_2$  | $f_3$  |
|--------------------------------------------------|--------|--------|--------|
| Min $f_1$ (The number of unserved casualties)    | 60,401.57 | 212    | 60,615 |
| Min $f_2$ (The number of ambulances)             | 85,069 | 75.49  | 28,873 |
| Min $f_3$ (The total time)                       | 91,342 | 212    | 27,851.78 |

According to the payoff table, when the RPM-weighted number of unserved casualties was optimized, the objective value was obtained as 60,401.57. All of the casualties with 1–4 and 5–8 RPM scores in Scenarios 8 and 9 are transferred to hospitals. The total number of available and additional ambulances is 212. The total transport time (the total of the first and second stages) over the periods is 60,615 min. When the number of ambulances ($f_2$) is minimized, a value of at least 75.49 is obtained. Here, the number of ambulances that can fill the hospital capacity without giving any priority to the casualties was obtained. It is seen that the number of RPM-weighted casualties is 85,069. Although the number of casualties transported is the same, a high value has been obtained as there is no priority. This means patients who have high RPM and thus low priority were transported, but low RPM and high priority patients could not be probably transported because of not considering the patients’ RPM score and solely minimizing the ambulances. The time spent in transportation ($f_3$) is much lower compared to the previous solution where $f_1$ is minimized. Finally, when the model solved according to the transportation time objective ($f_3$), it is seen that the number of unserved casualties ($f_1$) reaches the highest value. This is due to neglecting serving the casualties with high priority and solely minimizing the total transportation time.

According to the values in the payoff table, interval values were obtained for each objective function using the AUGMECON2 method. Value ranges are divided into eight equal intervals. Therefore, $f_{\text{max}} - f_{\text{min}}$, interval values were calculated for the objective functions $f_2$ and $f_3$. According to algorithm steps, 37 different Pareto optimal solutions were obtained, and these solutions are shown in Appendix A, Table A1. Since the model has three objective functions, the results are affected by the change in each of them. In order to see the effects of the objectives on each other, the model is evaluated for two objectives, by keeping the third one constant. Thus, the effect of the ambulance number and the hospital selection on the RPM-weighted number of casualties was examined.

Figure 4a shows the relationship between the number of unserved casualties ($f_1$) and the number of ambulances ($f_2$). While the number of ambulances increases, the number of casualties who cannot be transported decreases but remains constant after a certain point. Figure 4b shows the number of ambulances versus the total transportation time. As the total transportation time decreases, the number of ambulances increases and then remains constant as soon as the least total transportation time is reached. When the total time was short, that is, while the wounded were transported to the nearby hospitals, the casualties with higher RPM factor values had to be transported to ensure this. As the total time increases, a casualty with lower RPM points can be carried. The results from the Pareto-
optimal results show that when we want to minimize the number of unserved casualties, the number of ambulances and total transportation time increase. However, after a certain point, there is no significant change in the value of the weighted number of casualties up to a certain point.

![Graphs showing the effects of number of ambulances on (a) the sum of Respiratory rate, Pulse rate, and Motor response values (RPM)-weighted number of unserved casualties and (b) transportation time.](image)

**Figure 4.** The effects on the number of ambulances on (a) the sum of Respiratory rate, Pulse rate, and Motor response values (RPM)-weighted number of unserved casualties and (b) transportation time.

The decision-maker should evaluate the Pareto optimal solutions (shown in Table A1 at the Appendix A), and choose according to the primary objectives. In this ranking, as in many disaster studies, our priority is human life. Accordingly, we listed the purposes of human life (f1), resource use (f2) and transportation time in this order. In the table obtained, the lowest f1 values were first determined, then among these solutions, the solution with the least f2 values (resource use) and then the pareto optimal solution with the lowest f3 value were selected. This table’s advantage is that it is possible to evaluate and compare the results obtained according to different situation. Accordingly, the 26th Pareto optimal solution is presented, in which the number of unserved casualties is minimized while the number of ambulances and total transportation time is low. In the first stage of the model, the demand points are assigned to the EMSs and the minimum number of ambulances that must be located in the EMS are determined. Table 3 presents the first stage solutions.

