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A spreadsheet-based decision support tool for temporary-disaster-response facilities allocation

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ABSTRACT

In this study, we present a spreadsheet-based decision support tool for allocating temporary-disaster-response facilities for relief supplies distribution. The tool developed in this study mainly consists of three main components as its database, decision engine and user interface. We develop the tool to run on a spreadsheet environment rather than producing a standalone application by aiming at providing more convenience for the user to perform tasks such as data manipulation and reporting. The paper also presents an example case for illustration. The tool allows the user (i.e., decision makers) to allocate temporary-disaster-response facilities under many different after-disaster situations (scenarios) considering the possible uncertainties to occur after a disaster (i.e., different affected population rates, planning periods etc.). Although we present some example cases in the paper for illustration purposes, the flexibility of the tool allows its users to consider other cases with many other scenarios. The tool can be used to help decision makers for allocating temporary-disaster-response facilities for planning relief supplies distribution operations.

1. Introduction

Solving the challenging problems in Disaster Operations Management (DOM) requires the consideration of many stakeholders under time pressure, risk and uncertainty. It is noted from past experiences that poor management of disaster response operations increases the unwanted effects of disasters even more as in the case of Hurricane Katrina (Rolland et al., 2010). It is thus very important to utilize information technologies for decision makers in governmental and other relief organizations by developing sophisticated decision support systems to achieve more efficiency in disaster response and reduce such unwanted effects.

Allocating disaster-response facilities for relief supplies distribution is one of the most important problems in DOM gaining the attention of many researchers recently as noted in the literature review of the next section. It is also noted that some main problem characteristics are common in these studies, however, some variations are also observed due to the specifications of the corresponding problem considered, such as the one considered in this study; allocating Temporary-Disaster-Response (TDR) facilities for relief supplies distribution. In allocating such facilities, it is aimed at providing relief supplies to disaster victims for a short time period or temporarily (hence the name temporary-disaster-response facilities) until some relief organizations arrive at the affected area motivated by the fact discussed in the following paragraph.

It is very important to provide relief supplies to disaster victims since the survivors without any serious injuries might suffer due to the after-disaster conditions. Unfortunately, it is noted in some of the past disasters that great causalities might occur due to such after-disaster conditions among the survivors. It is just because the victims are not able to reach water, food and other necessary emergency supplies since it is not usually possible for relief organizations to reach the affected area in a timely manner, especially after a large-scale disaster, due to the chaotic after-disaster conditions as well as the damages caused by the disaster. Utilizing some local facilities (i.e., TDR facilities) to provide relief supplies to disaster victims temporarily right after the disaster might thus produce great benefits in reducing the unwanted effects of a disaster by satisfying the basic humanitarian needs of disaster victims in the short term. It is however a challenging task to allocate such facilities efficiently as detailed in the following sections of the paper where a sophisticated tool might make important contributions in the decision making process.

We also note that the management of such facilities is usually handled by local administrations rather than some central-governmental organizations due to the fact that it might be more preferable to employ a decentralized management scheme to improve the efficiency

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Nomenclature*

Database an organized collection of data
Database Management System (DBMS) a software package that handles data operations
Table a collection of related data stored in a form of columns and rows
Tuple a single row of a table containing information associated with a single record
Entity-Relationship (ER) Diagram a representation of the relationships of the entities in a database
Structured Query Language (SQL) a standardized programming language to interact with a database
SQL Query a general definition for a collection of SQL statements
SQL Stored Procedure a collection of SQL statements stored in the database server
SQL Server a relational DBMS (Microsoft)
Visual Basic a programming language (Microsoft)
Visual Basic for Applications (VBA) an implementation of Visual Basic (Microsoft)
Gurobi Optimizer a mathematical programming solver (Gurobi Optimization)
Mathematical Programming Language (MPL) a mathematical programming language (Maximal Software)
OptiMax a library to embed MPL models into end-user applications (Maximal Software)

of the relief efforts since it is usually more difficult for central-governmental organizations to focus on such local-level problems. Such a decentralized management scheme is also advantageous by reducing problem size significantly since each local administration is concerned for allocating the resources (i.e., TDR facilities etc.) only in the corresponding geographical area (i.e., district etc.). Utilizing a decision support tool for allocating TDR facilities for relief supplies distribution might yield a more efficient resource management for local administrations by performing what-if analyses in pre-disaster phase considering possible uncertainties to occur after a disaster.

In this study, we present such a decision support tool for allocating TDR facilities for relief supplies distribution by aiming at helping the corresponding decision makers in local administrations. It is developed to run on a spreadsheet environment rather than a standalone application to provide more convenience and flexibility for users to perform tasks such as data manipulation and reporting. Using the tool developed in the study, it is possible to allocate TDR facilities under many different after-disaster situations (scenarios) considering the possible uncertainties to occur after a disaster (i.e., different affected population rates, planning periods etc.). We also present some real-life cases for illustration.

The remainder of the paper is organized as follows. In the next section, we summarize the related literature by focusing the decision support systems developed in humanitarian logistics. It is followed by the details of the decision support tool developed in this study including three subsections explaining the corresponding components of the system. Integration of these components together as a decision support tool is explained in the following section. The implementation of the tool with a real-life example problem is presented in the following section. We finalize the paper by the concluding remarks in the last section.

2. Literature review

In this section, a brief literature review is presented on decision support systems in disaster operations management, and particularly in humanitarian logistics in disaster relief operations. The section is divided into two subsections. In the first subsection, we define humanitarian logistics and present the related literature by summarizing the corresponding studies in the area. The second subsection is devoted to decision support systems in disaster operations management. It also starts with a review of the decision support systems in disaster operations management in general and then summarizes the studies that focus on humanitarian logistics.

2.1. Humanitarian logistics

We can define humanitarian logistics as the process of planning, managing and controlling the flow of some type of disaster relief resources to affected people (Kovacs and Spens, 2007; Sheu, 2007; Natarajarathinam et al., 2009; Caunhye et al., 2012). In humanitarian logistics, some humanitarian concerns are primarily considered differently from general or commercial logistics. We note that the primary metrics of such a supply chain (i.e., a humanitarian or relief chain) are different from those of a commercial supply chain. In commercial supply chains, some monetary driven metrics are considered to measure the performance whereas satisfaction of humanitarian needs is more important in humanitarian chains. The interested reader can refer to the study of Beamon and Balcik (2008) for a comprehensive discussion on the performance measures of humanitarian chains.

It is also possible to further classify the humanitarian logistics studies into three categories as (i) facility allocation, (ii) distribution of relief supplies and transportation of disaster victims and (iii) and other operations such as traffic control and restoration of normal living conditions (Caunhye et al., 2012). On the other hand, it is also noted in many studies that allocation problems are usually considered together with relief supplies distribution and evacuation operations in an integrated manner by aiming at minimizing some kind of humanitarian cost. In the study of Balcik (2017), for instance, the author addresses site selection and routing decisions of the rapid needs assessment teams. In another study (Luan et al., 2019) that combines allocation and routing, authors also consider a location-routing problem to maximize the rescue efficiency. In the study of Yi and Ozdamar (2007), a mixed-integer-multi-commodity network flow model is developed for resource allocation and evacuation in an integrated manner. In another study, Nozick (2001) considers the minimum cost facility allocation problem with coverage constraints. Yazici and Ozbay (2007) consider the problem of determining the change in the capacity requirements and shelter locations and present a solution under changing link capacity requirements. Zhu et al. (2008) present a resource allocation model for local reserve depots under capacity constraints. Gormez et al. (2011) consider the problem of locating disaster response and relief facilities in the city of Istanbul.

As noted in these examples, such studies usually consider budget constraints, unsatisfied demands, capacities and types of facilities and inventory costs. The study of Li et al. (2011) states the importance of planning of facility allocation to increase the efficiency of the response operations. As we further note in the corresponding studies, numbers and locations of the facilities are usually considered in the decision making process (Fiedrich et al., 2000; Pan, 2010; Salmeron and Apte, 2010; and Kilci et al., 2015).

We also note the frequent consideration of evacuation operations in previous studies. The studies of Tufekci (1995), Yi and Ozdamar (2007), Bayram et al. (2015), Ai et al. (2016), Cheng et al. (2017), Uster et al. (2018), Gehlot et al. (2018) and Mirahadi et al. (2019) are some

* Model definitions for the mathematical programming model are presented in the corresponding subsection of the manuscript.

examples considering evacuation operations. Although the focus of Hasan and Ukkusuri (2011) is also evacuation, a different perspective is presented in the study where the authors aim at characterizing social influence in the evacuation decision making process. There are other studies also employing social networks in disaster operations management, such as the studies of Ai et al. (2016), Landwehr et al. (2016) and Shan et al. (2019) where the authors consider the utilization of social networks in disaster operations management. We further note the utilization of building information modeling in studies considering fire-related operations. The studies of Isikdag et al. (2008), Cheng et al. (2017) and Chen et al. (2018) are examples of such studies where the authors use building information modeling.

One of the most important issues decision makers have to deal in humanitarian logistics is uncertainty caused by the stochastic parameters of the problem. It is noted that stochastic programming-based approaches are used for certain types of facility allocation problems to deal with the corresponding uncertainties. In particular, such problems are nicely modeled with two-stage stochastic programs where the allocation (i.e., facility locations, capacities, inventory levels etc.) and service (i.e., distributions, transportations, routing etc.) decisions are made in the first and second stages of the program, respectively, as in the studies of Balcik and Beamon (2008), Mete and Zabinsky (2010), Rawls and Turnquist (2010, 2011), Kilci et al. (2015), Noyan et al. (2015), Cavdur et al. (2016), Erbeyoglu and Bilge (2019), and Sanci and Daskin (2019) although different perspectives for allocation as in the study of Shi et al. (2019) where the authors consider different models for planning emergency shelters. Similarly, in another study (Bayram et al., 2015), allocation of shelters is considered together with traffic management and evacuation. A detailed discussion on the pre-positioning of assets and supplies in disaster operations management is presented in the study of Sabbaghtorkan et al. (2019).

