



Dynamic relief-demand management for emergency logistics operations under large-scale disasters

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ABSTRACT

This paper presents a dynamic relief-demand management model for emergency logistics operations under imperfect information conditions in large-scale natural disasters. The proposed methodology consists of three steps: (1) data fusion to forecast relief demand in multiple areas, (2) fuzzy clustering to classify affected area into groups, and (3) multi-criteria decision making to rank the order of priority of groups. The results of tests accounting for different experimental scenarios indicate that the overall forecast errors are lower than 10% inferring the proposed method's capability of dynamic relief-demand forecasting and allocation with imperfect information to facilitate emergency logistics operations.

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1. Introduction

Emergency logistics management has emerged as a globally concerned theme as natural disasters ubiquitously occur around the world. For instance, Cyclone Nargis ruthlessly striking Myanmar coasts on May 02, 2008 accompanied with the military government's anomalous restrictions on foreign aid workers and equipment has reportedly affected about 2.5 million people who urgently needed aids to survive. This is followed by a 7.9 magnitude earthquake hitting Sichuan, the southwestern China on May 12, 2008, which has raised not only the worldwide shock about the news of thousands of victims trapped under the ground but also the growing awareness of the issues on emergency logistics and rescue, particularly for urgent relief-demand management.

Dynamic relief-demand management is the key to the success of emergency logistics operations under the condition of large-scale natural disasters. In reality, the difficulty of relief-demand management is rooted in the uncertainties of relief-demand information due to the following phenomena. First, unlike business logistics (BL) where consumers themselves are the demand information provider, the relief demander (i.e., disaster-affected people) may not be the same as the relief-demand information provider in the emergency logistics context. Instead, those on-the-spot reporters, rescuers and charities usually act as the main information sources; thus, leading to the asymmetry of relief-demand information. Second, the relief-demand information sources are diverse, and usually provide the data under chaotic conditions without the aid of decision support tools and enough time for verification. Furthermore, the relief-demand information needed for emergency logistics is a kind of area-based demand information, i.e., the aggregated relief demand associated with each affected area, rather than the disaggregate demand information which is conventionally treated in business logistics. Such demand, to a certain extent, features uncertainties, and is hard to be approximated using historical data. The aforementioned relief-demand information issues have caused serious impact on the performance of relief-demand management, as

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observed in the recent catastrophes such as the Chichi earthquake in Taiwan (1999), the tsunami in the Indian Ocean (2004), the hurricane Katrina in the US (2005), and the Myanmar cyclone (2008). Apparently, real-time relief-demand forecasting underlines the challenge of dynamic relief-demand management in the area of emergency logistics management (ELM).

Despite the urgent necessity of dynamic relief-demand management, there is no straightforward demand model available for the above issue. Instead, most of the existing demand models appear to be limited to general cases for business operations. From the literature review, we illustrate several related subjects associated with typical models in the following for further discussion.

In operations research and related application areas, the theory of time-series processes appears to be the most flexible to model demand dynamics over time. Therein, methods such as the AutoRegressive and Integrated Moving Average (ARIMA), exponential smoothing models, and independent identically distribution (IID) models have been widely used to deal with various problems of dynamic demand forecasting (Wei, 1990; Box et al., 1994; Aviv, 2003; Gilbert, 2005; Zhang, 2006). The common feature of these efforts is that the forecasts of time-varying demands have certain correlations with their historical values characterized in either linear or nonlinear forms with the dynamic evolution of the mean value of demand over time. Particularly, the previous literature adopts the first order autoregressive processes to deal with the demand variations under the impact of SCM phenomena, e.g., the bullwhip effects (Lee et al., 1997; Chen et al., 2000) and information sharing (Gavirneni et al., 1999; Lee et al., 2000; Raghunathan, 2001). Further, some researchers take into account the temporal heteroscedasticity of demand variance, thus evolving sophisticated models such as Generalized AutoRegressive Conditional Heteroscedasticity (GARCH) processes for dynamic demand forecasting (Baganha and Cohen, 1998; Gilbert, 2005; Zhang, 2006).

In contrast with the aforementioned time-series based demand models, real-time relief-demand forecasting must overcome more issues in demand uncertainties, as mentioned previously. Furthermore, its problem nature stems from the lack of previous demand information. This may lead to the difficulty in tracing the time-varying relief demand pattern merely using time-series data processing mechanisms. In brief, the existing time-series based demand models appear unsuitable for real-time relief-demand forecasting addressed in this study.

Despite the recent emergence of emergency logistics management that has increasingly drawn researchers' attention, most of the pioneering works appear to aim at addressing the issues of relief supply and distribution contingent on the plausible assumptions in terms of relief demands. Yi and Kumar (2007) propose an ant colony optimization (ACO) based heuristics, which decompose the original emergency logistics problem into two decision-making phases: the vehicle routes construction and the multi-commodity dispatch in disaster relief distribution. Therein, they treat wounded people, vehicles, and relief as commodities, and then solve such a multi-commodity network flow problem using the proposed ACO meta-heuristic algorithm. Based on certain idealistic assumptions with respect to disaster information acquisition and communication to simplify the disaster contextual background, Tzeng et al. (2007) formulate the corresponding relief distribution problem with a fuzzy multi-objective programming method. Distinctively, they conceptualize the satisfaction of fairness in formulating the multi-objective functions to avoid the possibility of a severely unfair relief distribution to certain affected areas in the relief distribution process. Considering the dynamics and uncertainties of relief demands in the crucial rescue period of a large-scale disaster, Sheu (2007) proposes an emergency logistics co-distribution approach for dynamically responding to the urgent relief demands in the crucial rescue period. The feature of Sheu's methodology is that two types of urgent relief including the daily consuming relief (e.g., water and meal boxes) and daily-used equipment for refugees (e.g., sleeping bags and camps) are considered. Furthermore, Sheu conceptualizes the buffer relief demand in the formulation of a simplified dynamic relief demand forecast model. Relatively, Chiu and Zheng (2007) aim to address the issue of dynamically assigning multiple emergency responses and evacuation traffic flows outbound from the affected areas using a proposed cell transmission-based linear model.

Accordingly, this study presents a dynamic relief-demand management model to address the above issue under the conditions of disorder and uncertain relief-demand information sourcing from affected areas during the crucial rescue period of a large-scale natural disaster. Rooted in the techniques of data fusion coupled with fuzzy clustering and TOPSIS, the proposed methodology embeds three mechanisms: (1) dynamic relief-demand forecasting, (2) affected-area grouping, and (3) identification of relief-demand urgency. Here the crucial rescue period refers to the initial three days following the onset of a disaster, which is the most critical period to search and rescue the trapped survivals. Relative to the previous literature, the proposed relief-demand management methodology has the following two distinctive features.

- (1) The model is capable of updating the time-varying numbers of survivals trapped in the affected areas so as to approximating the time-varying relief demands through data fusion techniques. Note that in the large-scale disaster contexts, the number of fatalities including the missing people may vary over time upon the severity of the disaster conditions, and meanwhile, the related information may come randomly from diverse information sources in affected areas. As such, the quality (e.g., accuracy) and reliability (e.g., information update frequency) of these multiple information sources appear to be uncontrollable under emergency conditions. Considering both the uncertain and dynamic features of relief demands mentioned above, first we propose to utilize the data fusion technique to deal with multiple sources of information in terms of the number of fatalities randomly collected from a given affected area. This is followed by the estimation of the aggregated relief demands needed in real time by the corresponding survivals. Such a measure is rare in the area of either demand forecasting or emergency logistics management.
- (2) To facilitate dynamic relief demand allocation and distribution, the proposed model dynamically groups the affected areas using fuzzy clustering, followed by the identification of group-based relief-demand urgency through the TOPSIS

process. Similar to the concepts of customer classification in logistics distribution and services (Sheu, 2006; Dondo and Cerda, 2007), this study proposes a fuzzy clustering-based model to group these affected areas, followed by the use of TOPSIS to identify the urgency of relief demand associated with each group. Compared to the previous literature, the main challenge we face here is the inaccessibility of related information. Unlike typical customer classification approaches, which normally use the data of customer orders and demand characteristics as the base for analysis, the data needed for either affected-area grouping or identifying the urgency of relief demands associated with these affected areas is not readily obtainable. Instead, the related information should be refined intricately from the instantaneous data and statistics by the spot reports. Therefore, we claim the hybrid use of such artificial inference (AI) and multi-criteria decision making (MCDM) methodologies to dynamically infer the urgency of time-varying relief demand associated with these affected-area groups under uncertainties in each time interval. Therein, the affected-area groups identified with greater urgency degrees in a given time interval will be scheduled to receive relief demands with higher priority to facilitate real-time emergency logistics management.

The remainder of the paper contains the following sections. Section 2 introduces the methodological framework of the proposed approach, including the two embedded mechanisms executed for dynamic relief-demand forecasting and identification of relief-demand urgency. Section 3 depicts a numerical study aiming at a real earthquake case, and the corresponding numerical results generated using the proposed method. Finally, Section 4 presents the concluding remarks and directions for future research.

2. Model formulation

Consider the occurrence of a large-scale disaster, e.g., an earthquake and tsunami, which has contributed to different degrees of damage in certain affected areas that need rescue and relief supply. In order to respond to the urgent relief demands from the affected areas, this study proposes the mechanism of dynamic relief-demand management, which permits forecasting time-varying relief demand and identifying the demand urgency associated with each affected area in real time. In addition, considering the urgency of relief demand to trapped survivals, the present study scope aims at the category of daily consuming relief (e.g., water and meal boxes) which may vary with the time of day.

Based on the above prerequisites, this study postulates three assumptions shown in the following to rationalize the proposed model.