**Table 3.** The emergency medical system (EMS) coverage and ambulance location-allocation solutions for Kartal case.

| Emergency Medical Service Stations | Assigned Demand Points | Located Number of Ambulances |
|-----------------------------------|------------------------|-----------------------------|
| EMS-1                             | D2-D5-D16              | 2                           |
| EMS-2                             | D15                    | 1                           |
| EMS-3                             | D3-D8-D10-D11-D12-D18-D20 | 3                         |
| EMS-4                             | D7                     | 1                           |
| EMS-5                             | D1-D4-D6-D9-D13-D14-D17 | 4                           |
| EMS-6                             | D19                    | 1                           |

The most important aim of the study is to minimize the number of casualties who cannot be transported by prioritizing them based on their RPM health scores. Therefore, in this context, Table 4 shows the number of unserved casualties according to the RPM scores, periods and scenarios. The table also includes the percentages of unserved casualties according to the expected total number of casualties in the first twelve hours. According to the results, all T1 and T2 group casualties were transported by ambulances in Scenarios 8 and 9. The correct prioritization in the model is seen when the RPM groups are compared. It has been observed that it is crucial to bring the injured to the nearest and available
hospital according to their urgency. This is only possible by using a data-driven decision support tool in order to find the available hospital at the nearest neighborhood.

Table 4. The number of unserved casualties by RPM value and period of the 26th solution based on scenarios.

| Scenario   | Number of Unserved Casualties (RPM Score 1–4) | Number of Unserved Casualties (RPM Score 5–8) | Number of Unserved Casualties (RPM Score 9–12) |
|------------|-----------------------------------------------|-----------------------------------------------|-----------------------------------------------|
|            | \( t = 1 \) | \( t = 2 \) | \( t = 3 \) | \% | \( t = 1 \) | \( t = 2 \) | \( t = 3 \) | \% | \( t = 1 \) | \( t = 2 \) | \( t = 3 \) | \% |
| Scenario 1 | 0 | 1150 | 2766 | 20.8 | 1544 | 3812 | 5940 | 60.0 | 2352 | 5176 | 7836 | 81.6 |
| Scenario 2 | 0 | 873 | 2321 | 18.8 | 1260 | 3296 | 5220 | 57.7 | 2112 | 4648 | 7060 | 81.5 |
| Scenario 3 | 0 | 708 | 2064 | 17.4 | 1122 | 3038 | 4846 | 56.5 | 1992 | 4380 | 6644 | 81.7 |
| Scenario 4 | 0 | 557 | 1761 | 16.4 | 722 | 2418 | 4018 | 50.7 | 1764 | 3880 | 5880 | 81.6 |
| Scenario 5 | 0 | 140 | 1180 | 10.8 | 526 | 1966 | 3326 | 47.5 | 1560 | 3424 | 5184 | 83.1 |
| Scenario 6 | 0 | 0 | 884 | 8.5 | 247 | 1251 | 2375 | 37.4 | 1348 | 2952 | 4472 | 84.7 |
| Scenario 7 | 0 | 0 | 549 | 6.5 | 0 | 242 | 1126 | 16.1 | 904 | 2260 | 3532 | 79.0 |
| Scenario 8 | 0 | 0 | 0 | 0.0 | 0 | 0 | 0 | 0.0 | 0 | 0 | 54 | 1.8 |
| Scenario 9 | 0 | 0 | 0 | 0.0 | 0 | 0 | 0 | 0.0 | 0 | 0 | 0 | 0.0 |