Although the aforementioned setting provides a nice modeling framework for such facility allocation problems, the quality of the solution depends on the scenarios of the stochastic program. Even if the problem is formulated correctly, the solution quality might still be poor due to the limitations in the scenario construction process. Developing a comprehensive scenario construction process however might require professional knowledge as well as a theoretical background in stochastic programming which might be limited applicability in practice. Utilization of information technologies to allow the integration of both of these aspects conveniently (professional knowledge and theoretical background) might help in the decision making process for the corresponding facility allocation problems and it motivates us to develop the decision support tool presented in this study. As also stated in the following subsection, we aim at providing such a decision support tool as the main contribution of our study for allocating TDR facilities for relief supplies distribution. Although the deterministic version of the stochastic programming model proposed in the study of Cavdur et al. (2016) is implemented as the decision engine of the developed tool, decision makers can allocate TDR facilities under many different after-disaster situations (scenarios) by considering the possible uncertainties to occur after a disaster (i.e., different affected population rates, planning periods etc.) by just defining the corresponding after-disaster scenarios using the convenient user interface of a spreadsheet environment.

2.2. Decision support systems in disaster operations management

There are many challenging problems in disaster operations management and, in particular, in humanitarian logistics. Involvement of complex decision making processes in these problems increases the unwanted effects of disasters even more especially when it is combined with poor management of disaster operations. It is thus very important to utilize information technologies and develop decision support systems to deal with these challenges which might produce significant benefits in reducing such unwanted effects of disasters (Mendonca et al., 2001; Thompson et al. 2006; Van de Walle and Turoff, 2008).

As stated by Ortuno et al. (2013), developing decision support systems for the management of humanitarian logistics operations receives an increasing interest in last decades. These systems however usually focus on inventory control rather than distribution and transportation operations. On the other hand, it is also noted that these studies usually focus on information management and lack sophisticated approaches in their decision making processes (Fiedrich et al., 2000; Ahmad and Simonovic, 2006).

It is further noted that, rather than providing decision support, the main focus of some studies is to propose some system designs for emergency situations. The study of Santos et al. (2016), for instance, presents the design of a Witness Unit (WU) to be used as an alternative communication network in early alerts for near-field tsunamis. In another study (Ergen et al., 2010), the authors propose the Search and Rescue Data Access Point (SR-DAP) system designed for storing and retrieving the required local information in/from data storage units that are deployed at buildings. Lee et al. (2013) propose an integrated approach to intelligent urban facilities management for real-time emergency response based on the integration of facilities-related information and the integration of management functions to overcome the drawbacks of conventional urban facilities management. The study of Lin et al. (2018) aims to develop a computational method, called the Artificial and Crowd Intelligence (ACI) filter, to overcome the drawbacks of crowdsourcing such as errors, duplications, and unstructured formats.

We prefer to consider the studies utilizing geographical information systems in this subsection separate from the aforementioned examples due to their higher levels of involvements with their decision making procedures. Pidd et al. (1996), for instance, discuss the concept of spatial decision support systems combining analytical modeling approaches and geographical information systems. As stated in the study of Zerger and Smith (2003), utilizing geographical information systems to understand the complex structure of a disaster is very important for improving the decision making process. Integrating geographical information systems with other features of the decision support systems might produce even better results as presented in the studies of De Silva and Eglese (2000), Chang et al. (2007), Chen et al. (2011) and Sahebjamnia et al. (2017) where the authors consider the integration of different approaches or modules, such as stochastic programming, simulators and rule-based modules.

We also note the studies that present decision support systems for facility allocation and other humanitarian chain operations such as the distribution of relief supplies and transportation of disaster victims. Ozdamar et al. (2004) propose a decision support system considering the dynamic time-dependent transportation problem where the optimal mixed pick-up and delivery schedules for vehicles as well as the quantities and types of loads. Kondaveti and Ganz (2009) propose a decision support system for resource allocation and distribution operations by first clustering disaster victims using their geographical coordinates and then planning resource allocation and distribution operations. In the study of Rekik et al. (2013), the authors propose a system combining network design, distribution planning and multi-criteria decision-making modules. El-Anwar et al. (2009) present an automated system to support decision-makers in optimizing post-disaster temporary housing arrangements. In another study (Zografos and Androutsopoulos, 2008), the authors present a decision support system for assessing alternative distribution routes in terms of travel time, risk and evacuation implications while coordinating the emergency response deployment decisions with the hazardous materials routes. The studies of Tufekci (1995) and Alvear et al. (2013) also consider evacuation operations in road tunnels and hurricane, respectively. In the study of Zhao and Liu (2018), a user-friendly decision support tool is presented for facilitating the process of optimizing urban emergency rescue facility locations in large-scale urban areas. Some studies propose agent-based decision support systems. Fikar et al. (2016), for

instance, develop a decision support system that coordinates the distribution activities of public and private organizations.

As a result, we note from our reviewer of the current literature that although there exist some studies presenting decision support systems considering allocation and distribution operations in disaster operations management, according to the best of our knowledge, none of the aforementioned studies consider the problem addressed in our study. Our main contribution is thus the development of a spreadsheet-based decision support tool for allocating TDR facilities for relief supplies distribution motivated by the aforementioned review of the related literature. The tool developed in this study mainly consists of three main components as its database, decision engine and user interface as detailed in the following pages of the manuscript. The tool is implemented on a spreadsheet environment rather than a standalone application by aiming at providing more convenience for its users to perform tasks such as data manipulation and reporting. Some example cases are also presented for illustration.

Using the tool developed in the study, decision makers can allocate TDR facilities under many different after-disaster situations (scenarios) considering the possible uncertainties to occur after a disaster (i.e., different affected population rates, planning periods etc.). We present some example cases for illustration purposes in the study; however, the flexibility of the tool allows its users to consider other cases with many different scenarios. Although some decision support systems are proposed for allocating disaster response facilities for relief supplies distribution, according to the best of our knowledge, none of these studies present such comprehensive framework presented in our study integrating a database, decision engine and easy-to-use user interface together to provide a flexible and functional tool for decision makers.

3. System components

This section details the three main components of the decision support tool developed in the study as its database, decision engine and user interface the details of which are presented in the following subsections, respectively. We implement the system on Microsoft Excel where Microsoft Visual Basic for Applications (VBA) is used for the integration of the components where we also utilize the built-in functions of the spreadsheet environment. The user interface is also designed using Microsoft Excel for providing interaction with the user. The database is implemented using Microsoft SQL Server whereas Maximal Software Mathematical Programming Language (MPL)-OptiMax and Gurobi Optimizer are used for the implementation of the decision engine. A three-tier system architecture (with presentation, business logic and data tiers) summarizing how the decision support tool works is shown in Fig. 1.

3.1. Database

We implement the database of the system using Microsoft SQL Server. The database consists of 11 tables as shown in Table 1. The entity-relationship diagram of the database is presented in Fig. 2. As noted in Table 1, we can classify the tables as the ones about disasters, network structure and model.

There are four tables about disasters which include information about the commodities (i.e., relief supplies), disasters, types of disasters and facilities (i.e., TDR facilities), respectively. The number of tables about network structure is three. As their names suggest, these tables include information about the nodes of the network (i.e., neighborhoods, districts, cities etc.), the risk levels of the nodes in the network for different types of disasters and paths of the network representing the connection links (i.e., roads etc.) between the neighborhoods.

It might be useful to explain the “definition” field of the “nodes” table in more detail as it defines different types of nodes in the network (i.e., neighborhoods, districts, cities etc.) as a 12-digit field consisting of four triplets each represents the corresponding level of a node. In other words, the field is divided into triplets as “RRR-CCC-DDD-NNN” where R, C, D and N represent the digits for Regions (or might be considered as states in some countries), Cities in the corresponding Region (or State), Districts in the corresponding City and Neighborhoods in the

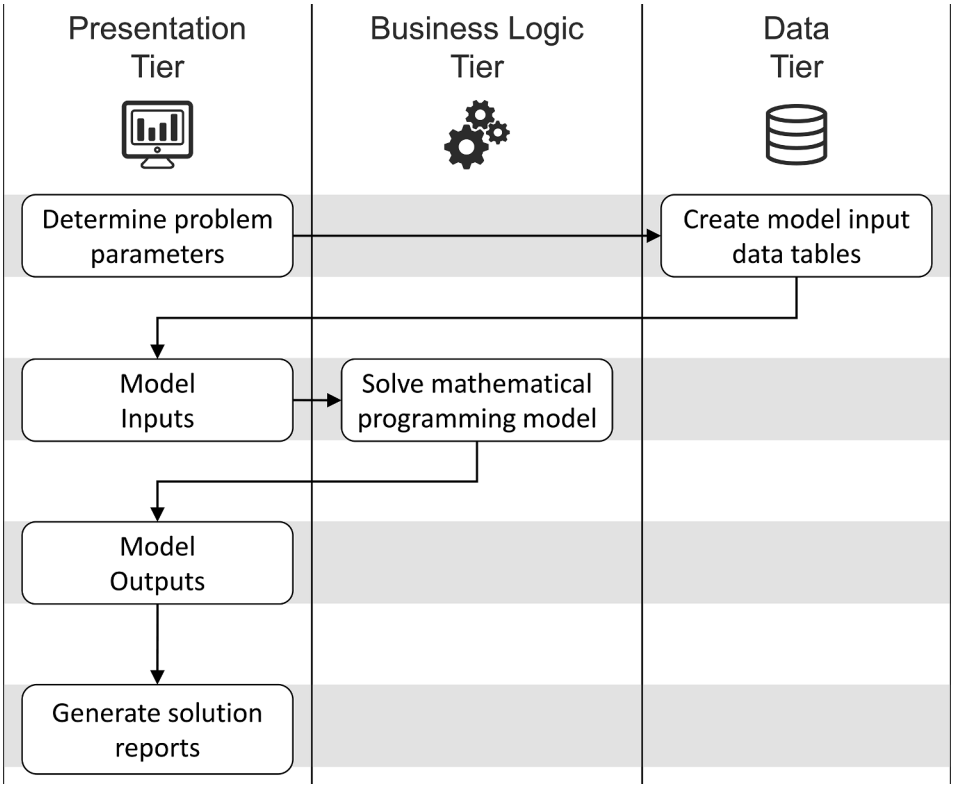


Fig. 1. Three-tier system architecture of the decision support tool.

Table 1
Database table definitions.