- (1) The number of affected areas (denoted by I) and the corresponding geographic relationships are given. This study presumes that such information can be readily accessible via advanced disaster detection technologies such as satellites and geographic information systems (GIS).
- (2) For each affected area, the corresponding socioeconomic statistics (e.g., the population size and composition) are available in the aftermath of a disaster. In general, such data are obtainable from the existing governmental databases.
- (3) The time-varying relief demand needed in a given affected area is highly correlated with the number of survivals.

Rooted in the above postulations, we propose a dynamic relief-demand management methodology, which involves three recursive mechanisms including: (1) dynamic relief-demand forecasting, (2) affected-area grouping, and (3) identification of area-based relief-demand urgency. The main purpose of the 1st mechanism is to update the accumulated number of fatalities associated with each affected area using multi-source information so as to approximate the area-based relief demand needed by the trapped survivals. The forecasts in terms of the area-based accumulated fatalities outputted from the 1st mechanism are then inputted to the 2nd mechanism for further use of affected-area grouping, followed by the identification of area-based relief-demand urgency executed in the 3rd mechanism. Through the integration with the function of relief distribution, the proposed methodology actuates the aforementioned three mechanisms recursively, where the output from the proposed method is updated each time interval to achieve the complementary synergism of emergency logistics operations, as illustrated in Fig. 1. Note that the proposed three mechanisms including dynamic relief-demand forecasting, affected-area grouping and distribution priority identification are very important especially in the case of the shortage of emergency logistics resources, e.g., the supplied relief, vehicles and servers, which usually occurs in the aftermath of a large-scale disaster. The following subsections present the details about the proposed recursive mechanisms.

2.1. Dynamic relief-demand forecasting

This mechanism aims to forecast the time-varying relief demand associated with each affected area in a given time interval through two computational procedures: (1) updating the accumulated number of fatalities, and (2) relief demand approximation. Our rationale of executing these two procedures is that the main users of relief demands are the trapped survivals, which can be approximated by the corresponding population size minus the instantaneous number of fatalities in a given affected area. Once the instantaneous number of fatalities in a given affected area is determined, the amount of relief demands can then be readily forecasted.

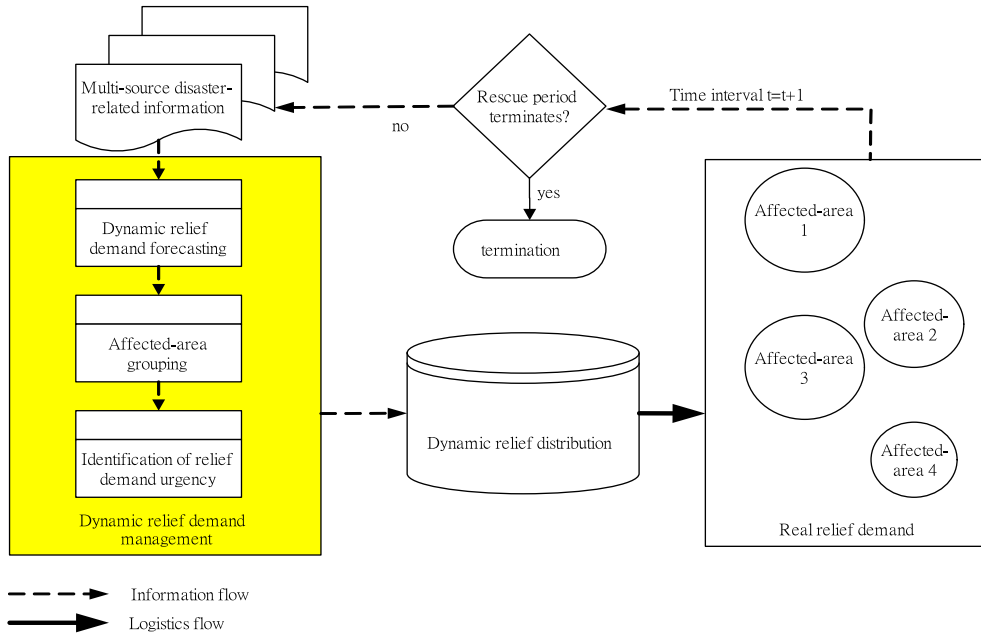


Fig. 1. Scheme of dynamic relief-demand management.

Nevertheless, accurate information regarding the accumulated number of fatalities in each affected area may not be easily collectable in the aftermath of a disaster. In practice, multiple sources may provide such information on the spot under urgent and uncertain conditions, thus forming the multi-sensor data fusion problem¹, which relies on sophisticated fusion process by combining data from multiple sources to improve the accuracy of information (Hall and Llinas, 1997).

Following the general principles of multi-sensor fusion (Bloch and Maitre, 1998; Chung and Shen, 2000), we propose an entropy-based weighting technique, which includes the procedures of belief modeling, data classification, entropy² estimation, weight approximation, and weighted data aggregation to fuse multi-source fatality data in real time. Given that for each affected area (denoted by i), there are a total of j_i types of information sources (e.g., on-spot reporters, local public sectors, and private rescue teams), which are mutually independent to provide the instantaneous data points concerning the count of area-wide fatalities observed (denoted by $x_{j_i}^k(t)$, $\forall j_i$, and $k = 1, 2, \dots, K_{j_i}(t)$). Wherein, $K_{j_i}(t)$ represents total number of data points provided by a given type of source j_i in affected area i in time interval t . To formulate the belief³ of information, let us further assume that each data point ($x_{j_i}^k$) provided by a given type of source j_i , affected area i in a given time interval t follows a Gaussian process with the time-varying mean ($u_{j_i}(t)$) and variance ($\xi_{j_i}^2(t)$) values. Then, using the Gaussian process defined above, we specify a total of M levels of information belief strength to account for the reliability of the collected data measured in different linguistic levels for data classification. For instance, in Fig. 2, levels 1, 2, and 3 represent three levels of information belief-strengths signaled with “highly reliable”, “reliable”, and “poorly reliable”, respectively. Therein, the area under the Gaussian curve associated with a given information belief-strength level “ m ” corresponds to the probability of information belief-strength located in that level, which can be calculated by the corresponding cumulative density function ($F_{x_{j_i}^k(\cdot)}$) bounded by $u_{j_i}(t) \pm (m-1)\xi_{j_i}(t)$ and $u_{j_i}(t) \pm m\xi_{j_i}(t)$. Accordingly, a given data point ($x_{j_i}^k(t)$) is assigned to level m if

$$u_{j_i}(t) + (m-1)\xi_{j_i}(t) \leq x_{j_i}^k(t) < u_{j_i}(t) + m\xi_{j_i}(t) \vee u_{j_i}(t) - m\xi_{j_i}(t) \leq x_{j_i}^k(t) < u_{j_i}(t) - (m-1)\xi_{j_i}(t), \quad \forall (i, j, t) \quad (1)$$

Next is the entropy estimation. First, using Eq. (1), we can approximate the posterior probability ($p(m|x_{j_i}^k(t), k = 1, 2, \dots, K_{j_i}(t))$) of a given information belief-strength level “ m ” associated with a given information source j_i in an affected area i in time interval t by

$$p(m|x_{j_i}^k(t), k = 1, 2, \dots, K_{j_i}(t)) = \frac{\sigma_{j_i}^m(t)}{K_{j_i}(t)}, \quad \forall m \quad (2)$$

¹ In reality, multi-sensor data fusion has drawn remarkable attention for military applications, e.g., automated target recognition, remote sensing, autonomous vehicle guidance, and civilian applications, e.g., monitoring of manufacturing processes, robotics, and provision of real-time traffic information (Abidi and Gonzalez, 1992; Pohl and Van Generen, 1998; Akselrod et al., 2007). The concept of multi-sensor data fusion is oriented from animals' instincts to use multiple senses for more accurate assessment of the surrounding environments including threats identification so as to improve their chances of survival. Such a multi-sensor data fusion mechanism has been proved to be more advantageous than merely using single data source in numerous areas.

² Claude Shannon (1948) introduces the concept of entropy, which has been widely employed in numerous scientific fields to assess the degree of uncertainty or disorder in a closed system.

³ “Belief” refers to the decision maker’s evaluation of the reliability of information oriented from a given source.

Note: “Level” means information belief-strength level

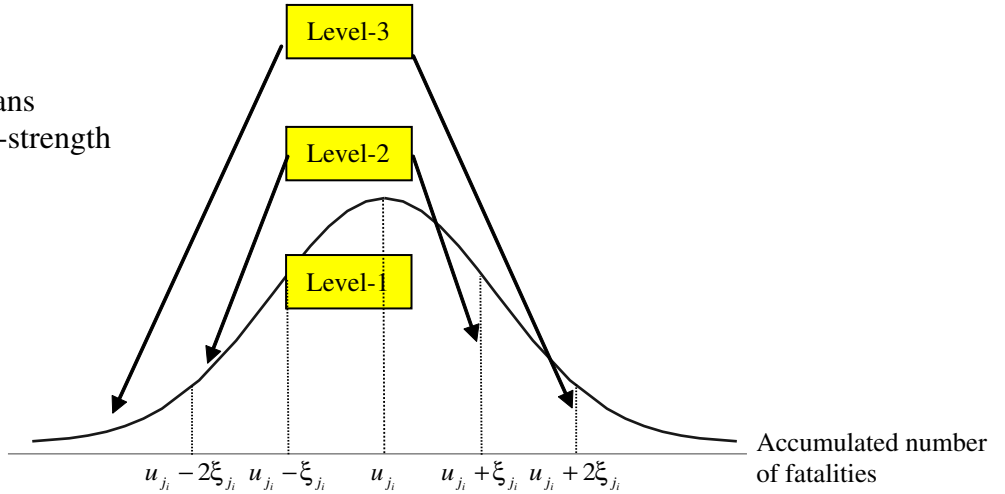


Fig. 2. Illustration of information belief-strength levels.

where $K_{j_i}(t)$ represents the total number of data points provided by the type of information source j_i , in an affected area i in a given time interval t ; $o_{j_i}^m(t)$ represents the number of data points out of $K_{j_i}(t)$ assigned to be in the information belief-strength level m , and thus, $\sum_{m=1}^M o_{j_i}^m(t) = K_{j_i}(t)$. Then, the entropy formula introduced by Shannon (1948), which has been extensively used for uncertainty measurement, is adopted to measure the probabilistic uncertainty of the aggregate belief strength, termed as the entropy ($H_{j_i}(t)$), associated with a given information source j_i in time interval t . Therefore, $H_{j_i}(t)$ is given by

$$H_{j_i}(t) = - \sum_{m=1}^M p(m|x_{j_i}^k(t), k = 1, 2, \dots, K_{j_i}(t)) \log [p(m|x_{j_i}^k(t), k = 1, 2, \dots, K_{j_i}(t))], \quad \forall (i, j, t) \quad (3)$$

It is noteworthy that according to the property of Shannon’s entropy, $H_{j_i}(t)$ is directly proportional to the magnitude of uncertainty of a given information source; the smaller the information uncertainty, the smaller the entropy.