The model also decides on the minimum number of ambulances that will be required. Table 5 shows the number of ambulances required to transport the casualties after the disaster, according to scenarios and periods, at the 26th solution. Determining the number of ambulances according to the periods is important to better organize the transfer ambulance resources from other regions to the disaster area. Scenario 1 is the worst case, and results of Scenarios 1, 2 and 4 show that although all ambulance capacities are used, all of T1 type (most urgent) casualties could be transported to the hospitals only in the first period. In Scenarios 1 and 2, both hospital damage rates and road damage rates are higher than Scenario 3. The number of ambulances should be higher as less available capacity will be reached in longer periods. On the other hand, when Scenarios 3 and 4 are compared, the road damage ratio is equal in both scenarios, but the hospital damage rate is higher in Scenario 3. For this reason, the additional ambulance requirement is less in Scenario 3, unlike Scenario 4, as the number of casualties that can be carried for the same periods will be less. Scenarios 5, 8 and 9 are different scenarios prepared for the same magnitude of the disaster. Looking at Table 4, similar results to Scenario 4 emerge in Scenario 5, which contains a more pessimistic data group than those in Scenarios 8 and 9. In Scenario 5, 187 ambulances are sufficient to transport all of the casualties to the available hospital capacities. In Scenario 7, the number of casualties recorded was lower than those of some scenarios, and it was observed that the number of ambulances required for Scenario 7 was higher than those of other scenarios except Scenarios 1, 2 and 4. Because of the expected low level of hospital damage, the available capacity is more than that of other scenarios. The study was conducted for the first critical hours when available hospital capacities were used. In optimistic scenarios (Scenarios 8 and 9), all T1 and T2 group casualties can be delivered to the hospitals by directing ambulances. Although the expected number of casualties in Scenario 8 was higher than the total hospital capacities, all T1 and T2 injured were transported to the hospitals with total 143 additional ambulances.

The number of transported casualties based on RPM score at each demand point overall scenarios are shown in Figure 5, for the 26th solution. The figure includes the population of demand points. It is seen that there is a proportion between the number of transported casualties and the population of the region. Besides, it was observed that wounded people with lower RPM scores were carried more than others in each demand points.

Finally, we evaluated the existing system (current state) according to the unserved casualties in the demand points where the data-driven decision support tool/system is not used, that is, the casualty is not tracked, the hospital capacities are not monitored, the ambulance movements are carried out according to the closest distance. In the mathematical model developed, results were obtained by minimizing the transportation time as the primary objective function for the same number of ambulances for scenarios based on reports. In Figure 6, the unserved casualties from the demand points were colored.
separately in four intervals. Figure 6a shows the case with the data-driven decision support tool/system, and Figure 6b shows the case where no data-driven decision support is utilized. When the figures are compared, it is clearly seen that the number of unserved casualties in Figure 6a is much less than that in Figure 6b. If we express it mathematically, while the average number of unserved casualties is expected to be approximately 3000 in the proposed system with decision support, this number exceeds 6000 in the system using the closest distance rule (no decision support tool). Besides, it is seen that tracking and coordination process with the proposed decision support tool/system is much better than the current state (with no decision support tool), not only in terms of efficiency but also in terms of equity, and hence better decisions are made.

Table 5. The additional number of ambulances based on scenario and periods according to the 26th solution.

| Scenario | To Minimize the Number of Unserved Casualties (According to 26th Solution) |
|----------|--------------------------------------------------------------------------|
|          | t = 1                      | t = 2                      | t = 3                      | Total |
| Scenario 1 | 200                             | 0                           | 0                           | 200   |
| Scenario 2 | 200                             | 0                           | 0                           | 200   |
| Scenario 3 | 194                             | 0                           | 0                           | 194   |
| Scenario 4 | 200                             | 0                           | 0                           | 200   |
| Scenario 5 | 187                             | 0                           | 0                           | 187   |
| Scenario 6 | 176                             | 24                          | 0                           | 200   |
| Scenario 7 | 171                             | 18                          | 11                          | 200   |
| Scenario 8 | 96                              | 26                          | 21                          | 143   |
| Scenario 9 | 53                              | 15                          | 13                          | 81    |

Figure 5. The number of transported casualties based on RPM score at demand points at the 26th solution.
Figure 6. The average number of unserved casualties at demand points according to (a) the proposed and (b) the existing system.

We suggest managerial implication according to the results:

- While making the coverage decisions, the population of the region, existing resources and the expected rare events must be considered. Besides, making multi-objectives decisions for disaster relief will make planning more effective.
- It is necessary to plan ambulance allocation based on scenarios for disaster relief. Adding ambulances can decrease the number of unserved casualties by considering RPM scores. Because of the hospital capacities, the increasing number of ambulances cannot significantly decrease the value of the T1 and T2 casualties transported to the hospitals after a certain level.
- If the severity of the disaster is great, hospital capacities will be insufficient even in the first critical hours. A centralized transportation system will play a major role in case detection so that emergency cases can be handled with priority. The prior arrival of the most urgent cases to the hospitals prevents the usage and exhaustion of the hospital capacities by the relatively less urgent cases.
- In order to reduce the RPM-weighted number of unserved casualties, ambulances must be dispatched according to the obtained real-time data from the information/decision support system. Choosing only the nearest distances prevents both the transportation of urgent casualties and the damages the equity in service provided to the demand points.
- If the optimistic scenario occurs, all T1 and T2 group casualties can be transported to the hospitals with the number of correctly planned ambulances. However, more ambulance services and medical care points will be needed in other scenarios, especially after the second period.
- In the study, it was observed that the ambulance assignment, according to only the nearest locations, had a negative effect on the number of unserved casualties. If the dispatching strategy is developed according to the RPM of the casualties, the transportation time will increase; however, the number of transported casualties will increase. However, the number of transported casualties will be more.

6. Conclusions and Future Research

In this study, we aim to minimize the number of unserved casualties, the number of ambulances, and the total transportation time by creating scenarios based on uncertain factors. Besides, a decision support tool is proposed and assumed to monitor hospitals’ available capacities, coordinate the ambulances, and track casualties. Hence, we developed
a multi-objective two-stage stochastic programming model for multiple periods to evaluate the problem related to ambulance management as a whole, based on the proposed decision support tool. To the best of our knowledge, for large-scale disasters, there is no other study assigning triage points to the emergency stations before the event and decide on the number of ambulances that may be required by minimizing the number of unserved casualties and the time spent in transportation, based on their health status. This is the unique aspect of our study. The study presents the decisions to be taken before the disaster to carry out a fast and effective casualty transportation operation by solving three different objectives at the same time. In this respect, it is an important study that can help decision-makers. The real case application also revealed the utility of our model. The proposed model was applied to the case of a disaster in the Kartal district with twenty demand points, located in Istanbul City, in Turkey. The developed multi-objective two-stage stochastic model was solved with the AUGMECON2 algorithm, which was stated to give good results in previous studies. In this way, the Pareto optimal solutions set has been obtained. The best solution was decided by taking the opinions of the decision-makers from the experiments included in this solution set. Primarily, the decisions regarding the solution that minimizes the number of unserved casualties were evaluated, and it was compared the best solution the aspect of transportation time in order to see the effect of the proposed system. All of the decisions examined in these comparisons were evaluated in terms of number and equity. Finally, managerial implication strategies were presented to contribute decision-makers according to the results obtained.

This study differs from many studies in that it shows how advanced technology can be used in disaster management. Advances in communication technologies and the existing information systems enable real-time data flow. In this study, the contribution of the information system to the casualty transportation problem was presented. Therefore, the study is comprehensive and holistic.

In future research, more comprehensive models that include technological developments can be developed, for disaster relief planning. In addition to these, the planning of temporary medical centers and medical personnel can be included for a long response period at the same time. Finally, in this study, it is assumed that ambulances are identical and can only transport one casualty. In a future study, the model can be developed by considering different types of vehicles and transportation capacities.

Author Contributions: Conceptualization, N.C. and S.I.S.; methodology, N.C. and S.I.S.; investigation, N.C. and S.I.S.; data curation, N.C. and S.I.S.; writing—original draft preparation, N.C.; writing—review and editing, N.C. and S.I.S.; visualization, N.C.; supervision, S.I.S.; project administration, S.I.S. All authors have read and agreed to the published version of the manuscript.

Funding: This research has been supported by Istanbul Technical University with the grant number MGA-2019-42242.

Conflicts of Interest: The authors declare no conflict of interest. The funders had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript, or in the decision to publish the results.

Appendix A

Table A1. Pareto Optimal Solutions for the Case Study.

| The Experiment Number | $f_1$  | $f_2$  | $f_3$  | The Experiment Number | $f_1$  | $f_2$  | $f_3$  |
|-----------------------|-------|-------|-------|-----------------------|-------|-------|-------|
| #1                    | 77,792.98 | 75.49 | 31,947.17 | #20                  | 60,403.07 | 177.86 | 60,602.37 |
| #2                    | 63,778.53 | 109.54 | 44,229.66 | #21                  | 68,471.09 | 194.93 | 31,946.71 |
| #3                    | 63,763.61 | 109.48 | 52,423.86 | #22                  | 62,154.57 | 194.90 | 40,137.83 |
| #4                    | 69,199.93 | 126.62 | 31,947.08 | #23                  | 62,154.57 | 194.90 | 40,137.83 |
| #5                    | 65,225.87 | 126.68 | 36,041.47 | #24                  | 60,915.48 | 194.92 | 44,231.90 |
Table A1. Cont.