Table name	Table definition
Commodities	Commodities. Related to “Disasters” and “Facilities”
Disasters	Disasters. Related to “Commodities”, “Facilities” and “DisasterTypes”
DisasterTypes	Disaster Types. Related to “Disasters” and “NodeRisks”
Facilities	Facilities. Related to “Commodities” and “Disasters”
Nodes	Nodes. Related to “NodeRisks” and “Paths”
NodeRisks	Node Risks. Related to “DisasterTypes” and “Nodes”
Paths	Paths. Related to “Nodes”
ModelConfigurations	Model Configurations. Related to corresponding model tables
ModelConfigurationParams	Model Configuration Parameters. Related to corresponding model tables
ModelParameters	Model Parameters. Related to corresponding model tables
ModelTypes	Model Types. Related to corresponding model tables

corresponding District, respectively. Using such a representation schema presents a logical way of defining all neighborhoods in a country.

For instance, if we want to refer the neighborhoods of the Yildirim district of Bursa city of Marmara Region in Turkey, which represents the case in the illustrative example presented in the following pages, using a simple query, we can retrieve the range starting from 005-016-003-001 to 005-016-003-064 representing the first and last alphabetically-ordered neighborhoods (i.e., Akcaglayan and 75 Yil neighborhoods) of the district, respectively, distinguished by the last three digits of the field. Note that although it is an example from Turkey, it could easily be adapted to be used for other countries. For the countries with different geographical organizations, like the US, for instance, the digits representing regions could be adapted to represent states.

The remaining tables store information about the decision engine (i.e., the integer programming model presented in the following subsection) implementation. It is noted that different types of models (i.e., “ModelTypes” with different parameter settings (i.e., “ModelParameters”) can be configured (i.e., “ModelConfigurations” and “ModelConfigurationParameters”) using the flexible structure provided by the last four tables of the database shown in Table 1. Since these tables include some technical details, it is somewhat a more complicated process to propose an efficient design about them. We thus present more details about these tables are in the following paragraph for the convenience of the interested readers.

A *model type* defines a particular type of a mathematical programming model, such as the one presented in this study (i.e., the integer programming model presented in the following subsection). If another mathematical programming model to be introduced, it is defined with a new tuple in the model type table in the database. Since each model has its own set of parameters, the parameters of each model type are presented in the *model parameters* table.

The total number of TDR facilities, for instance, is one of the parameters of the integer programming model presented in the following subsection, and thus, defined with a tuple in the model parameters table. A *model configuration* defines a particular and preferably meaningful combination of some model parameter realizations together. Similarly, the table for *model configuration parameters* includes the predefined realizations of the model parameters for the corresponding combination. In other words, the tables of model configuration and model configuration parameters provide a convenient way of defining all parameters of a particular model. Decreasing the available budget in our problem, for instance, might require setting more than one parameter of the integer programming model presented in the following subsection, such as the total number of facilities and the number of facilities per neighborhood. By defining the corresponding model configuration, say the *lower-budget model configuration*, with its respective parameter realizations, we can simply set the model configuration as lower-budget to change its respective parameters at once. Obviously, these tables have some defined relationships among themselves as shown in the entity-relationship diagram to ensure that the aforementioned schema works as intended. We present more details on the predefined model configurations in the following pages while explaining the example case used for illustration.

We also construct several Structured Query Language (SQL) stored-procedures as listed in Table 2 to ensure system integration (i.e., creating model inputs dynamically through the user interface developed). Although these stored-procedures are technically some components of the database, they also act as the building blocks of the whole tool to ensure system integration by performing tasks such as creating model inputs dynamically through the user interface. Due to this inter-component membership and functionality of the corresponding procedures, these are both referred in this subsection (i.e., 3.1. Database) for the sake of completeness as well as in the next section (i.e., 4. System Integration) of the paper where more details are provided in terms of their functionality.

3.2. Decision engine

We adapt the decision engine from the study of Cavdur et al. (2016) where a two-stage stochastic programming model for the TDR facility allocation problem is proposed. The authors consider the uncertainty in relief supplies demands in the stochastic program using the scenarios to model different after-disaster situations causing the variation in relief supplies demands. In this study, we utilize the integer programming model given in this subsection which can be configured to run under different disaster scenarios defined by the user.

The study of Cavdur et al. (2016) presents a two-stage stochastic program for allocating TDR facilities for relief supplies distribution by taking into consideration the demand uncertainty of relief supplies. The proposed model minimizes the total number of facilities, travel distance of disaster victims and unsatisfied demand amount where the first and second stage variables are used for facility allocation and service decisions, respectively. The uncertainty in demand is modeled using the scenarios of the stochastic program each represents a different after-disaster situation determining the arrivals of the central humanitarian organizations at the affected area and thus the demand of relief supplies. The authors also consider other problem characteristics such as balancing the supply amounts and limiting the service levels. We refer the interested reader to the study of Cavdur et al. (2016) for more details.

On the other hand, we think that one of the shortcomings of the stochastic programming model presented in the study of Cavdur et al. (2016) (as well as some others presented in similar studies) is about the limited representation of the uncertain after-disaster situations using some predefined scenarios. Even if the stochastic environment is sufficiently captured with a comprehensive scenario construction approach, it might still lack the flexibility to define one’s (i.e., decision makers, disaster operations management professionals) own scenarios to analyze some certain situations.

In this study, we aim at providing such flexibility by presenting a decision support tool which makes it possible for the user (i.e. decision

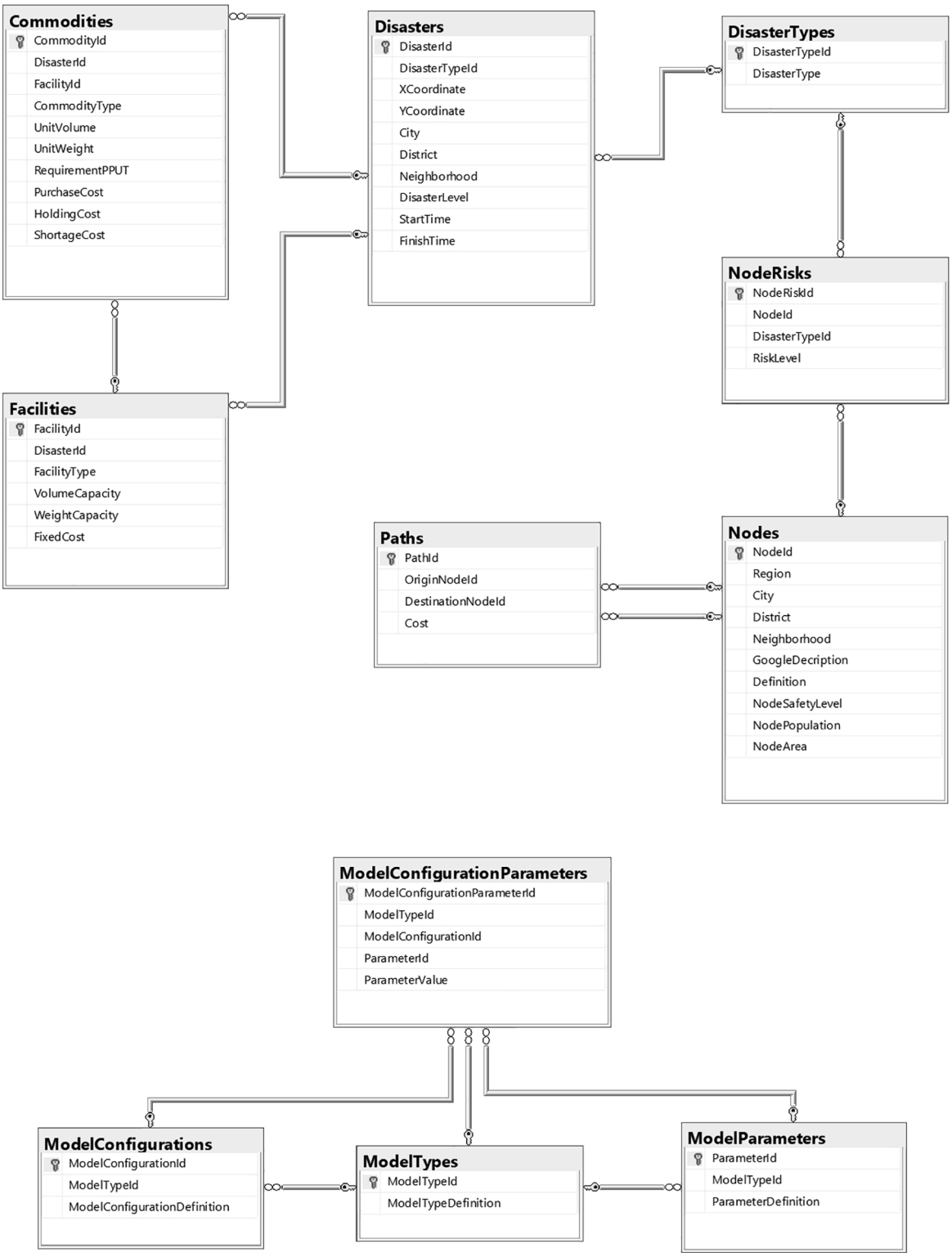


Fig. 2. Database entity-relationship diagram.

makers) to define scenarios by changing the problem parameters of TDR facility allocation for relief supplies distribution. We thus consider the following deterministic version of the stochastic program presented in the study of Cavdur et al. (2016) and integrate it into the tool developed in our study so that its inputs are dynamically determined using the spreadsheet-based graphical user interface as explained in the

Table 2
SQL stored-procedures for generating model inputs dynamically.

Procedure name	Procedure definition
`InputFacilities`	Generates model inputs (facilities)
`InputCommodities`	Generates model inputs (commodities)
`InputNodes`	Generates model inputs (network structure, neighborhood-level)
`InputCosts`	Generates model inputs (costs)
`InputDemands`	Generates model inputs (demands)
`InputConfigurationParameters`	Generates model inputs (configuration parameters)

following subsection.