Given the estimated entropies of Eq. (3), the next step is to determine the appropriate weights ($w_{j_i}(t), \forall j_i$) associated with the information sources to fuse the weighted multi-source data. In the proposed model, we adopt the team consensus approach (Basir and Shen, 1992; Chung et al., 1997) to approximate these weighting values, which reflect the relative reliability associated with these sources of information. That is, sources with higher entropies (i.e., more uncertainties) receive smaller weights. In order to obtain the optimal weight value assigned to each information source, the weight-approximation problem can be formulated with the objective ($\Omega_i(t)$) that the sum of the squares of weighted entropies is minimized subject to the condition that the sum of weights is equal to one, as shown in.

$$\min \quad \Omega_i(t) = \sum_{j_i=1}^{J_i} w_{j_i}^2(t) \times H_{j_i}^2(t), \quad \forall i \quad (4)$$

$$\text{s.t.} \quad \sum_{j_i=1}^{J_i} w_{j_i}(t) = 1 \quad \text{and} \quad w_{j_i}(t) > 0, \quad \forall i \quad (5)$$

Note that the above problem can be reformulated in the form of Lagrangian function, and be solved using Kuhn–Tucker conditions. Accordingly, we can readily derive the optimal solution of $w_{j_i}^*(t)$ given by

$$w_{j_i}^*(t) = \frac{1}{H_{j_i}^2(t) \sum_{j_i=1}^{J_i} H_{j_i}^{-2}(t)}, \quad \forall j_i \quad (6)$$

Then, the accumulated number of fatalities ($X_i(t)$) associated with a given affected area i in a given time interval t can be approximated by

$$X_i(t) = \sum_{j_i=1}^{J_i} w_{j_i}^*(t) \times u_{j_i}(t) \quad (7)$$

Up to this stage, all the instantaneous numbers of fatalities can be forecasted using the proposed multi-source information fusion model, followed by updating the instantaneous number of survivals ($S_i(t)$) trapped in each given affected area i in time interval t given by

$$S_i(t) = \delta_i - X_i(t), \quad \forall i \quad (8)$$

where δ_i represents the existing population of affected area i which is assumed to be available in advance from the socio-economic database of the corresponding local government.

Once $S_i(t)$ is estimated, we can project the instantaneous relief demand ($D_i(t)$) of affected area i in time interval t by adopting the aforementioned 4th assumption and the concept of safety stock which is prepared to avoid the phenomenon of relief demand over the corresponding supply in each affected area. According, the proposed dynamic relief-demand forecasting model is formulated as

$$D_i(t) = a \times S_i(t) \times \bar{L} + z_{1-\alpha} \times \text{VAR}_i(t) \times \sqrt{\bar{L}} \quad (9)$$

where a is a parameter representing the average hourly relief demand needed per survival in affected area i ; \bar{L} is a parameter preset to specify the upper bound of the tolerable lead time for relief distribution to any given affected area, and can be predetermined by the system decision maker; $z_{1-\alpha}$ represents the respective statistical value given that the tolerable possibility of time-varying relief demand shortage is α ; and $\text{VAR}_i(t)$ represents the temporal variability of relief demand associated with affected area i observed in time interval t , which is given by

$$\text{VAR}_i(t) = \sqrt{\frac{\sum_{\varepsilon=0}^{t-1} [D_i(t-\varepsilon) - \bar{D}_i(t)]^2}{t}} \quad (10)$$

where $\bar{D}_i(t)$ represents the time-varying mean value with respect to the forecasted relief demand, and it is given by

$$\bar{D}_i(t) = \frac{\sum_{\varepsilon=0}^{t-1} D_i(t-\varepsilon)}{t} \quad (11)$$

It is noteworthy that in Eq. (9), the amount of potential relief shortage during \bar{L} is given by $z_{1-\alpha} \times \text{VAR}_i(t) \times \sqrt{\bar{L}}$. Such a formulation is rooted in the concept of safety stock, which has been extensively used for normal inventory control (Simchi-Levi et al., 2000). Therein, both the factors of relief shortage probability (α) and the upper bound of the relief distribution headway (\bar{L}) associated with any given affected area are taken into account such that the following relief demand condition holds.

$$\text{Prob}(\text{relief demand during } \bar{L} \leq a \times S_i(t) \times \bar{L} + z_{1-\alpha} \times \text{VAR}_i(t) \times \sqrt{\bar{L}}) = 1 - \alpha \quad (12)$$

The above simplification treatment proposed to address the concern of relief demand shortage appears reasonable in the operational cases of emergency relief supply. Particularly, the model takes into account the time spent in data processing and allocating logistics resources during the crucial rescue period. This may also clarify our rationale of incorporating the upper bound of the relief distribution headway (\bar{L}) rather than the variable lead time which is filled with uncertainties into the model for dynamic relief-demand forecasting.

2.2. Affected-area grouping

To facilitate relief demand allocation, this phase aims to group the affected areas through the proposed multi-criteria fuzzy clustering technique. Such a mechanism is very important for dynamic resource allocations of emergency logistics particularly under the condition that relief supplied and related logistics resources are less than the demand in the aftermath of a large-scale disaster.

Adapted from classical clustering methodologies, fuzzy clustering is applicable not only for data compression but also for data categorization (Bezdek, 1973; Sugeno and Yasukawa, 1993; Nasibov and Ulutagay, 2007). In contrast with classical clustering which specifies crisp boundaries to assign a datum to one specific cluster, the techniques of fuzzy clustering are more flexible. In reality, it is not easy to define the boundary between clusters precisely in many practical cases. In addition, some data points may belong to more than one cluster with different degrees of likelihood, as exhibited in characterizing the severity of damage in the affected areas in the study.

Accordingly, we propose a multi-criteria fuzzy clustering method to perform the corresponding affected-area grouping mechanism. Such a relief-demand processing measure provides emergency logistical operations with benefits, not only for efficiently identifying the degrees of area-based relief-demand urgency but also for rapidly allocating the available resources in response to a variety of relief demands in different groups of affected areas.

First, we specify five criteria defined in the following for grouping affected areas.

- (1) $e_i^1(t)$ represents the time-varying ratio of the number of trapped survivals estimated relative to the local population in a given affected area i in a given time interval t , where $e_i^1(t)$ can be measured readily by $e_i^1(t) = \frac{S_i(t)}{\delta_i}$. Intuitively, a great value of $e_i^1(t)$ indicates a urgent need of relief associated with the corresponding affected area.
- (2) $e_i^2(t)$ represents the population density associated with a given affected area i , measured by $e_i^2(t) = \frac{\delta_i}{\text{Area}_i}$, $\forall t$, where Area_i is the superficial measure of a give affected area. Usually, a higher population density associated with a given affected area may infer a higher potential of damage in the aftermath of a large-scale disaster, and thus should be assigned with a higher degree of urgency for rescue and relief demand.

- (3) $e_i^3(t)$ represents the proportion of the frail population, e.g., children and the elders, relative to the total number of population trapped in a given affected area i in a given time interval t . According to Shiono and Krimgold (1989), the survival probability of trapped victims in disasters decreases with time, depending on their physical conditions and severity of injuries, where children and the elders can be regarded as the frail communities who need relief and rescue most urgently. Therefore, the corresponding proportion is taken into account in determining the relief demand priority.
- (4) $e_i^4(t)$ represents the time difference between the present time interval t and the time of the previous relief arrival to a given affected area i . Note that in practical operations of emergency logistics, this criterion may rely mainly on the previous decisions of relief supply and distribution operations; the longer the aforementioned time difference, the more urgent the associated affected area that needs relief.
- (5) $e_i^5(t)$ refers to the significance of building damage conditions, such as serious or complete destruction observed in a given affected area i in a given time interval t . In general, the damage conditions of the building may reflect the severity of the disaster effects on the survival probabilities of trapped people. Accordingly, a relatively greater degree of building damage conditions may indicate a higher urgency of relief demand from the corresponding affected area.

Among the aforementioned five criteria, $e_i^1(t)$, $e_i^2(t)$, and $e_i^3(t)$ are quantitative, and are measured by the collected data including the corresponding local population and superficial measure, as well as the forecasted number of fatalities. In contrast, it may not be easy to quantify both $e_i^4(t)$ and $e_i^5(t)$ particularly under emergency conditions, and to a certain extent, must rely on linguistic measurement.

Due to the above features of criteria, this study treats the affected-area grouping as a multi-criteria fuzzy data classification problem. Let $E_i(t)$ be 5×1 urgency-criterion vector associated with each given affected area i , given by

$$E_i(t) = [e_i^1(t), e_i^2(t), e_i^3(t), e_i^4(t), e_i^5(t)]^T \tag{13}$$

Correspondingly, the aforementioned five criteria embedded in $E_i(t)$ assess the relief-demand urgency of a given affected area i . However, due to the chaotic situations and limited time available for data processing under emergency conditions, it is indispensable to measure these criteria with linguistic terms. Herein we design five linguistic terms including “very high”, “high”, “medium”, “low”, and “very low” (i.e., *VH, H, M, L, VL* for short) to facilitate the measurement of these five criteria. Therefore, we have $\psi[e_i^n(t)]$ representing the linguistic measurement associated with $e_i^n(t)$ embedded in $E_i(t)$ for each given affected area in a given time interval t .