| The Experiment Number | $f_1$ | $f_2$ | $f_3$ | The Experiment Number | $f_1$ | $f_2$ | $f_3$ |
|-----------------------|-------|-------|-------|-----------------------|-------|-------|-------|
| #6                    | 68,761.43 | 143.75 | 31,947.17 | #25 | 60,409.34 | 194.92 | 48,327.80 |
| #7                    | 60,422.11 | 143.75 | 52,424.20 | #26 | 60,401.57 | 183.60 | 52,420.97 |
| #8                    | 60,422.00 | 143.73 | 60,614.98 | #27 | 60,402.71 | 194.87 | 56,319.15 |
| #9                    | 68,532.64 | 160.79 | 31,946.00 | #28 | 60,401.57 | 194.92 | 60,610.92 |
| #10                   | 64,484.71 | 160.73 | 36,042.06 | #29 | 79,871.20 | 212.00 | 27,851.75 |
| #11                   | 62,353.25 | 160.80 | 40,137.88 | #30 | 68,248.07 | 212.00 | 31,941.25 |
| #12                   | 61,030.86 | 160.80 | 44,232.76 | #31 | 64,550.41 | 212.00 | 36,039.83 |
| #13                   | 68,375.21 | 177.84 | 31,947.12 | #32 | 62,069.27 | 212.00 | 40,136.89 |
| #14                   | 64,493.62 | 177.85 | 36,042.49 | #33 | 60,875.88 | 212.00 | 44,232.77 |
| #15                   | 62,250.23 | 177.74 | 40,137.26 | #34 | 60,401.67 | 212.00 | 48,325.51 |
| #16                   | 60,969.67 | 177.81 | 44,232.74 | #35 | 60,402.65 | 212.00 | 52,423.90 |
| #17                   | 60,582.86 | 177.87 | 48,328.79 | #36 | 60,401.57 | 212.00 | 56,519.20 |
| #18                   | 60,413.51 | 177.83 | 52,420.47 | #37 | 60,401.57 | 212.00 | 60,610.15 |
| #19                   | 60,410.34 | 177.78 | 56,517.04 |                   |       |       |       |