Indices:
i, j : neighborhood; $i, j = 1, \cdots, n_N$
k, p, q : commodity; $k, p, q = 1, \cdots, n_C$
Parameters:
d_{jk} : demand of commodity k in neighborhood j
c_{ij} : cost (i.e., distance) between neighborhoods i and j
v_k : unit volume of commodity k
w_k : unit weight of commodity k
V : volume capacity of a TDR facility
W : weight capacity of a TDR facility
r_{pq} : supply-ratio between commodities p and q
n_i : maximum number of TDR facilities that can be allocated in neighborhood i
N_T : total number of TDR facilities available
s_i : safety level of neighborhood i
S_T : safety level threshold
α : maximum number of neighborhoods that a neighborhood can serve
β : maximum number of neighborhoods that a neighborhood can be served by
λ : scaling factor
γ : penalty for unit unmet demand
M : a big number
Variables:
z_i : number of facilities opened in neighborhood i
y_{ij} $= \begin{cases} 1, & \text{if neighborhood } i \text{ serves neighborhood } j \\ 0, & \text{otherwise} \end{cases}$
x_{ijk} : amount of commodity k to be supplied from neighborhood i to neighborhood j
u_{jk} : amount of unmet demand of commodity k in neighborhood j

Objective function:

$$\min f = \lambda\left(\sum_{i=1}^{n_N} z_i\right) + \sum_{i=1}^{n_N}\sum_{j=1}^{n_N} c_{ij}\left(\sum_{k=1}^{n_C} x_{ijk}\right) + \sum_{j=1}^{n_N}\sum_{k=1}^{n_C} \gamma u_{jk} \tag{1}$$

Subject to:

$$\sum_{i=1}^{n_N} x_{ijk} = d_{jk} - u_{jk}, \quad \forall j, k \tag{2}$$

$$r_{pq} x_{ijp} = r_{qp} x_{ijq}, \quad \forall i, j, p, q; p > q; p, q \in k \tag{3}$$

$$\sum_{j=1}^{n_N}\sum_{k=1}^{n_C} v_k x_{ijk} \le V z_i, \quad \forall i \tag{4}$$

$$\sum_{j=1}^{n_N}\sum_{k=1}^{n_C} w_k x_{ijk} \le W z_i, \quad \forall i \tag{5}$$

$$z_i \le \sum_{j=1}^{n_N}\sum_{k=1}^{n_C} x_{ijk}, \quad \forall i \tag{6}$$

$$\sum_{j=1}^{n_N} y_{ij} \le \alpha, \quad \forall i \tag{7}$$

$$\sum_{i=1}^{n_N} y_{ij} \le \beta, \quad \forall j \tag{8}$$

$$\sum_{k=1}^{n_C} x_{ijk} \le M y_{ij}, \quad \forall i, j \tag{9}$$

$$y_{ij} \le \sum_{k=1}^{n_C} x_{ijk}, \quad \forall i, j \tag{10}$$

$$z_i \le n_i, \quad \forall i \tag{11}$$

$$\sum_{i=1}^{n_N} z_i \le N_T \tag{12}$$

$$z_i = 0, \quad \forall i \in \{i: s_i \le S_T\} \tag{13}$$

$$z_i \in \mathbb{Z}^+ \cup \{0\}, \quad \forall i \tag{14}$$

$$y_{ij} \in \{0, 1\}, \quad \forall i, j \tag{15}$$

$$x_{ijk} \in \mathbb{Z}^+ \cup \{0\}, \quad \forall i, j, k \tag{16}$$

$$u_{jk} \in \mathbb{Z}^+ \cup \{0\}, \quad \forall j, k \tag{17}$$

The objective function of the integer programming model (Eq. (1)) consists of the minimization three components as the total (i) number of facilities allocated, (ii) weighted-distance traveled by disaster victims and (iii) unsatisfied demand. Eq. (2) ensures that the total amount of supply equals to the satisfied demand. Supply-ratios between different

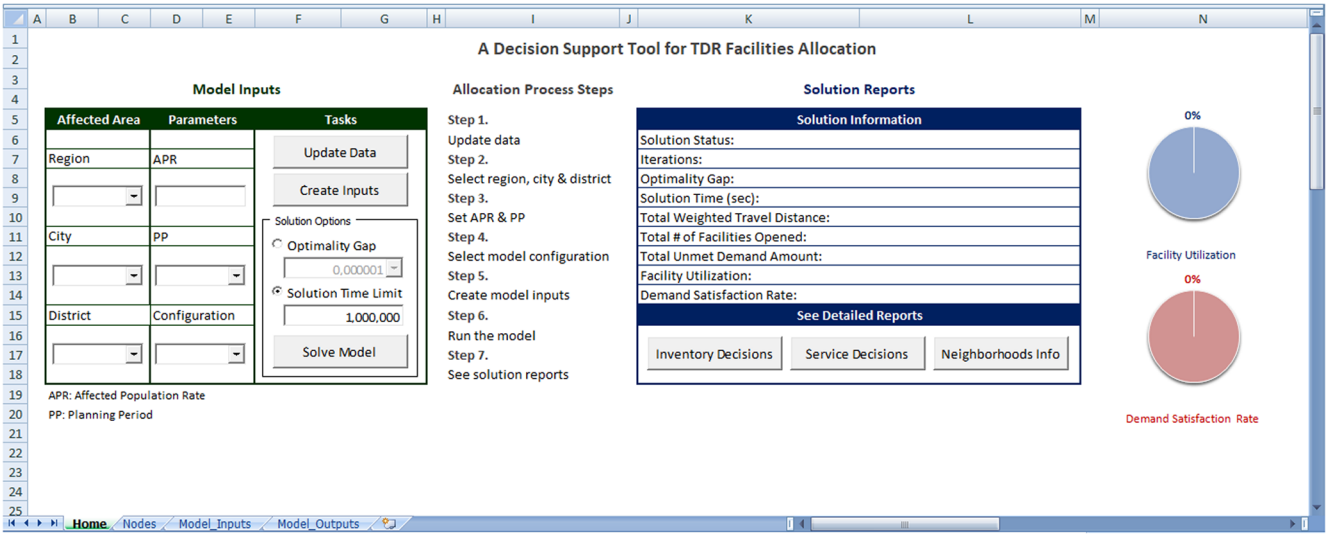


Fig. 3. User interface of the tool-initial status.

commodity types are defined by Eq. (3) by ensuring that all commodities from the same neighborhood are supplied according to a certain (balanced) supply-ratio based on some standards and assumptions presented in Cavdur et al. (2016). Eqs. (4) and (5) are about the capacity restrictions in terms of volume and weight, respectively. Eq. (6) provides the relationship between the corresponding decision variables. Eqs. (7) and (8) restricts the number of neighborhoods a neighborhood can serve and be served by, respectively, to limit the service levels of the neighborhoods considering the possible chaotic situations after a disaster. Eqs. (9) and (10) relates the corresponding decision variables where a sufficiently big number M can be defined as $M = \sum_{k=1}^{n_C} \sum_{j=1}^{n_N} d_{jk}$. Eq. (11) restricts the number of facilities allocated in a single neighborhood and Eq. (12) limits the total number of facilities. Eq. (13) prevents allocating facilities in the neighborhoods whose safety levels are below the required threshold value for safety. Eqs. (14)–(17) represent variable definitions.

We note that in the deterministic TDR facility allocation model presented in this subsection, the uncertain demand of the stochastic model ($d_{jk}(\xi)$ demand of commodity k in neighborhood j for scenario (ξ) is independent of scenario and thus expressed as d_{jk}. Obviously, the random variable ξ representing the scenario is also removed from the second stage variables of the stochastic program to make them scenario independent in the deterministic model resulting the integer programming model. For more details, we refer the interested reader to the study of Cavdur et al. (2016).

3.3. User interface

Since the decision support tool developed in the study itself implemented on Microsoft Excel, we also design the graphical user interface on it as a spreadsheet to provide more flexibility and functionality for the user by utilizing the convenience of a spreadsheet environment. There are four worksheets named as (i) Home, (ii) Nodes, (iii) Model Inputs and (iv) Model Outputs in the user interface. The first worksheet (Home) is the main part of the user interface including all controls. The remaining worksheets are designed for storing different types of problem data. In particular, Nodes worksheet includes the network data including all neighborhoods entered into the database server. The contents of the worksheet can be updated whenever some changes occur in the database (adding new neighborhoods etc.). The last two worksheets (Model Inputs and Model Outputs) include all necessary model data (i.e., problem parameters based on the model configuration determined by the user) and solution vectors, respectively.

A screenshot of the user interface is shown in Fig. 3. As shown in the figure, the user interface is divided into two main panels of controls. On the left-hand-side, the user can update problem data, generate model inputs and solve the model. Similarly, the controls to get detailed solution reports are placed on the right-hand side of the user interface. There are also some basic instructions in the middle section of the worksheet in order to guide system users how to use the tool.

We note that the controls on the left-hand side of the user interface can be classified with respect to their functionalities. The first subset of these controls is designed to define the affected area by selecting the corresponding region (state), city and district. It is also noted that affected area definition is a three-step process where a particular geographical hierarchical level of the network is defined in each step (i.e., starts with regions, continues with cities and ends with districts). As a result, depending on the selection made in the first step (i.e., selected region or state), the set of possible selections in the second step (i.e., cities of the selected region or state) are generated dynamically and depending on the selection made in the second step (i.e., selected city), the set of possible selections in the third step (i.e., districts of the selected city) are generated dynamically. In other words, in each step, the set of possible selections for the user are generated dynamically depending on the selections made in the previous step. When the user selects the Marmara region (in Turkey), for instance, only the cities of the Marmara region are listed. Similarly, the districts of a particular city (say Bursa, for instance, as the city for which the case study is conducted) are listed based on the city selection of the user. After selecting a district, another procedure finally defines the affected area (i.e., the network structure) by retrieving the neighborhoods of the corresponding district.

Second set of problem parameters can be classified as disaster-related parameters since they are used to determine the Affected Population Rate (APR) and Planning Period (PP). We initially present some predefined combinations of affected population rates (from 75% to 95%) and planning periods (from 8 h to 72 h) for illustration, however, any meaningful parameter value can be adapted by the tool by simply introducing the desired quantities.

The final control referred to as Model Configurations is also distinguished from the others since it represents some combinations of some of the other model parameters which are not directly related to the affected area or disaster. Examples of these are the available budget (or the number of facilities) for all affected area as well as per neighborhood and the service level restrictions. Although some predefined model configurations are used for the example case presented in the study, many other model configurations can be defined by the user to represent various situations simply by adding the corresponding tuples into the database. The tool also allows the user to refer to the configurations using meaningful descriptions. Motivated by the study of Cavdur et al. (2016), we use the same descriptions as predefined model configurations, such as “Standard”, “Lower Budget” etc. We present more details on the predefined configurations in the following pages while explaining the example case used for illustration.