In the following, this study borrows the ideas of Sheu (2007) to develop a fuzzy clustering-based algorithm, which conducts three sequential procedures: (1) binary transformation, (2) generation of fuzzy correlation matrix, and (3) clustering. First, the proposed algorithm transforms the linguistic measurements of the criteria embedded in $E_i(t)$ into binary codes, where each linguistic criterion by a 4-bit binary code, e.g., “0000” for the linguistic term “very low” and “1111” for “very high”. Accordingly, the linguistic measurement ($\psi[e_i^n(t)]$) of a given linguistic urgency criterion n can then be transformed into a binary code ($\psi_i^n(t)$) with four bits (i.e., $\sigma_{i,\ell}^n(t)$ for $\ell = 1, 2, 3$, and 4), and is given by

$$\psi_i^n(t) = [\sigma_{i,1}^n(t), \sigma_{i,2}^n(t), \sigma_{i,3}^n(t), \sigma_{i,4}^n(t)], \quad \forall(i, n, t) \tag{14}$$

To facilitate data processing in real-world applications, the following standardization procedure with respect to $\sigma_{i,\ell}^n(t)$ is suggested, and the corresponding standardized value of $\sigma_{i,\ell}^n(t)$ ($\tilde{\sigma}_{i,\ell}^n(t)$) is given by

$$\tilde{\sigma}_{i,\ell}^n(t) = \frac{\sigma_{i,\ell}^n(t) - \bar{\sigma}_\ell^n(t)}{STD[\hat{\sigma}_\ell^n(t)]}, \quad \forall(i, \ell, n, t) \tag{15}$$

where $\bar{\sigma}_\ell^n(t)$ and $STD[\hat{\sigma}_\ell^n(t)]$ correspond to the values of mean and standard deviation with respect to $\sigma_{i,\ell}^n(t)$, respectively. Then, we have the standardized binary urgency criterion ($\tilde{\psi}_i^n(t)$), which is given by

$$\tilde{\psi}_i^n(t) = [\tilde{\sigma}_{i,1}^n(t), \tilde{\sigma}_{i,2}^n(t), \tilde{\sigma}_{i,3}^n(t), \tilde{\sigma}_{i,4}^n(t)], \quad \forall(i, n, t) \tag{16}$$

Given the number of affected areas I postulated in the first assumption, and $\tilde{\psi}_i^n(t)$ estimated in the previous procedure, a time-varying $I \times I$ fuzzy correlation matrix ($\mathbf{F}(t)$) is estimated, where each element ($f_{p,q}(t)$) of $\mathbf{F}(t)$ represents the correlation between a given pair of affected areas p and q . The mathematical forms of $\mathbf{F}(t)$ and $f_{p,q}(t)$ are given by

$$\mathbf{F}(t) = \begin{bmatrix} f_{11}(t) & f_{12}(t) & f_{13}(t) & \cdots & f_{1I}(t) \\ f_{21}(t) & f_{22}(t) & \cdots & \cdots & \vdots \\ f_{31}(t) & \cdots & \ddots & & \vdots \\ \vdots & \cdots & \cdots & \ddots & \vdots \\ f_{I1}(t) & \cdots & \cdots & \cdots & f_{II}(t) \end{bmatrix}_{I \times I} \tag{17}$$

$$f_{pq}(t) = 1 - \frac{1}{\beta} \sqrt{\sum_{n=1}^5 \sum_{\ell=1}^4 [\tilde{\sigma}_{p\ell}^n(t) - \tilde{\sigma}_{q\ell}^n(t)]^2} \tag{18}$$

where β represents a parameter pre-determined for the upper and lower boundaries of $f_{p,q}(t)$, i.e., 1 and 0, respectively, and j represents a given bit code. It is also noteworthy that drawn from Eqs. (17) and (18), $\mathbf{F}(t)$ is a symmetric matrix. According to the fundamentals of fuzzy clustering technologies, the estimated fuzzy correlation matrix $\mathbf{F}(t)$ should be processed through the composition operation, such that the condition $\tilde{\mathbf{F}}(t) \circ \tilde{\mathbf{F}}(t) = \tilde{\mathbf{F}}(t)$ holds, where $\tilde{\mathbf{F}}(t)$ represents the composite fuzzy correlation matrix of $\mathbf{F}(t)$. To obtain $\tilde{\mathbf{F}}(t)$, a routine of the max–min composition operation with respect to each given element of $\mathbf{F}(t)$ (e.g., $f_{p,q}(t)$) is proposed as $f_{pq} = \max_{i=1}^l \{\min\{f_{pi}(t), f_{iq}(t)\}\}$. Such a routine should be conducted until the aforementioned condition, i.e., $\tilde{\mathbf{F}}(t) \circ \tilde{\mathbf{F}}(t) = \tilde{\mathbf{F}}(t)$, is satisfied.

The next step clusters the affected areas into several groups based on the elements ($f_{p,q}(t)$) of the estimated fuzzy correlation matrix ($\mathbf{F}(t)$). Such a cluster function is executed in each time interval until the termination of the crucial rescue period. To execute this mechanism, five computational steps are required, as summarized in the following.

Step 0: Initialize the computational iteration. Let $t = 1$; set the column-search index $\vartheta = 1$; input the composite fuzzy correlation matrix ($\tilde{\mathbf{F}}(t)$); start the iteration from the first column of $\tilde{\mathbf{F}}(t)$ (denoted by $\tilde{\mathbf{f}}_1(t)$), and let $p = \vartheta$.

Step 1: Given an affected area p , remove the row of $\tilde{\mathbf{F}}(t)$ associated with p ($\tilde{\mathbf{f}}_p(t)^T$). Note that once an affected area is targeted, it is not necessary to re-cluster the targeted area in a given time interval t . Therefore, the algorithm removes the corresponding row $\tilde{\mathbf{f}}_p(t)^T$ from $\tilde{\mathbf{F}}(t)$ to facilitate the following clustering process.

Step 2: Find the maximum element in $\tilde{\mathbf{f}}_p(t)$ (denoted by $\hat{f}_{pq}(t)$), and then conduct the following cluster procedures in sequence.

- If $\hat{f}_{pq}(t) > \lambda_1$, assign the affected area q to the same group as the targeted affected area p , and remove the row of $\tilde{\mathbf{F}}(t)$ associated with q ($\tilde{\mathbf{f}}_q(t)^T$), where λ_1 is a pre-determined threshold. Otherwise, go back to *Step 2*, and continue checking other elements of $\tilde{\mathbf{f}}_p(t)$ by the above rule until there is no element that meets the aforementioned clustering condition. If so, remove $\tilde{\mathbf{f}}_p(t)$ from $\tilde{\mathbf{F}}(t)$, as all the elements of $\tilde{\mathbf{f}}_p(t)$ have been considered.
- If there are affected areas assigned at this stage, then let all the assigned areas be the targeted areas (i.e., let $p = q$), and go back to *Step 1* to process the elements of $\tilde{\mathbf{F}}(t)$ associated with these target areas. Otherwise, let $p = \vartheta$, and go back to *Step 1* to continue the cluster process for the next affected-area group.

Step 3: Terminate the affected-area grouping algorithm if no column remains. Otherwise, go back to *Step 1* for the next iteration.

2.3. Identification of relief-demand urgency

The main purpose of this phase is to determine the relief-demand urgency associated with each clustered affected-area group g utilizing TOPSIS, which is a well-known multi-criteria decision-making (MCDM) methodology used to rank the order of priority of alternatives. The basic idea of TOPSIS is that the most preferred alternative should not only have the shortest distance from the ideal solution, but also have the longest distance from the anti-ideal solution (Chen and Hwang, 1992; Opricovic and Tzeng, 2004). Drawing from the above concept of TOPSIS, this study develops the respective decision rules to identify the relief-demand urgency associated with the affected-area groups by assessing the relative significance of their weighted urgency-criterion vectors. The following summarizes the main steps involved in the proposed TOPSIS-based decision rules.

Step 1. Formation of an assessment matrix

Suppose that there are “ G ” affected-area groups identified in a given time interval t through the aforementioned clustering process. We can then have a ($G \times 5$) assessment matrix ($\Theta(t)$) given by

$$\Theta(t) = \begin{bmatrix} \theta_1^1(t) & \theta_1^2(t) & \cdots & \theta_1^5(t) \\ \theta_2^1(t) & \ddots & \cdots & \theta_2^5(t) \\ \vdots & \vdots & \ddots & \vdots \\ \theta_G^1(t) & \theta_G^2(t) & \cdots & \theta_G^5(t) \end{bmatrix}_{G \times 5} \quad (19)$$

In Eq. (20), each given element $\theta_g^n(t)$ represents the mean value of a given urgency criterion “ n ” associated with a given affected-area group “ g ” which is obtained by

$$\theta_g^n(t) = \frac{\sum_{i_g \in g} e_{i_g}^n(t)}{N_g}, \quad \forall g \quad (20)$$

where i_g represents any given affected area that belongs to group g and N_g denotes the number of affected areas belonging to that group. Considering the different measurement scales associated with these urgency criteria, the proposed method executes a standardization procedure to validate the following multi-criteria assessment process. Accordingly, each given element ($\tilde{\theta}_g^n(t)$) of $\Theta(t)$ is further standardized as $\tilde{\theta}_g^n(t) = \frac{\theta_g^n(t)}{\sum_{g=1}^G \theta_g^n(t)}$.