References

1. Oksuz, M.K.; Satoglu, S.I. A Two-Stage Stochastic Model for Location Planning of Temporary Medical Centers for Disaster Response. *Int. J. Disaster Risk Reduct.* 2020, 44, 101426. [CrossRef]
2. Lettieri, E.; Masella, C.; Radaelli, G. Disaster Management: Findings from a Systematic Review. *Disaster Prev. Manag.* 2009, 18, 117–136. [CrossRef]
3. Caunhye, A.M.; Nie, X.; Pokharel, S. Optimization Models in Emergency Logistics: A Literature Review. *Socio-Econ. Plan. Sci. Socio-Econ. Plan. Sci.* 2012, 46, 4–13. [CrossRef]
4. Rawls, C.G.; Turnquist, M.A. Pre-Positioning and Dynamic Delivery Planning for Short-Term Response Following a Natural Disaster. *Socio-Econ. Plan. Sci.* 2012, 46, 46–54. [CrossRef]
5. Flores, I.; Ortuño, M.T.; Tirado, G.; Vitoriano, B. Supported Evacuation for Disaster Relief through Lexicographic Goal Programming. *Mathematics* 2020, 8, 648. [CrossRef]
6. Monzón, J.; Liberatore, F.; Vitoriano, B. A Mathematical Pre-Disaster Model with Uncertainty and Multiple Criteria for Facility Location and Network Fortification. *Mathematics* 2020, 8, 529. [CrossRef]
7. Safeer, M.; Anbuudayasankar, S.P.; Balkumar, K.; Ganesh, K. Analyzing Transportation and Distribution in Emergency Humanitarian Logistics. *Procedia Eng.* 2014, 97, 2248–2258. [CrossRef]
8. Jin, S.; Jeong, S.; Kim, J.; Kim, K. A Logistics Model for the Transport of Disaster Victims with Various Injuries and Survival Probabilities. *Ann. Oper. Res.* 2015, 230, 17–33. [CrossRef]
9. Bozorgi-Amiri, A.; Jabalalmeli, M.S.; Al-e-Hashem, S.M.J.M. A Multi-Objective Robust Stochastic Programming Model for Disaster Relief Logistics under Uncertainty. *OR Spectr.* 2013, 35, 905–933. [CrossRef]
10. Tili, T.; Abidi, S.; Krichen, S. A Mathematical Model for Efficient Emergency Transportation in a Disaster Situation. *Am. J. Emerg. Med.* 2018, 36, 1585–1590. [CrossRef] [PubMed]
11. Talarico, L.; Meisel, F.; Sörensen, K. Ambulance Routing for Disaster Response with Patient Groups. *Comput. Oper. Res.* 2015, 56, 120–133. [CrossRef]
12. Jotshi, A.; Gong, Q.; Batra, R. Dispatching and Routing of Emergency Vehicles in Disaster Mitigation Using Data Fusion. *Socio-Econ. Plan. Sci.* 2009, 43, 1–24. [CrossRef]
13. Altay, N.; Labonte, M. Challenges in Humanitarian Information Management and Exchange: Evidence from Haiti. *Disasters* 2014, 38, 550–572. [CrossRef]
14. Wamba, S.F.; Akter, S.; Edwards, A.; Chopin, G.; Gnanzou, D. How ‘Big Data’ Can Make Big Impact: Findings from a Systematic Review and a Longitudinal Case Study. *Int. J. Prod. Econ.* 2015, 165, 234–246. [CrossRef]
15. Bharosa, N.; Lee, J.; Janssen, M. Challenges and Obstacles in Sharing and Coordinating Information during Multi-Agency Disaster Response: Propositions from Field Exercises. *Inf. Syst. Front.* 2010, 12, 49–65. [CrossRef]
16. Bélanger, V.; Ruiz, A.; Soriano, P. Recent Optimization Models and Trends in Location, Relocation, and Dispatching of Emergency Medical Vehicles. *Eur. J. Oper. Res.* 2019, 272, 1–23. [CrossRef]
17. Zhou, L.; Wang, S.; Xu, Z. A Multi-Factor Spatial Optimization Approach for Emergency Medical Facilities in Beijing. *ISPRS Int. J. Geo-Inf.* 2020, 9, 361. [CrossRef]
18. Brotoerre, L.; Laporte, G.; Semet, F. Ambulance Location and Relocation Models. *Eur. J. Oper. Res.* 2003, 147, 451–463. [CrossRef]
19. Andersson, T.; Värbrand, P. Decision Support Tools for Ambulance Dispatch and Relocation. *J. Oper. Res. Soc.* 2007, 58, 195–201. [CrossRef]
20. Huang, Y.; Nilsang, S.; Cheng, C.-Y. Robust Ambulance Base Allocation Strategy with Social Media and Traffic Congestion Information. *J. Ambient Intell. Hum. Comput.* 2020, 1–14. [CrossRef]
21. Gendreau, M.; Laporte, G.; Semet, F. A Dynamic Model and Parallel Tabu Search Heuristic for Real-Time Ambulance Relocation. Parallel Comput. 2001, 27, 1641–1653. [CrossRef]