Note that any combination of the aforementioned problem parameters defines a particular after-disaster situation or a scenario for the decision engine of the previous subsection. After all problem parameters are set by the user, a scenario with the corresponding setting of the parameters is constructed by running the stored-procedures in the database. Considering the stochastic nature of the problem, the tool can be used to generate many different scenarios desired by the user to represent various after-disaster situations to help the user during the decision-making process.

Similarly, there are three command buttons on the tasks section of the control panel which (i) connects to the server and updates the data in the worksheet, (ii) generates model data based on the corresponding problem parameters and model configuration settings and (iii) runs the decision engine to solve the model and reports the results. We also note that, before initiating the solution procedure, the user can also interact with the decision engine (i.e., solver) by either setting up an optimality gap (with a default value of 10^{-6}) or limiting the solution time (with a default value of 10^{+6}) using the corresponding controls under the tasks section to allow a tradeoff between the time and quality of a solution. Note that it is also possible to evaluate the corresponding tradeoff with the presented details (i.e., solution status, optimality gap, solution time etc.) in the general solution information section on the right-hand side of the user interface as also referred the corresponding parts of the paper.

The components on the right-hand side of the of the user interface are for reporting purposes as noted in Fig. 3. A summary table (i.e., General Solution Information) represents the performance measures of the model as well as some technical information about the decision engine (i.e., solver). There are also three command buttons on this control panel to see detailed solution reports which are generated from the solution vectors in order to provide more meaningful results to the user. We can classify these detailed solution reports as (i) inventory decisions, (ii) service decisions and (iii) neighborhoods information, each of which is shown when the corresponding button is clicked by scrolling down the page. Since Fig. 3 shows the interface before performing any allocations as in its initial state, it does not include any

results. After performing some allocations for the example case, another screenshot of the user interface is presented in the following pages for illustration of the reporting capabilities of the tool.

4. System integration

After the development of the three main components, they are integrated to work under the decision support framework designed in the study. As stated earlier, the decision support tool is implemented on Microsoft Excel where Microsoft Visual Basic for Applications (VBA) is used for the integration of the components where we also utilize the built-in functions of Microsoft Excel. Additionally, the database component is designed using Microsoft SQL Server. Maximal Software Mathematical Programming Language (MPL)-OptiMax with Gurobi Optimizer are used for developing the decision engine.

It is noted that the SQL procedures introduced in previous pages in the section of the database component (i.e., in Table 2 of Section 3.1) are presented in this section in terms of their functionality since the corresponding procedures are extensively used for system integration especially for generating model data dynamically for the decision engine component. Fig. 4 briefly describes how these procedures are used for generating the corresponding model data dynamically. Note that, in Fig. 4, the prefixes "T", "SP" and "UI" are used to represent the Tables, SQL Stored-Procedures and User Interface parameters, respectively, to distinguish between the different types of objects of the system for the convenience of the reader.

As noted from Fig. 4, model input data are categorized with respect to the corresponding type of model components represented by them

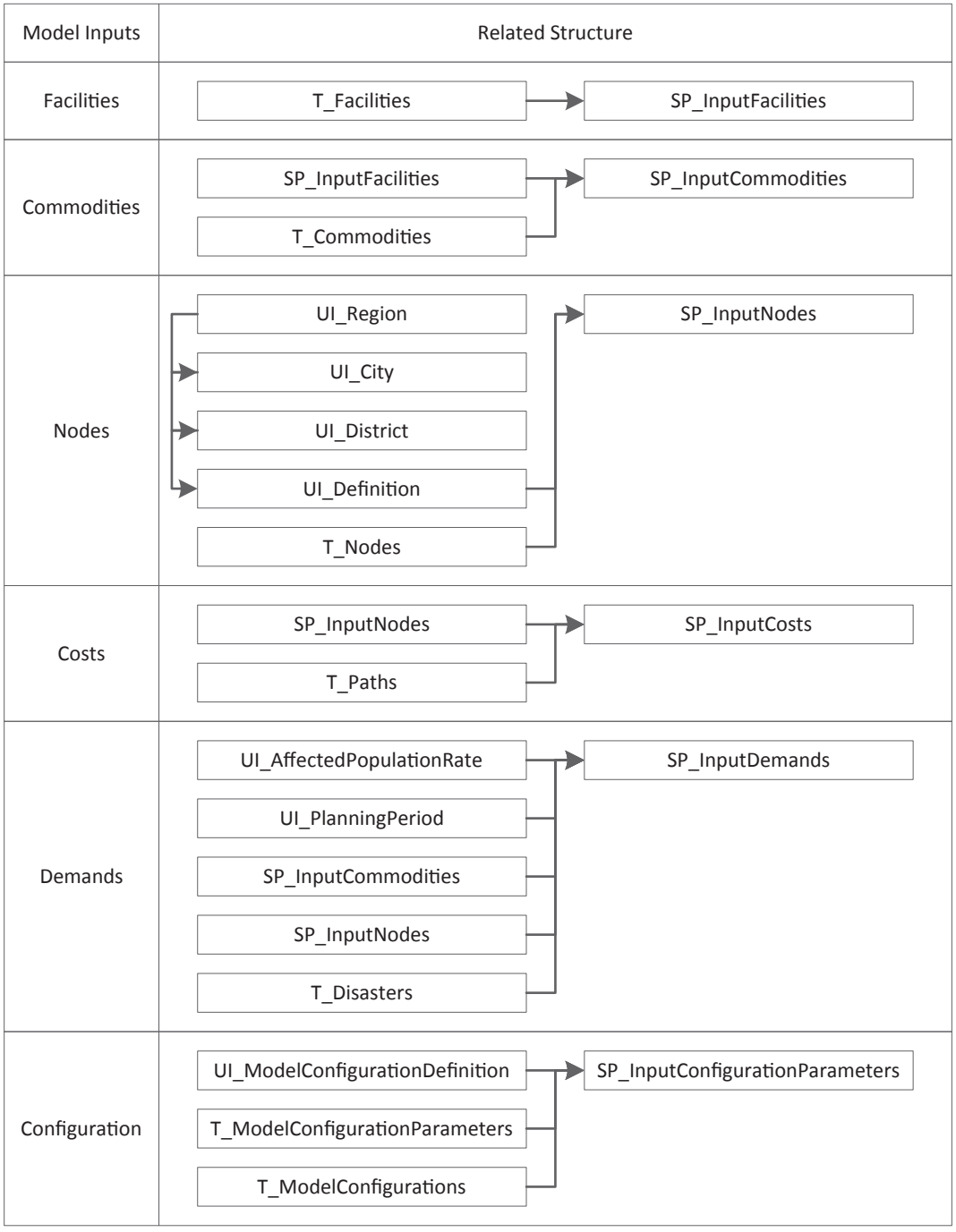


Fig. 4. Overall procedural structure for generating model inputs dynamically.

such as commodities, facilities etc. Within the context of such a classification, the last procedure in the figure is distinguished from the others since it is related the generation of the model configurations discussed earlier whereas the other procedures are used for generating a particular type of model data (i.e., commodities, facilities etc.).

We detail the demand generation stored-procedure as an example (SP_InputDemands) since it sufficiently explains the overall idea of the data generation process. A similar reasoning can be used for the other procedures. The procedure (SP_InputDemands) uses the results of two other stored-procedures to generate commodities and nodes (SP_InputCommodities and SP_InputNodes) in addition to the table about disasters (T_Disasters) and also the parameters from the user interface about the affected population rate (UI_AffectedPopulationRate) and planning period (UI_PlanningPeriod) determined by the user. As a result, the stored-procedure SP_InputDemands generates the corresponding demands by using a particular commodities-affected area-disaster information combination as its inputs.

The stored-procedure SP_InputCommodities also gets inputs from another stored-procedure (SP_Input_Facilities) and the table about commodities (T_Commodities). It is finally noted that SP_InputNodes interacts with the user interface by receiving the inputs about the affected area entered using the interface (UI_Region, UI_City, UI_District) as well as the table about nodes (T_Nodes).

We also note the relationships between the corresponding user interface controls (combo boxes for selecting the region, city and district of the affected area) during the process. In other words, when the user makes the region selection, we retrieve the cities in the region for the user. Similarly, when a city is selected, all districts in the city are presented to the user dynamically so that the user can define her/his scenario appropriately. The idea behind the other procedures which are not mentioned here can be analyzed similarly.

5. Implementation with an example case

In this section, an example case is presented for illustration purposes. Using the available data from the study of Cavdur et al. (2016), we consider a district with 64 neighborhoods (i.e., Yildirim district of Bursa city of Marmara region) in Turkey as the affected area with an affected population rates from 75% to 95% and five different model configurations as (i) standard, (ii) lower budget, (iii) lower safety & service levels, (iv) higher safety & service levels and (v) lower demand satisfaction are considered in the example case. We also consider five different planning periods ranging from 8 h to 72 h (i.e., 8 h, 16 h, 24 h, 48 h and 72 h) as in the scenarios of the stochastic programming model proposed by Cavdur et al. (2016).

Note that although the example case has some similarities to the one presented in the study of Cavdur et al. (2016), it is just for convenience due to data availability. In other words, we can consider any other case easily as long as the necessary data (i.e., distance matrix, populations etc.) are available about the corresponding neighborhoods of the district for which we want to construct the case using the flexibility of the tool. On the other hand, when defining a scenario, it is important to be tedious while determining the affected population rates, planning periods and especially model configurations since unreasonable considerations of the model parameters might produce results which are not meaningful in practice (i.e., defining very low-high budgets which are not valid in the real-life problem etc.).

In fact, such issues might be considered easily by an efficient utilization of model configurations. In our case, for instance, we consider the aforementioned five different model configurations. The first model configuration is referred to as the standard configuration (i.e., MC Standard) and adapted from the study of Cavdur et al. (2016). The second one (i.e., MC Lower Budget) limits both the number of TDR facilities per neighborhood and the total number of TDR facilities available. Following two configurations (i.e., MC Lower Safety-Service Levels and Higher Safety-Service Levels) are defined to see the effects of lower and higher safety and service levels, respectively. In the last configuration (MC5 Lower Demand Satisfaction), the unit cost of unsatisfied demand is decreased resulting with lower demand satisfaction rates. These model configurations are listed in Table 3 where each parameter is defined representing the corresponding configuration.