Step 2. Approximation of criteria weights

In this step, we approximate the criteria weights using the entropy theory. First, drawing from the measure of Deng et al. (2000), the entropy value ($\eta_n(t)$) associated with a given urgency criterion n is derived as

$$\eta_n(t) = - \sum_{g=1}^G \tilde{\theta}_g^n(t) \log [\tilde{\theta}_g^n(t)], \quad \forall n \tag{21}$$

By Eq. (6), we can then have the corresponding weight ($\varpi_n(t)$) given by

$$\varpi_n(t) = \frac{1}{[\eta_n(t)]^2 \sum_{g=1}^{G_i} [\eta_n(t)]^{-2}}, \quad \forall n \tag{22}$$

Step 3. Specification of the upper and lower bounds of the standardized urgency criteria ($\tilde{\theta}_g^n(t)$)

Herein, we replace the terms “ideal solutions” and “anti-ideal solutions” typically used in TOPSIS with “upper bounds” and “lower bounds” to indicate the boundaries of urgency criteria. Therefore, the corresponding sets of upper and lower bounds (i.e., $\bar{\mathbf{A}}$ and $\underline{\mathbf{A}}$) associated with these standardized urgency criteria are given, respectively, by

$$\bar{\mathbf{A}} = \left\{ \max_g(\tilde{\theta}_g^n(t)) | g = 1, 2, \dots, G; n = 1, 2, \dots, 5 \right\} = \{A_n^+ | n = 1, 2, \dots, 5\} \tag{23}$$

$$\underline{\mathbf{A}} = \left\{ \min_g(\tilde{\theta}_g^n(t)) | g = 1, 2, \dots, G; n = 1, 2, \dots, 5 \right\} = \{A_n^- | n = 1, 2, \dots, 5\} \tag{24}$$

Step 4. Calculate the Euclidean distance-based separations of each affected-area group from the upper and lower bounds of all urgency criteria, respectively. That is, for each affected-area group g , the aggregate Euclidean distance-based separations ($\bar{C}_g(t)$ and $\underline{C}_g(t)$) from $\bar{\mathbf{A}}$ and $\underline{\mathbf{A}}$ are calculated by

$$\bar{C}_g(t) = \sqrt{\sum_{n=1}^5 [\varpi_n(t) (\tilde{\theta}_g^n(t) - A_n^+)]^2}, \quad \forall g \tag{25}$$

$$\underline{C}_g(t) = \sqrt{\sum_{n=1}^5 [\varpi_n(t) (\tilde{\theta}_g^n(t) - A_n^-)]^2}, \quad \forall g \tag{26}$$

Step 5. Calculate the relative urgency index ($\zeta_g(t)$) associated with a given affected-area group g by

$$\zeta_g(t) = \frac{\underline{C}_g(t)}{\bar{C}_g(t) + \underline{C}_g(t)}, \quad \forall g \tag{27}$$

Based on the estimates of $\zeta_g(t)$ through the above five computational steps, we can then readily rank the relative urgency of relief demand associated with these affected-area groups to facilitate the relief demand allocation and distribution. Note that the above two dynamic mechanisms including relief-demand forecasting and identification of relief-demand urgency embedded in the proposed methodology can be executed recursively for each time interval until the termination of emergency logistics operations.

3. Numerical results

The main purpose of this numerical study is to demonstrate the potential applicability of the proposed model in dynamically forecasting area-based relief demands for quickly responding to the needs of affected people with different urgency levels in the aftermath of a large-scale natural disaster. Differing from other practical cases of business operations in which data are readily obtainable via survey and projection from historical database, the research in emergency logistics management like this study commonly has serious problems in acquiring enough real data for model calibration and validation. Accordingly, this paper aims at a real earthquake event used as the scenario, and then illustrates the potential performance of the proposed model using simulated data in the following numerical study.

The studied case aims at the massive Chichi earthquake (7.3 on the Richter scale), which occurred in central Taiwan on September 21, 1999. Reportedly, the earthquake and its after shocks cause 2455 deaths in total, more than 8000 injuries, and the destruction of 38,935 homes (Executive Yuan of Taiwan, 1999). The main affected region is located in central Taiwan

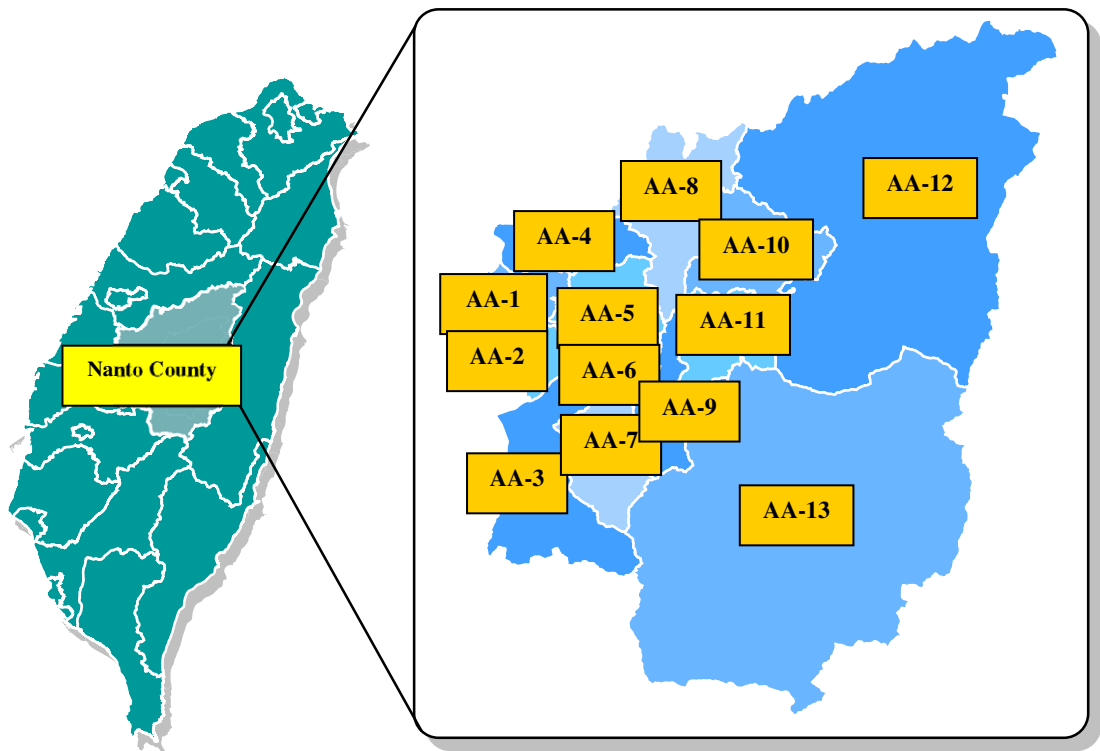
covering thirteen towns, as shown in Fig. 3. Therefore, this studied case regards these thirteen towns as the main affected areas in the following test scenario.

The main procedures executed in the numerical study include: (1) data acquisition, (2) model testing, and (3) scenario design and analyses, which are detailed in the following subsections.

3.1. Data acquisition

The stage of data acquisition aims to generate the data needed for model testing. Given the number and locations of the affected areas by the 1st assumption, the proposed method is employed to determine the time-varying consuming relief demands in the crucial rescue period. Here the unit length of a time interval is set to be 4 h (thrice a day). Therefore, the test scenario involves fifteen time intervals, i.e., 5 days, termed as the test period. This study uses the official statistics in the 921 earthquake special report (Executive Yuan of Taiwan, 1999) as the historical database to test the model's validity, where Table 1 summarizes the aggregate statistics in terms of the disaster effects as well as the corresponding population data associated with the affected areas of the study site.

Based on the official statistical report (Executive Yuan of Taiwan, 1999), this study collects the instantaneous data points ($X_i(t)$) regarding the accumulated number of fatalities associated with each affected area i in each time interval t during the 5-day test period. The data obtained at this stage are used for the comparison with the output of the model (i.e., the projections of $X_i(t)$ based on the multi-source data fusion results). Note that these are post-event statistical data, which are not perfectly available in the aftermath of the earthquake. That is, the acquisition of adequate real data for dynamic relief-demand forecasting is nearly impossible in this study case. This is also the reason why we propose the model to predict the accumulated number of fatalities through the mechanism of multi-source data fusion. Moreover, due to the concern of missing data points existing in the collected real data points (i.e., $X_i(t)$), this study generates the simulation data replacing the missing data points to complete the historical database. The following details the simulation-data generation procedure.



Note: AA is the abbreviation of “affected area”

AA-1: Nanto city AA-2: Minchian AA-3: Tzushan AA-4: Tzautung AA-5: Chungliiao
 AA-6: Chichi AA-7: Luku AA-8: Goushin AA-9: Sweyli AA-10: Puli
 AA-11: Youchi AA-12: Renai AA-13: Shinyi

Fig. 3. Illustration of study site.

Table 1
Statistics of disaster effects and population of the affected areas.