22. Gong, Q.; Batta, R. Allocation and Reallocation of Ambulances to Casualty Clusters in a Disaster Relief Operation. IIE Trans. 2007, 39, 27–39. [CrossRef]
23. Knight, V.A.; Harper, P.R.; Smith, L. Ambulance Allocation for Maximal Survival with Heterogeneous Outcome Measures. Omega 2012, 40, 918–926. [CrossRef]
24. Salman, F.S.; Gül, S. Deployment of Field Hospitals in Mass Casualty Incidents. Comput. Ind. Eng. 2014, 74, 37–51. [CrossRef]
25. Na, H.S.; Banerjee, A. A Disaster Evacuation Network Model for Transporting Multiple Priority Evacuees. IIE Trans. 2015, 47, 1287–1299. [CrossRef]
26. Zhang, Z.; Liu, M.; Lim, A. A Memetic Algorithm for the Patient Transportation Problem. Omega 2015, 54, 60–71. [CrossRef]
27. Schneeberger, K.; Doerner, K.F.; Kurz, A.; Schilde, M. Ambulance Location and Relocation Models in a Crisis. Cent. Eur. J. Oper. Res. 2016, 24, 1–27. [CrossRef]
28. Fancello, G.; Mancini, S.; Fadda, P. An Emergency Vehicles Allocation Model for Major Industrial Disasters. Transp. Res. Procedia 2017, 25, 1164–1179. [CrossRef]
29. Dean, M.D.; Nair, S.K. Mass-Casualty Triage: Distribution of Victims to Multiple Hospitals Using the SAVE Model. Eur. J. Oper. Res. 2014, 238, 363–373. [CrossRef]
30. Jacobson, E.U.; Argon, N.T.; Ziya, S. Priority Assignment in Emergency Response. Oper. Res. 2012, 60, 813–832. [CrossRef]
31. Paul, J.A.; Batta, R. Improving Hurricane Disaster Preparedness: Models for Optimal Reallocation of Hospital Capacity. Int. J. Oper. Res. 2011, 10, 194–213. [CrossRef]
32. Mills, A.F.; Argon, N.T.; Ziya, S. Dynamic Distribution of Patients to Medical Facilities in the Aftermath of a Disaster. Oper. Res. 2018, 66, 716–732. [CrossRef]
33. Shin, K.; Lee, T. Emergency Medical Service Resource Allocation in a Mass Casualty Incident by Integrating Patient Prioritization and Hospital Selection Problems. IIE Trans. 2020, 52, 1141–1155. [CrossRef]
34. Farahani, R.Z.; Lotfi, M.M.; Baghaian, A.; Ruiz, R.; Rezapour, S. Mass casualty management in disaster scene: A systematic review of OR&MS research in humanitarian operations. Eur. J. Oper. Res. 2020, 287, 787–819. [CrossRef]
35. Sacco, W.J.; Navin, D.M.; Fiedler, K.E.; Ii, R.K.W.; Long, W.B.; Buckman, R.F. Precise Formulation and Evidence-Based Application of Resource-Constrained Triage. Acad. Emerg. Med. 2005, 12, 759–770. [CrossRef]
36. Mavrotas, G.; Florios, K. An Improved Version of the Augmented $\epsilon$-Constraint Method (AUGMECON2) for Finding the Exact Pareto Set in Multi-Objective Integer Programming Problems. Appl. Math. Comput. 2013, 219, 9652–9669. [CrossRef]
37. Mavrotas, G. Effective Implementation of the $\epsilon$-Constraint Method in Multi-Objective Mathematical Programming Problems. Appl. Math. Comput. 2009, 213, 455–465. [CrossRef]
38. The Population Data, The Turkish Statistical Institute. Available online: https://biruni.tuik.gov.tr/medas/?kn=95&locale=tr. (accessed on 16 December 2020).
39. JICA. The Study on A Disaster Prevention/Mitigation Basic Plan in Istanbul Including Seismic Microzonation in the Republic of Turkey; Volume II; Final Report; Japan International Cooperation Agency: Tokyo, Japan, 2002.
40. Istanbul İli Olası Deprem Kayıp Tahminlerinin Güncellenmesi Projesi | Deprem ve Zemin İnceleme Müdürlüğü. Available online: https://depremzemin.ibb.istanbul/calismalarimiz/tamamlanmis-calismalar/istanbul-ilili-olasi-deprem-kayip-tahminlerinin-guncellenmesi-projesi/ (accessed on 16 December 2020).
41. Kalemoglu, M. Emergency Department Management in Bombing and Blast Incidents. Internet J. Rescue Disaster Med. 2004, 5, 1.
42. Ball, M.O.; Lin, F.L. A Reliability Model Applied to Emergency Service Vehicle Location. Oper. Res. 1993, 41, 18–36. [CrossRef]
43. McCord, G.C.; Liu, A.; Singh, P. Deployment of Community Health Workers across Rural Sub-Saharan Africa: Financial Considerations and Operational Assumptions. Bull. World Health Organ. 2012, 91, 244–253B. [CrossRef]