Table 4 represents a summary of the performance measures for the optimal solutions of the experiments. Although the performance measures worsen for longer planning periods in general, depending on the model configuration, the corresponding worsening is observed in terms of different performance measures. For instance, it is noted that the first performance measure (weighted-distance) keeps increasing in the first model configuration whereas, in the second model configuration, a sudden increase (from 54 to 1,439,097 between planning periods of 24 and 48 h) is observed for the third performance measure (unsatisfied demand) which is an expected result since the second model configuration limits the total number of facilities available (lower budget), and thus, it is not possible to allocate more than 100 facilities resulting greater amounts of unsatisfied demand for longer planning periods as observed for the last two planning periods (48 h and 72 h) in the results.

The next model configuration-pair (MC3 and MC4) represents the effects of changing safety and service levels. The results indicate the significant effects of the restrictions on the safety and service levels on the performance measures. It is noted that lowering safety level allows allocating facilities in more neighborhoods, and thus, producing better scores especially in terms of the first performance measure (weighted-distance). In the other model configuration (MC4), however, a higher safety level is required which is achieved by allowing higher service levels also at the expense of worsening the performance measures. In other words, the third model configuration allows allocating TDR facilities in more neighborhoods by lowering safety requirements and limiting service levels, and thus, making it easier for disaster victims to reach these facilities whereas disaster victims walk longer distances in the second case (i.e., the fourth model configuration) where it is allowed to allocate facilities only in very safe neighborhoods which however can now serve more neighborhoods.

The final model configuration (lower demand satisfaction) represents the worst case for the humanitarian metrics since it assumes the lowest unit cost of unsatisfied demand. As a result, it produces the worst results in terms of the third performance measure (unsatisfied demand); worse than those of the second configuration (i.e., lower budget) for longest planning period of 72.

Additional experiments are also performed for validation purposes. Using a similar setting to that of Table 4, we increase the affected population rate to 95% for the new set of experiments. The results are presented in Table 5 where the effects of the increase in the affected population rate are noted in the allocations. As noted from the results, similar interpretations to those of Table 4 are also applicable for the corresponding allocations of Table 5.

In addition to the controls for performing allocations, some simple reporting features are also available with the tool. After the allocations are performed, the user can analyze the results using the user interface. Although it is possible to check out the original solution vectors by

Table 3
Model configuration definitions.

Configuration	N_T	n_i	S_T	M	λ	α	β	γ
MC1-Standard	900	100	0.975	1,000,000	1,000	10	10	15
MC2-Lower Budget	100	10	0.975	1,000,000	1,000	10	10	15
MC3-Lower Safety-Service Level	900	100	0.950	1,000,000	1,000	5	5	15
MC4- Higher Safety-Service Level	900	100	0.990	1,000,000	1,000	20	20	15
MC5-Lower Demand Satisfaction	900	100	0.975	1,000,000	1,000	10	10	1

Table 4
Optimal solutions-performance measures (PMs) for different model configurations (MCs) and planning periods (PPs) for an affected population rate of 75%

Configuration	PP1 (8 h)	PP2 (16 h)	PP3 (24 h)	PP4 (48 h)	PP5 (72 h)
MC1-PM1	1,554,672	3,107,557	4,661,563	9,322,530	13,984,987
MC1-PM2	29	54	75	148	217
MC1-PM3	47	51	55	56	54
ST (sec.)	1.69	0.67	0.92	0.48	0.59
MC2-PM1	1,554,673	3,169,942	5,148,141	4,227,351	2,216,516
MC2-PM2	29	52	73	100	100
MC2-PM3	47	53	54	1,439,097	3,886,609
ST (sec.)	1.16	1.47	1.05	2.44	2.33
MC3-PM1	585,224	1,169,064	1,754,939	3,506,653	5,258,919
MC3-PM2	40	61	80	153	224
MC3-PM3	47	51	49	55	51
ST (sec.)	2.02	1.38	1.97	3.16	0.94
MC4-PM1	2,735,426	5,470,881	8,205,382	16,410,294	24,615,667
MC4-PM2	25	48	72	143	213
MC4-PM3	48	59	55	93	56
ST (sec.)	1.97	7.70	3.98	1.78	0.16
MC5-PM1	59,639	119,589	196,290	359,058	521,760
MC5-PM2	14	22	30	55	80
MC5-PM3	541,777	1,084,130	1,608,161	3,250,325	4,890,386
ST (sec.)	0.42	0.36	0.31	0.39	0.31

ST: Solution Time

Table 5
Optimal solutions-performance measures (PMs) for different model configurations (MCs) and planning periods (PPs) for an affected population rate of 95%

Configuration	PP1 (8 h)	PP2 (16 h)	PP3 (24 h)	PP4 (48 h)	PP5 (72 h)
MC1-PM1	1,968,834	3,938,050	5,906,028	11,808,550	17,713,942
MC1-PM2	36	64	96	187	273
MC1-PM3	45	42	45	47	43
ST (sec.)	0.83	0.64	0.73	0.38	0.42
MC2-PM1	1,968,828	4,206,593	6,843,167	2,837,351	1,684,721
MC2-PM2	36	63	94	100	100
MC2-PM3	45	53	54	2,744,448	5,844,613
ST (sec.)	1.19	1.19	1.06	1.84	8.05
MC3-PM1	740,184	1,481,055	2,221,442	4,440,868	6,663,149
MC3-PM2	43	69	103	193	281
MC3-PM3	43	41	40	45	43
ST (sec.)	1.44	0.98	0.81	0.92	0.92
MC4-PM1	3,464,610	6,929,102	10,394,019	20,787,183	31,184,779
MC4-PM2	31	60	90	181	272
MC4-PM3	50	53	66	49	63
ST (sec.)	2.03	0.34	1.33	1.51	0.28
MC5-PM1	73,439	146,871	223,823	455,842	676,469
MC5-PM2	17	27	38	71	101
MC5-PM3	688,339	1,376,600	2,061,957	4,114,586	6,179,193
ST (sec.)	0.27	0.25	0.27	0.30	0.30

ST: Solution Time

opening the corresponding worksheet of the tool, a summary of the results is presented on the main worksheet (i.e., user interface) of the tool for the convenience of the user. We can divide the reporting section into four categories where the results are classified as the (i) general solution information, (ii) inventory decisions, (iii) service decisions and (iv) detailed neighborhood information are presented.

Fig. 5 represents the user interface after an allocation is performed where the performance measures of the problem (i.e., total number of facilities allocated, weighted-travel distance of disaster victims and amount of unsatisfied demand) as well as two other metrics about the facility utilizations and demand satisfaction rates are presented as it also shows general solution information. For the example problem represented in Fig. 5, 89 facilities are allocated with a weighted-travel distance of 5,594,883 and unsatisfied demand amount of 42 which approximately results with a facility utilization of 93% and a demand satisfaction rate of 100%.

In addition to the performance measures of the problem presented as general solution information, some technical details about the solution are also presented in the general solution information section as shown in Fig. 5, such as the solution status, optimality gap and solution time.

It is also possible to produce detailed solution reports using the corresponding controls in the user interface as shown in Fig. 6. In particular, Fig. 6(a) summarizes inventory decisions including the name of the neighborhood as well as the number of facilities and relief supplies amounts in the facilities for each neighborhood where TDR facilities are allocated. For the example solution shown in Fig. 6(a), it is noted, for instance, that there are four TDR facilities are allocated in Akcaglayan neighborhood where 48,081 L of water, 57,723 meal-ready-to-eat kits and 6409 medical kits are stored in the facilities.

A screenshot of the third subsection (i.e., service decisions) of the solution report is partially-shown in Fig. 6(b) where supply point-demand point relationships between the neighborhoods are presented. Since there are 64 neighborhoods in the table, a partial capture is shown in Fig. 6(b) to ensure readability. As noted from the figure, in addition to the disaster victims resides in Akcaglayan, it also serves three other close neighborhoods (i.e., Kaplikaya, Zeyniler and 75. Yil) as the corresponding neighborhoods do not contain any TDR facilities due to the constraints of the problem (i.e., safety conditions etc.).

Finally, Fig. 6(c) presents more detailed information for each neighborhood, such as the neighborhood status (i.e., if it is supply or demand point), affected population rate, safety level, number of TDR facilities allocated to the neighborhood, the number of neighborhoods served by the neighborhood and the supply neighborhood (i.e., the neighborhood which serves it). Note that it might be possible that a neighborhood only serves itself in which case the supply neighborhood is just the neighborhood itself.

Before concluding this section, we highlight some potential issues to consider due to problem dimensions. Although a real-life problem is solved to optimality in a few seconds using the tool developed in the study, it might not be possible to obtain the optimal solutions for larger-sized problems in reasonable time limits. Considering the occurrences of such situations, we finalize this section by presenting some figures about optimality gap and solution time. Using the aforementioned settings to set up an optimality gap or limit solution time as explained in the corresponding subsection (i.e., 3.3. User Interface) of the paper, it might be possible to obtain a good solution (even if it is not optimal) in reasonable time limits. Considering the results presented in Tables 4 and 5, for instance, it takes about 8 s to solve a problem instance corresponding to the largest solution time. We limit the solution time by approximately 50% each time and perform three allocations with the corresponding solver settings (i.e., solve the model by limiting the solution time to 4 s, 2 s and 1 s in each run) to illustrate the corresponding decision making capability of the tool. By noting that the optimal objective function value is 89,453,916 for the aforementioned problem instance, it is observed that we obtain solutions with objective values of 89,460,336 in the first two runs (0.007% worse than the optimal objective value) whereas the objective value in the third run is 89,555,315 (0.113% worse than the optimal objective value), representing an example case to utilize the capabilities of the tool to employ a tradeoff between the time and quality of a solution. Such tradeoffs might be more meaningful for decision makers especially for larger-size problems requiring longer solution times.