Affected area	Population size	# of frail population (elders and children)	Accumulated number of fatalities	Number of households	Number of buildings seriously damaged
AA-1	104,777	215	119	29,096	10,612
AA-2	42,754	1126	45	10,577	802
AA-3	62,269	342	151	16,367	5670
AA-4	96,833	2373	114	25,693	6560
AA-5	18,252	3892	206	4843	3928
AA-6	12,250	8656	62	3702	2534
AA-7	21,279	925	58	5603	2159
AA-8	24,643	567	123	6680	3785
AA-9	23,425	287	14	6792	1860
AA-10	88,271	161	267	24,661	12,808
AA-11	17,894	327	24	5083	3842
AA-12	15,358	298	4	4077	714
AA-13	17,869	314	3	4665	764
Total	545,874	19,483	1190	147,839	56,050

First, drawing from Fiedrich et al. (2000) and the aforementioned statistical data, this study postulates that the nation-wide accumulated number of fatalities $X(t)$ during the 5-day test period may follow a negative exponential function given by $\hat{X}(t) = \frac{\bar{X}}{e^{b(t-t_0)}}$, where $\hat{X}(t)$ is the projection of $X(t)$; \bar{X} is the total number of nation-wide fatalities reported; b is a positive parameter determining the shape of $g(t)$. Using the chi-square statistical values with respect to $X(t)$, the goodness-of-fit test is then conducted. Therein, the corresponding test result indicates that the projections $\hat{X}(t)$ yielded from the above negative exponential form are accepted to capture the time-varying pattern of $X(t)$. Fig. 4 presents both the real and projected trajectories of nation-wide accumulated fatalities for illustration. Accordingly, this study further assumes that the accumulated number of fatalities $X_i(t)$ associated with a given affected area i in a given time interval t also follows the same negative exponential form (i.e., $\hat{X}_i(t) = \frac{\bar{X}_i}{e^{b(t-t_0)}}$, $\forall i$). The missing data points are then projected to complement the historical database used for model testing.

The next step is to simulate the instantaneous data points $(x_{j_i}^k(t), \forall(j_i, t))$ in terms of the instantaneous accumulated numbers of fatalities provided by multiple information sources. As stated in Section 2.1, the proposed model uses these multi-source data points as the input for approximating the accumulated fatality number in each affected area and time interval via data fusion process. This study considers the local city centers (LC for short), rescue teams (RT for short), and on-spot reporters (OR for short) as three major types of sources to provide the fatality-related information from each affected area in each time interval. For simplicity, these multi-source data points $(x_{j_i}^k(t), \forall(j_i, t))$ are assumed to follow respective normal distributions characterized with respective mean values (denoted by $u_{LC}(t)$, $u_{RT}(t)$, and $u_{OR}(t)$, respectively) and variance ($\xi_{LC}^2(t)$, $\xi_{RT}^2(t)$, and $\xi_{OR}^2(t)$, respectively). The study generates the above dynamic mean values $u_{j_i}(t)$ by $u_{j_i}(t) = u_{j_i}(t-1) + \Delta u_{j_i}(t)$. Wherein, $\Delta u_{j_i}(t)$ represents the increment of the mean value of the accumulated fatality number observed by a given type of source j_i in a given affected area i and time interval t , and is assumed to follow a respective uniform distribution rang-

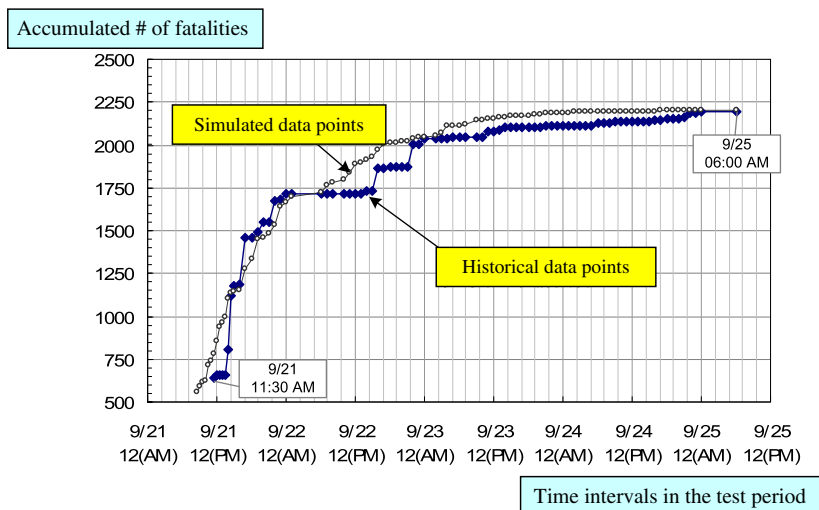


Fig. 4. Real and simulated trajectories of nation-wide accumulated fatalities.

ing between 0 and a specific upper bound. Furthermore, this study postulates the condition $\zeta_{LC}^2(t) < \zeta_{RT}^2(t) < \zeta_{OR}^2(t)$ considering the different levels of information reliability associated with different sources, where the lower value the variance, the more reliable the information provided. Therefore, a total of $K_{j_i}(t)$ data points associated with each given type of information source (j_i) in each given affected area i and time interval t are simulated, and used as the input of the proposed model for the approximation of accumulated fatality numbers.

3.2. Model testing

This stage aims to test the model’s performance particularly in fusing multi-source fatality data for dynamic relief-demand forecasting. Based on the simulated multi-source fatality data mentioned above, this study uses the proposed model to project the accumulated fatality number associated with each affected area in each time interval, and then compares the forecast results with the historical database. Fig. 5 presents the comparison results. In addition, to assess the model’s validity, the results are also examined using the measures of chi-square statistics χ_i^2 given by $\chi_i^2 = \sum_{t=1}^{15} \frac{[\hat{X}_i(t) - X_i(t)]^2}{X_i(t)}$, $\forall i$, and mean absolute percentage error (MAPE) with respect to $X_i(t)$. Table 2 presents the corresponding test results.

The results shown in Fig. 5 and Table 2 indicate that there is no strong reason to reject the goodness of fit of the fused multi-source fatality data generated by the proposed model in reproducing the accumulated number of fatalities in the study case. Overall, the patterns of accumulated fatalities generated by the proposed method are congruent with the patterns of the historical database. Furthermore, all the results of chi-square tests, including the area-based and aggregate results, are accepted under a very high significant level (i.e., 0.95) implying that there is no obvious reason to reject the predicted accumulated fatality numbers. In addition, the overall MAPE test results are also accepted. Therein, all of the MAPE measures with respect to the numbers of time-varying fatalities are lower than the threshold of 0.2, which is frequently used as an acceptable criterion for the evaluation of MAPE-based tests. More strictly, 77% of them satisfy the demanding threshold of 0.1. Accordingly, the performance of the proposed model in dynamically forecasting the numbers of fatalities is accepted.

After demonstrating the validity of the proposed model in multi-source fatality data fusion, the following illustrates the output of the proposed model in terms of relief-demand forecasting and affected-area grouping coupled with urgency identification by Fig. 6 and Table 3.

According to the observation from Fig. 6, it appears that the forecasts of the time-varying relief demands may not significantly change over time during the test period. The main reason is that the number of fatalities accounts merely for a slight percentage (i.e., 0.002) of the total number of affected people in the study case, despite the variations of accumulated fatalities. Accordingly, the number of survivals derived by the number of residents minus fatalities changes smoothly with time, thus contributing to the above phenomenon observed in Fig. 6.

Nevertheless, it does not mean that there is no challenge to respond to the time-varying relief demands in this study. Note that the forecasted results of Fig. 6 are unable to characterize the urgency of relief demands associated with these affected areas. Furthermore, the urgency of relief demand appears to vary with time due to the uncertainties of relief supply and distribution conditions in the aftermath of a disaster. This argument is true particularly under the serious supply–demand unbalance condition, where relief supplied is far from the relief demanded in certain affected areas. Apparently, the above issue requires further research in dynamic demand allocation for relief-demand management.

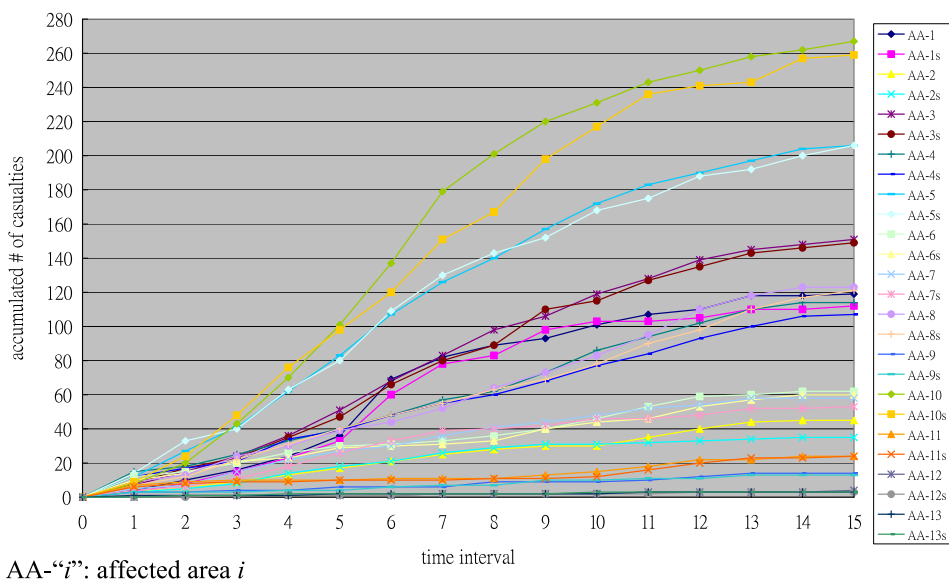


Fig. 5. Comparison results (accumulated numbers of fatalities).

Table 2
Test results (forecasted numbers of fatalities).