6. Conclusions

In this study, we present a spreadsheet-based decision support tool for allocating temporary disaster response facilities for relief supplies distribution. The decision support tool is developed in this study has three main components as its database, decision engine and user

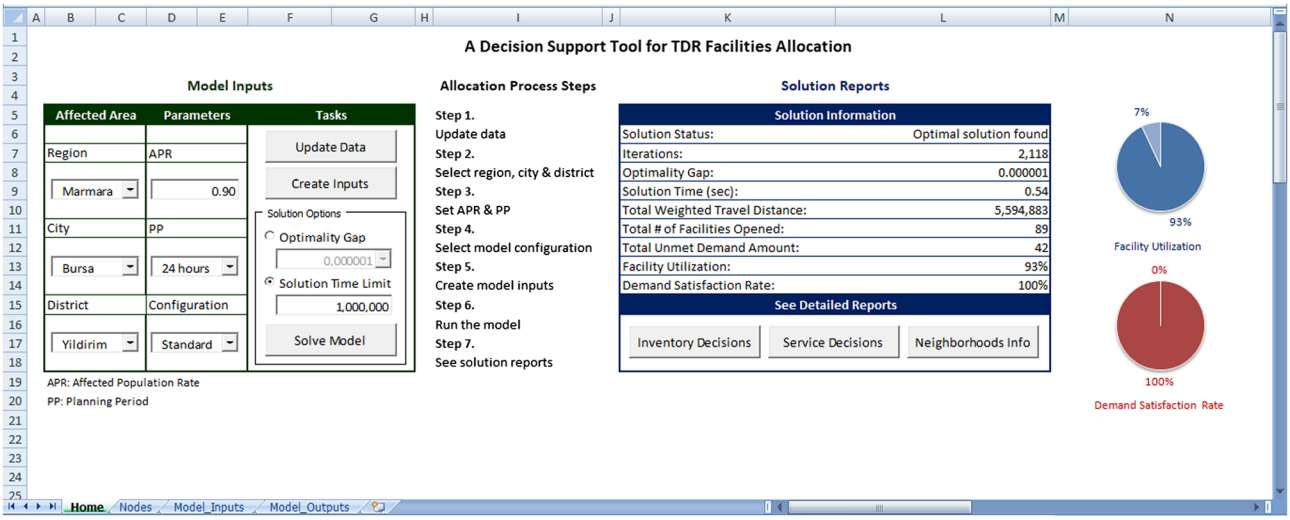


Fig. 5. User interface after an allocation – general solution information.

interface. We develop each component using appropriate platforms and integrate these components on the spreadsheet environment. We also present an example case for illustrating the decision support tool where various scenarios are defined and the corresponding facility allocations are performed. Using a spreadsheet environment for developing the decision support tool provides more flexibility and functionality for the user for performing the tasks such as data manipulation and reporting. Although we present some example cases in the paper for illustration purposes, the flexibility of the tool allows the user to consider other cases with different scenarios. We think that the tool presented in the study might be a useful tool to help decision makers to allocate temporary disaster response facilities for relief supplies distribution.

In future studies, some extensions might be considered. We can adapt the tool to consider different types of facilities and relief supplies. The database component might be even more comprehensive to store some additional data in future studies such as some additional parameters for new models and algorithms to integrate to the decision engine of the tool. In such a case, corresponding models and algorithms should also be developed under the decision engine component. Improving the user interface might also be desired for providing even more flexibility and functionality for the user. Using different platforms for the tool, such as developing a standalone or Web-based application might be also considered in future studies.

Inventory Decisions

Supplier Node	# of Facilities Opened	Quantity of Water Stored	Quantity of MRE-Kit Stored	Quantity of Medical-Kit Stored
Akcaglayan	4	48,081	57,723	6,409
Baglaralti	23	340,472	408,736	45,374
Baruthane	17	256,469	307,894	34,183
Degirmenonu	4	55,737	66,913	7,429
Karamazak	1	15,243	18,299	2,032
Maltepe	7	105,818	127,035	14,103
Mehmetakifersoy	9	134,332	161,267	17,904
Mollaarap	2	30,476	36,587	4,062
Musababa	4	56,178	67,443	7,488
Siracevizler	2	17,194	20,642	2,292
Umurbey	2	30,126	36,168	4,017
Yesil	5	70,611	84,771	9,414
Yesilyayla	6	89,545	107,499	11,933
Zumrutevler	3	45,200	54,263	6,024

(a) Inventory Decisions

Service Decisions

Demand Node	Supplier Node
Akcaglayan	Akcaglayan
Kaplikaya	Akcaglayan
Zeyniler	Akcaglayan
75.Yil	Akcaglayan
Arabayatagi	Baglaralti
Baglaralti	Baglaralti
Cinaronu	Baglaralti
Erikli	Baglaralti
Esenevler	Baglaralti

(b) Service Decisions

Detailed Neighborhood Information

Select a neighborhood

Akcaglayan

Node Type	Supplier
Affected Population	16,382
Safety Level	1
# of TDR-Facilities	4
# of Nodes Served	4
Supplier Node	Akcaglayan

(c) Detailed Neighborhood Information

Fig. 6. Detailed solution reports.

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References

Ahmad, S., Simonovic, S.P., 2006. An intelligent decision support system for management of floods. Water Resour. Manage. 20 (3), 391–410. https://doi.org/10.1007/s11269-006-0326-3.

Ai, F., Comfort, L.K., Dong, Y., Znati, T., 2016. A dynamic decision support system based on geographical information and mobile social networks: a model for tsunami risk mitigation in Padang, Indonesia. Saf. Sci. 90, 62–74. https://doi.org/10.1016/j.ssci.2015.09.022.

Alvear, D., Abreu, O., Cuesta, A., Alonso, V., 2013. Decision support system for emergency management: road tunnels. Tunn. Undergr. Space Technol. 34, 13–21. https://doi.org/10.1016/j.tust.2012.10.005.

Balcik, B., 2017. Site selection and vehicle routing for post-disaster rapid needs assessment. Transport. Res. Part E: Logist. Transportat. Rev. 101, 30–58. https://doi.org/10.1016/j.tre.2017.01.002.

Balcik, B., Beamon, B.M., 2008. Facility location in humanitarian relief. Int. J. Logist. 11 (2), 101–121. https://doi.org/10.1080/13675560701561789.

Bayram, V., Tansel, B.C., Yaman, H., 2015. Compromising system and user interests in shelter location and evacuation planning. Transport. Res. Part B: Methodol. 72, 146–163. https://doi.org/10.1016/j.trb.2014.11.010.

Beamon, B.M., Balcik, B., 2008. Performance measurement in humanitarian relief chains. Int. J. Publ. Sector Manage. 21 (1), 4–25. https://doi.org/10.1108/095135508108.

Caunhye, A.M., Nie, X., Pokharel, S., 2012. Optimization models in emergency logistics: a literature review. Socio-Econ. Plann. Sci. 46 (1), 4–13. https://doi.org/10.1016/j.seps.2011.04.004.

Cavdur, F., Kose-Kucuk, M., Sebatli, A., 2016. Allocation of temporary disaster response facilities under demand uncertainty: an earthquake case study. Int. J. Disaster Risk Reduct. 19, 159–166. https://doi.org/10.1016/j.ijdrr.2016.08.009.

Chang, M.S., Tseng, Y.L., Chen, J.W., 2007. A scenario planning approach for the flood emergency logistics preparation problem under uncertainty. Transport. Res. Part E: Logist. Transport. Rev. 43 (6), 737–754. https://doi.org/10.1016/j.tre.2006.10.013.

Chen, A.Y., Pena-Mora, F., Ouyang, Y., 2011. A collaborative GIS framework to support equipment distribution for civil engineering disaster response operations. Autom. Constr. 20 (5), 637–648. https://doi.org/10.1016/j.autcon.2010.12.007.

Chen, X.S., Liu, C.C., Wu, I.C., 2018. A BIM-based visualization and warning system for fire rescue. Adv. Eng. Inf. 37, 42–53. https://doi.org/10.1016/j.aei.2018.04.015.

Cheng, M.Y., Chiu, K.C., Hsieh, Y.M., Yang, I.T., Chou, J.S., Wu, Y.W., 2017. BIM integrated smart monitoring technique for building fire prevention and disaster relief. Autom. Constr. 84, 14–30. https://doi.org/10.1016/j.autcon.2017.08.027.

De Silva, F.N., Eglese, R.W., 2000. Integrating simulation modelling and GIS: spatial decision support systems for evacuation planning. J. Oper. Res. Soc. 51 (4), 423–430. https://doi.org/10.1057/palgrave.jors.2600879.

El-Anwar, O., El-Rayes, K., Elnashai, A., 2009. An automated system for optimizing post-disaster temporary housing allocation. Autom. Constr. 18 (7), 983–993. https://doi.org/10.1016/j.autcon.2010.12.007.

Erbeyoglu, G., Bilge, U., 2019. A robust disaster preparedness model for effective and fair disaster response. Eur. J. Oper. Res. https://doi.org/10.1016/j.ejor.2019.07.029.

Ergen, E., Sariel-Talay, S., Guven, G., Avdan, G., 2010. Local information access for search and rescue using wireless data storage mediums. J. Comput. Civil Eng. 25 (4), 263–274. https://doi.org/10.1061/(ASCE)CP.1943-5487.0000093.

Fiedrich, F., Gehbauer, F., Rickers, U., 2000. Optimized resource allocation for emergency response after earthquake disasters. Saf. Sci. 35 (1–3), 41–57. https://doi.org/10.1016/S0925-7535(00)00021-7.

Fikar, C., Gronalt, M., Hirsch, P., 2016. A decision support system for coordinated disaster relief distribution. Expert Syst. Appl. 57, 104–116. https://doi.org/10.1016/j.eswa.2016.03.039.

Gehlot, H., Zhan, X., Qian, X., Thompson, C., Kulkarni, M., Ukkusuri, S.V., 2018. A-RESCUE 2.0: a high-fidelity, parallel, agent-based evacuation simulator. J. Comput. Civ. Eng. 33(2), 04018059. https://doi.org/10.1061/(ASCE)CP.1943-5487.0000802.

Gormez, N., Koksalan, M., Salman, F.S., 2011. Locating disaster response facilities in Istanbul. J. Oper. Res. Soc. 62 (7), 1239–1252. https://doi.org/10.1057/jors.2010.67.

Hasan, S., Ukkusuri, S.V., 2011. A threshold model of social contagion process for evacuation decision making. Transport. Res. Part B: Methodol. 45 (10), 1590–1605. https://doi.org/10.1016/j.trb.2011.07.008.