Affected area	Chi-square value	Critical point	Degree of freedom	Result
<i>1. Chi-square tests (significant level = 0.95)</i>				
AA-1	5.0	5.9	13	Accepted
AA-2	1.6	5.9	13	Accepted
AA-3	2.3	5.9	13	Accepted
AA-4	4.6	5.9	13	Accepted
AA-5	2.9	5.9	13	Accepted
AA-6	3.1	5.9	13	Accepted
AA-7	4.1	5.9	13	Accepted
AA-8	4.3	5.9	13	Accepted
AA-9	2.1	5.9	13	Accepted
AA-10	3.7	5.9	13	Accepted
AA-11	2.0	5.9	13	Accepted
AA-12	2.6	5.9	13 </td <td>Accepted</td>	Accepted
AA-13	2.5	5.9	13	Accepted
Aggregate	40.7	161.7	193	Accepted
Affected area	MAPE estimate (%)	Threshold (%)	Result	
<i>2. MAPE measures</i>				
AA-1	8.2	20	Accepted	
AA-2	6.0	20	Accepted	
AA-3	4.9	20	Accepted	
AA-4	6.4	20	Accepted	
AA-5	4.6	20	Accepted	
AA-6	6.7	20	Accepted	
AA-7	9.4	20	Accepted	
AA-8	6.8	20	Accepted	
AA-9	10.6	20	Accepted	
AA-10	5.4	20	Accepted	
AA-11	8.5	20	Accepted	
AA-12	10.6	20	Accepted	
AA-13	16.7	20	Accepted	
Aggregate	8.1	20	Accepted	

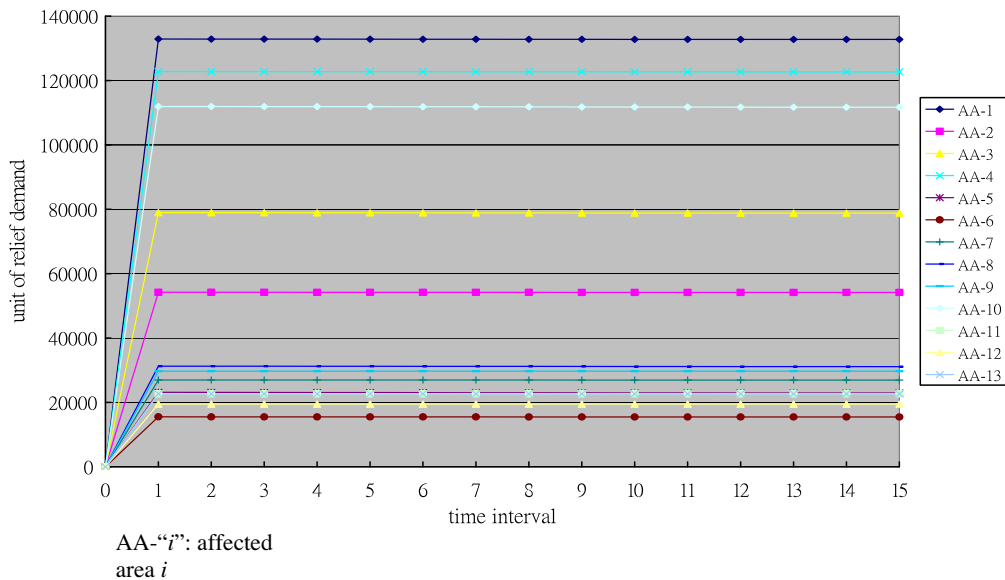


Fig. 6. Results of relief-demand forecasting.

In contrast, the results of Table 3 may address the concern in relief-demand urgency. As can be seen in Table 3, Chungliao, Chichi, and Youchi (denoted by AA-5, AA-6, and AA-11) remain as the affected areas with the highest priority for relief supply although their relief demands are significantly fewer than the other areas. The forecasted relief demand amounts of Tzautung and Puli (denoted by AA-4 and AA-10) are significantly greater than all the others (except AA-1); however, the

Table 3
Clustering results of affected areas with different urgencies.

Time interval $t = 1$		Time interval $t = 2$		Time interval $t = 3$	
Group g with relief-demand urgency	Group member i_g (affected area)	Group g with distribution priority	Group member i_g (affected area)	Group g with distribution priority	Group member i_g (affected area)
<i>Test period: day-1</i>					
1	AA-5, AA-6	1	AA-5, AA-6	1	AA-5, AA-6, AA-7, AA-11
2	AA-1, AA-7, AA-8, AA-11	2	AA-1, AA-7, AA-8, AA-11	2	AA-1, AA-4, AA-8
3	AA-4, AA-10	3	AA-4, AA-10	3	AA-2, AA-10
4	AA-2, AA-3, AA-9, AA-12, A-13	4	AA-2, AA-3, AA-9, AA-12, A-13	4	AA-3, AA-9, AA-12, A-13
Time interval $t = 4$		Time interval $t = 5$		Time interval $t = 6$	
<i>Test period: day-2</i>					
1	AA-5, AA-6, AA-11	1	AA-5, AA-6, AA-11	1	AA-5, AA-6, AA-11
2	AA-1, AA-2, AA-4, AA-10	2	AA-1, AA-2, AA-4, AA-10	2	AA-1, AA-10
3	AA-3, AA-7, AA-8, AA-9	3	AA-3, AA-7, AA-8, AA-9	3	AA-2, AA-3, AA-4, AA-7, AA-8, AA-9
4	AA-12, A-13	4	AA-12, A-13	4	AA-12, A-13
Time interval $t = 7$		Time interval $t = 8$		Time interval $t = 9$	
<i>Test period: day-3</i>					
1	AA-5, AA-6, AA-11	1	AA-5, AA-6, AA-11	1	AA-5, AA-6, AA-11
2	AA-1, AA-3,	2	AA-1, AA-3	2	AA-1
3	AA-2, AA-4, AA-7, AA-8, AA-10	3	AA-2, AA-4, AA-7, AA-8, AA-10	3	AA-2, AA-3, AA-4, AA-7, AA-8, AA-10
4	AA-9, AA-12, A-13	4	AA-9, AA-12, A-13	4	AA-9, AA-12, A-13
Time interval $t = 10$		Time interval $t = 11$		Time interval $t = 12$	
<i>Test period: day-4</i>					
1	AA-5, AA-6, AA-11	1	AA-5, AA-6, AA-11	1	AA-5, AA-6, AA-11
2	AA-1, AA-8	2	AA-1, AA-8	2	AA-1, AA-2, AA-8
3	AA-2, AA-3, AA-4, AA-7, AA-9, AA-10	3	AA-2, AA-3, AA-4, AA-7, AA-9, AA-10	3	AA-3, AA-4, AA-7, AA-9, AA-10
4	AA-12, A-13	4	AA-12, A-13	4	AA-12, A-13
Time interval $t = 13$		Time interval $t = 14$		Time interval $t = 15$	
<i>Test period: day-5</i>					
1	AA-5, AA-6, AA-11	1	AA-5, AA-6, AA-11	1	AA-5, AA-6, AA-11
2	AA-1, AA-8	2	AA-1, AA-8	2	AA-1, AA-8
3	AA-2, AA-3, AA-4, AA-7, AA-9, AA-10	3	AA-2, AA-3, AA-4, AA-7, AA-9, AA-10	3	AA-2, AA-3, AA-4, AA-7, AA-9, AA-10
4	AA-12, A-13	4	AA-12, A-13	4	AA-12, A-13

Note: The lower the number shown in the column of “group-based relief-demand urgency” the higher urgency the relief demands with.

Table 4

Description of the experimental scenarios.

Features scenario	Main information sources	# of data points/time interval/source	Data deviation among different sources
1 (Most favorable)	1. Local city center 2. Rescue team 3. On-spot reporter	30	Insignificant
2	1. Local city center 2. Rescue team 3. On-spot reporter	30	Significant
3	1. Local city center 2. Rescue team 3. On-spot reporter	10	Insignificant
4	1. Local city center 2. Rescue team 3. On-spot reporter	10	Significant
5	1. Local city center 2. Rescue team/on-spot reporter	30	Insignificant
6	1. Local city center 2. Rescue team/on-spot reporter	30	Significant
7	1. Local city center 2. Rescue team/on-spot reporter	10	Insignificant
8 (Most unfavorable)	1. Local city center 2. Rescue team/on-spot reporter	10	Significant

Table 5

Numerical results of the experimental scenarios.

Scenario	MAPE estimate (%)	Threshold (%)	Result	Relative improvement to the most unfavorable scenario (%)
1 (Original case, most favorable)	8.1	20	Accept	
2	10.7	20	Accept	–24.3
3	9.4	20	Accept	–13.8
4	18.2	20	Accept	–55.5
5	14.4	20	Accept	–43.8
6	15.8	20	Accept	–48.7
7	16.9	20	Accept	–52.1
8 (Most unfavorable)	28.2	20	Not accept	–71.3

identified demand urgency associated with these two areas is merely ranked with the 3rd priority, not as urgent as AA-5, AA-6, and AA-11. This is because that the proposed model takes into account other disaster-induced impacts (e.g., the percentage of fatalities and building damage conditions) in clustering these affected areas and assessing their relief-demand urgency. As mentioned previously, such affected-area grouping and relief-demand urgency identification are indispensable in the process of dynamic relief demand allocation. This may hold true particularly under the condition that the corresponding emergency logistics resources including relief supplied are deficient, which usually exists in the aftermath of a large-scale disaster. Therefore, the proposed model requires the mechanism of differentiating the relief-demand urgency among these affected areas to facilitate the operations of emergency logistics distribution.

3.3. Scenario design

Despite the acceptability of the proposed model's forecast results demonstrated above, it is found that the information of accumulated fatalities remains as the key to relief-demand forecasting and urgency identification. Considering the uncertainties of fatality-related information acquisition and the induced effects on the accuracy of multi-source data fusion for real applications, this study further designs nine experimental scenarios, where factors including the numbers of information sources and data points collected in each time intervals as well as the deviations of data points among information sources are taken into account. Table 4 summarizes the description of the designed experimental scenarios and the corresponding parameters/input-data adjusted. Using the estimates of MAPE and the same evaluation measures, Table 5 presents the corresponding numerical results associated with these scenarios, where the original performance of the proposed method shown in the previous scenario is also included to indicate the relative performance of these scenarios.

The following provides the findings observed from Table 5.

- (1) Overall, the uncertainties of multi-source data acquisition may not be a critical issue in the study except under the condition of inadequate data points coupled with the significant data deviation as exhibited in scenario 8 (the most

unfavorable scenario). Therein, almost all the MAPE measures satisfy the threshold of acceptance, i.e., 20%, according to the results of Table 5.