Isikdag, U., Underwood, J., Aouad, G., 2008. An investigation into the applicability of building information models in geospatial environment in support of site selection and fire response management processes. Adv. Eng. Inf. 22 (4), 504–519. https://doi.org/10.1016/j.aei.2008.06.001.

Kilci, F., Kara, B.Y., Bozkaya, B., 2015. Locating temporary shelter areas after an earthquake: a case for Turkey. Eur. J. Oper. Res. 243 (1), 323–332. https://doi.org/10.1016/j.ejor.2014.11.035.

Kondaveti, R., Ganz, A., 2009. Decision support system for resource allocation in disaster management. In: Engineering in Medicine and Biology Society, Annual International Conference of the IEEE. IEEE, pp. 3425–3428. https://doi.org/10.1109/IEMBS.2009.5332498.

Kovacs, G., Spens, K.M., 2007. Humanitarian logistics in disaster relief operations. Int. J. Phys. Distribut. Logist. Manage. 37 (2), 99–114. https://doi.org/10.1108/096000307107.

Landwehr, P.M., Wei, W., Kowalchuck, M., Carley, K.M., 2016. Using tweets to support disaster planning, warning and response. Saf. Sci. 90, 33–47. https://doi.org/10.1016/j.ssci.2016.04.012.

Lee, J., Jeong, Y., Oh, Y.S., Lee, J.C., Ahn, N., Lee, J., Yoon, S.H., 2013. An integrated approach to intelligent urban facilities management for real-time emergency response. Autom. Constr. 30, 256–264. https://doi.org/10.1016/j.autcon.2012.11.008.

Li, X., Zhao, Z., Zhu, X., Wyatt, T., 2011. Covering models and optimization techniques for emergency response facility location and planning: a review. Math. Methods Oper. Res. 74 (3), 281–310. https://doi.org/10.1007/s00186-011-0363-4.

Lin, W.Y., Wu, T.H., Tsai, M.H., Hsu, W.C., Chou, Y.T., Kang, S.C., 2018. Filtering disaster responses using crowdsourcing. Autom. Constr. 91, 182–192. https://doi.org/10.1016/j.autcon.2018.03.016.

Luan, S., Yang, Q., Zhou, H., Jiang, Z., Wang, W., Wang, Z., Chu, R., 2019. The HSABA for emergency location-routing problem. Math. Probl. Eng. https://doi.org/10.1155/2019/5391687.

Mendonca, D., Beroggi, G.E., Wallace, W.A., 2001. Decision support for improvisation during emergency response operations. Int. J. Emergency Manage. 1 (1), 30–38. https://doi.org/10.1504/IJEM.2001.000507.

Mete, H.O., Zabinsky, Z.B., 2010. Stochastic optimization of medical supply location and distribution in disaster management. Int. J. Prod. Econ. 126 (1), 76–84. https://doi.org/10.1016/j.ijpe.2009.10.004.

Mirahadi, F., McCabe, B., Shahi, A., 2019. IFC-centric performance-based evaluation of building evacuations using fire dynamics simulation and agent-based modeling. Autom. Constr. 101, 1–16. https://doi.org/10.1016/j.autcon.2019.01.007.

Natarajarathinam, M., Capar, I., Narayanan, A., 2009. Managing supply chains in times of crisis: a review of literature and insights. Int. J. Phys. Distribut. Logist. Manage. 39 (7), 535–573. https://doi.org/10.1108/096000309109.

Noyan, N., Balcik, B., Atakan, S., 2015. A stochastic optimization model for designing last mile relief networks. Transport. Sci. 50 (3), 1092–1113. https://doi.org/10.1287/trsc.2015.0621.

Nozick, L.K., 2001. The fixed charge facility location problem with coverage restrictions. Transport. Res. Part E: Logist. Transport. Rev. 37 (4), 281–296. https://doi.org/10.1016/S1366-5545(00)00018-1.

Ortuno, M.T., Cristobal, P., Ferrer, J.M., Martin-Campo, F.J., Munoz, S., Tirado, G., Vitoriano, B., 2013. Decision aid models and systems for humanitarian logistics. A survey. In: Vitoriano, B., Montero, J., Ruan, D. (Eds.), Decision Aid Models for Disaster Management and Emergencies. Atlantis Press, Paris, pp. 17–44. https://doi.org/10.2991/978-94-91216-74-9_2.

Ozdamar, L., Ekinci, E., Kucukyazici, B., 2004. Emergency logistics planning in natural disasters. Ann. Oper. Res. 129 (1–4), 217–245. https://doi.org/10.1023/B:ANOR.0000030690.27939.39.

Pan, A., 2010. The applications of maximal covering model in typhoon emergency shelter location problem. Industrial Engineering and Engineering Management (IEEM) 2010 IEEE International Conference 1727–1731. https://doi.org/10.1109/IEEM.2010.5674577.

Pidd, M., De Silva, F.N., Eglese, R.W., 1996. A simulation model for emergency evacuation. Eur. J. Oper. Res. 90 (3), 413–419. https://doi.org/10.1016/0377-2217(95)00112-3.

Rawls, C.G., Turnquist, M.A., 2010. Pre-positioning of emergency supplies for disaster response. Transport. Res. Part B: Methodol. 44 (4), 521–534. https://doi.org/10.1016/j.trb.2009.08.003.

Rawls, C.G., Turnquist, M.A., 2011. Pre-positioning planning for emergency response with service quality constraints. OR Spectrum 33 (3), 481–498. https://doi.org/10.1007/s00291-011-0248-1.

Rekik, M., Ruiz, A., Renaud, J., Berkoune, D., Paquet, S., 2013. A decision support system for humanitarian network design and distribution operations. In: Zeimpekis, V., Ichoua, S., Minis, I. (Eds.), Humanitarian and Relief Logistics. Springer, NY, pp. 1–20. https://doi.org/10.1007/978-1-4614-7007-6_1.

Rolland, E., Patterson, R.A., Ward, K., Dodin, B., 2010. Decision support for disaster management. Oper. Manage. Res. 3 (1–2), 68–79. https://doi.org/10.1007/s12063-010-0028-0.

Sabbaghtorkan, M., Batta, R., He, Q., 2019. Prepositioning of assets and supplies in disaster operations management: review and research gap identification. Eur. J. Oper. Res. https://doi.org/10.1016/j.ejor.2019.06.029.

Sahebjamnia, N., Torabi, S.A., Mansouri, S.A., 2017. A hybrid decision support system for managing humanitarian relief chains. Decis. Support Syst. 95, 12–26. https://doi.org/10.1016/j.dss.2016.11.006.

Salmeron, J., Apte, A., 2010. Stochastic optimization for natural disaster asset prepositioning. Prod. Oper. Manage. 19 (5), 561–574. https://doi.org/10.1111/j.1937-5956.2009.01119.x.

Sanci, E., Daskin, M.S., 2019. Integrating Location and network restoration decisions in relief networks under uncertainty. Eur. J. Oper. Res. 279 (2), 335–350. https://doi.org/10.1016/j.ejor.2019.06.012.

Santos, R., Mosse, D., Znati, T., Comfort, L., 2016. Design and implementation of a Witness Unit for opportunistic routing in tsunami alert scenarios. Saf. Sci. 90, 75–83. https://doi.org/10.1016/j.ssci.2015.09.014.

Shan, S., Zhao, F., Wei, Y., Liu, M., 2019. Disaster management 2.0: a real-time disaster damage assessment model based on mobile social media data – a case study of Weibo

(Chinese Twitter). Saf. Sci. 115, 393–413. https://doi.org/10.1016/j.ssci.2019.02.029.
Sheu, J.B., 2007. Challenges of emergency logistics management. Transport. Res. Part E: Logist. Transport. Rev. 43 (6), 655–659. https://doi.org/10.1016/j.tre.2007.01.001.
Shi, Y., Zhai, G., Xu, L., Zhu, Q., Deng, J., 2019. Planning emergency shelters for urban disasters: a multi-level location-allocation modeling approach. Sustainability 11 (16), 4285. https://doi.org/10.3390/su11164285.
Thompson, S., Altay, N., Green III, W.G., Lapetina, J., 2006. Improving disaster response efforts with decision support systems. Int. J. Emergency Manage. 3 (4), 250–263. https://doi.org/10.1504/IJEM.2006.011295.
Tufekci, S., 1995. An integrated emergency management decision support system for hurricane emergencies. Saf. Sci. 20 (1), 39–48. https://doi.org/10.1016/0925-7535(94)00065-B.
Uster, H., Wang, X., Yates, J.T., 2018. Strategic Evacuation Network Design (SEND) under cost and time considerations. Transport. Res. Part B: Methodol. 107, 124–145. https://doi.org/10.1016/j.trb.2017.11.010.
Van de Walle, B., Turoff, M., 2008. Decision support for emergency situations. IseB 6 (3), 295–316. https://doi.org/10.1007/978-3-540-48716-6_3.
Yazici, M.A., Ozbay, K., 2007. Impact of probabilistic road capacity constraints on the spatial distribution of hurricane evacuation shelter capacities. Transport. Res. Record: J. Transportat. Res. Board 2022, 5–62. https://doi.org/10.3141/2022-07.
Yi, W., Ozdamar, L., 2007. A dynamic logistics coordination model for evacuation and support in disaster response activities. Eur. J. Oper. Res. 179 (3), 1177–1193. https://doi.org/10.1016/j.ejor.2005.03.077.
Zerger, A., Smith, D.I., 2003. Impediments to using GIS for real-time disaster decision support. Comput. Environ. Urban Syst. 27 (2), 123–141. https://doi.org/10.1016/S0198-9715(01)00021-7.
Zhao, M., Liu, X., 2018. Development of decision support tool for optimizing urban emergency rescue facility locations to improve humanitarian logistics management. Saf. Sci. 102, 110–117. https://doi.org/10.1016/j.ssci.2017.10.007.
Zhu, J., Huang, J., Liu, D., Han, J., 2008. Resources allocation problem for local reserve depots in disaster management based on scenario analysis. In: In the 7th International Symposium on Operations Research and its Applications, China, pp. 395–407.
Zografos, K.G., Androutsopoulos, K.N., 2008. A decision support system for integrated hazardous materials routing and emergency response decisions. Transport. Res. Part C: Emerg. Technol. 16 (6), 684–703. https://doi.org/10.1016/j.trc.2008.01.004.