- (2) By comparing the results of scenarios 1, 2, and 3, it is inferred that relative to the number of data points, data deviation among different information sources can be a critical factor that significantly influences the prediction of accumulated fatality numbers. As exhibited in Table 5, despite the limited number of data points collected from multiple sources, the forecast results of data fusion remain valid if the variations of multi-source data are not significant. In contrast, a high level of data deviation among different information sources may significantly affect the corresponding fatality prediction even if the number of data points is adequate.
- (3) Through the comparison of the results of scenarios 3 and 7, it appears that the variety of information types appears to have certain effect on the fatality accumulation approximation. The results of scenario 7 imply that given limited types of information sources providing fatality-count data, the performance of multi-source data fusion is sensitive to the condition of either the number of data points or multi-source data deviation. The comparison of the results of scenarios 4 and 8 may draw the same argument. This finding further suggests the advantage of using diverse information sources to improve accumulated fatality-count approximation under such a chaotic condition as in the aftermath of a disaster, where the issues of inadequacy of available data points and data deviation exist.

Overall, the test results shown above have imply that the proposed method is promising in dynamic relief-demand management which serves as a decision support tool for emergency logistics operations. Particularly, the proposed method permits forecasting the quantities of relief in real time and grouping these affected areas based on their urgency in relief demand. Such a sophisticated process is indispensable for dynamic relief-demand management particularly under the serious deficiency of supplied relief and logistics resources (e.g., vehicles and rescuers) in the aftermath of a large-scale disaster.

4. Concluding remarks

This paper has presented a relief-demand management model for dynamically responding to the relief demands of affected people under emergency conditions of a large-scale disaster. The proposed model involves three major mechanisms: (1) dynamic relief-demand forecasting, (2) affected-area grouping, and (3) determination of relief-demand urgency. The methodologies used in this study include multi-source data fusion, fuzzy clustering and TOPSIS. Based on the accumulated number of fatalities approximated through multi-source data fusion techniques, the time-varying relief demand associated with each given affected area is forecasted, followed by the use of a fuzzy clustering-based approach to group these affected areas, and then the identification of group-based relief-demand urgency by TOPSIS.

This study has conducted a numerical study with a real large-scale earthquake disaster to illustrate the applicability of the proposed method. Furthermore, eight scenarios represented by the different conditions of fatality-related information acquisition are designed to test the model's capability of dealing with the uncertainties of collected data as usually encountered in disasters. The test results have revealed that the overall performance of the model is satisfactory by comparing the forecasted results with historical database.

The contribution of the paper to the emergency logistics literature (Chiu and Zheng, 2007; Sheu, 2007; Tzeng et al., 2007; Yi and Kumar, 2007) is that the proposed model permits not only approximating relief demands in real time under information uncertainty and disorder conditions but also dynamically allocating relief demands based on the identified relief-demand urgency degrees associated with affected areas. Such dynamic relief-demand management mechanisms are rarely found in the previous literature.

Nevertheless, there is still a great potential for improving the performance of relief-demand management. First, it is noteworthy that the proposed model is used for relief-demand management, which serves as a decision support tool for emergency logistics operations, where the government is the real decision maker of the proposed model. Nevertheless, it is possible to share the forecasted relief-demand information with the local charity and non-governmental organizations for relief supply chain coordination, which may warrant more research effort. Furthermore, more advanced technologies can be incorporated into the framework to improve the system performance in not only relief-demand forecasting but also affected-area grouping and priority identification. The methodological integration with dynamic relief supply and resource allocation mechanisms is also worth investigating. Such model extension is particularly important to carry out the ultimate goals of emergency logistics management.

Finally, we expect that the proposed dynamic relief-demand management approach can make benefits available not only for improving the performance of relief-demand management, but also for clarifying the urgent need of more research effort in emergency logistics management and related areas toward the ultimate goal of "maximizing the value of lives" saved under disasters.

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References

- Abidi, M.A., Gonzalez, R.C., 1992. *Data Fusion in Robotics and Machine Intelligence*. Boston, MA, Academic.
- Akselrod, D., Sinha, A., Kirubarajan, T., 2007. Hierarchical Markov decision processes based distributed data fusion and collaborative sensor management for multitarget multisensor tracking applications. In: *Proceedings of IEEE International Conference on Systems, Man and Cybernetics*, 7–10, October, 2007, Montreal, Canada.
- Aviv, Y., 2003. A time-series framework for supply chain inventory management. *Operations Research* 51 (2), 210–227.
- Baganha, M.P., Cohen, M.A., 1998. The stabilizing effect of inventory in supply chains. *Operations Research* 46 (3), 72–83.
- Basir, O.A., Shen, H.C., 1992. Sensory data integration: a team consensus approach. In: *Proceedings of IEEE International Conference on Robotics and Automation*, vol. 2, 12–14, May, 1992, Nice, France, pp. 1683–1688.
- Bezdek, J.C., 1973. *Fuzzy mathematics in pattern classification*. Ph.D. Thesis, Cornell University, USA.
- Bloch, I., Maitre, H., 1998. Fusion of image information under impression. In: Bouchon-Meunier, B. (Ed.), *Aggregation and Fusion of Imperfect Information*. Springer-Verlag, New York, pp. 189–213.
- Box, G.E.P., Jenkins, G.M., Reinsel, G.C., 1994. *Time Series Analysis: Forecasting and Control*, third ed. Prentice Hall, Englewood Cliffs, NJ.
- Chen, S.J., Hwang, C.L., 1992. *Fuzzy Multiple Attribute Decision Making Methods and Applications*. Springer-Verlag, New York.
- Chen, F., Drezner, Z., Ryan, J., Simichi-Levi, D., 2000. Quantifying the bullwhip effect in a simple supply chain: the impact of forecasting, lead times, and information. *Management Science* 26 (3), 436–443.
- Chiu, Y.-C., Zheng, H., 2007. Real-time mobilization decisions for multi-priority emergency response resources and evacuation groups: model formulation and solution. *Transportation Research Part E* 43 (6), 710–736.
- Chung, A.C.S., Shen, H.C., 2000. Entropy-based Markov chains for multisensor fusion. *Journal of Intelligent and Robotic Systems* 29, 161–189.
- Chung, A.C.S., Shen, H.C., Basir, O.B., 1997. A decentralized approach to sensory data integration. In: *Proceedings of IEEE International Conference on Intelligent Robots and Systems*, vol. 3, 7–11, September, 1997, pp. 1409–1414.
- Deng, H., Yeh, C.H., Willis, R.J., 2000. Inter-company comparison using modified TOPSIS with objective weights. *Computers and Operations Research* 27 (10), 963–973.
- Dondo, R., Cerda, J., 2007. A cluster-based optimization approach for the multi-depot heterogeneous fleet vehicle routing problem with time windows. *European Journal of Operational Research* 176, 1478–1507.
- Executive Yuan, Taiwan, 1999. The 921 earthquake special report: casualty and damage.
- Fiedrich, F., Gehbauer, F., Rickers, U., 2000. Optimized resource allocation for emergency response after earthquake disasters. *Safety Science* 35, 41–57.
- Gavirneni, S., Kapuscinski, R., Tayur, S., 1999. Value of information in capacitated supply chains. *Management Science* 45 (1), 16–24.
- Gilbert, K., 2005. An ARIMA supply chain model. *Management Science* 51 (2), 305–310.
- Hall, D.L., Llinas, J., 1997. An introduction to multisensor data fusion. *Proceedings of The IEEE* 85 (1), 6–23.
- Lee, H.L., Padmanabhan, P., Whang, S., 1997. Information distortion in a supply chain: the bullwhip effect. *Management Science* 43 (4), 546–558.
- Lee, H.L., So, K.C., Tang, C.S., 2000. The value of information sharing in a two-level supply chain. *Management Science* 46 (5), 626–643.
- Nasibov, E.N., Ulutagay, G., 2007. A new unsupervised approach for fuzzy clustering. *Fuzzy Sets and Systems* 158, 2118, 2133.
- Opricovic, S., Tzeng, G.-H., 2004. Compromise solution by MCDM methods: a comparative analysis of VIKOR and TOPSIS. *European Journal of Operational Research* 156, 445–455.
- Pohl, C., Van Genereen, J.L., 1998. Multisensor image fusion in remote sensing: concepts, methods, and applications. *International Journal of Remote Sensing* 19, 823–854.
- Raghunathan, S., 2001. Information sharing in a supply chain: a note on its value when demand is nonstationary. *Management Science* 47 (4), 605–610.
- Shannon, C.E., 1948. A mathematical theory of communication. *The Bell System Technical Journal* 27 (July), 379–423.
- Sheu, J.-B., 2006. A novel dynamic resource allocation model for demand-responsive city logistics distribution operations. *Transportation Research Part E* 42 (6), 445–472.
- Sheu, J.-B., 2007. An emergency logistics distribution approach for quick response to urgent relief demand in disasters. *Transportation Research Part E* 43 (6), 687–709.
- Shiono, K., Krimgold, F., 1989. A computer model for the recovery of trapped people in a collapsed building: development of a theoretical framework and direction for future collection. In: *Proceedings of the International Workshop on Earthquake Injury Epidemiology*, The Johns Hopkins University, July, 1989.
- Simchi-Levi, D., Kaminsky, P., Simchi-Levi, E., 2000. *Designing and Managing the Supply Chain-Concepts, Strategies, and Case Studies*. McGraw-Hill, Singapore.
- Sugeno, M., Yasukawa, T., 1993. A fuzzy-logic-based approach to qualitative modeling. *IEEE Transactions on Systems* 24, 1279–1284.
- Tzeng, G.-H., Cheng, H.-J., Huang, T.D., 2007. Multi-objective optimal planning for designing relief delivery systems. *Transportation Research Part E* 43 (6), 673–686.
- Wei, W.W.S., 1990. *Time Series Analysis: Univariate and Multivariate Methods*. Addison-Wesley Publishing Company, New York.
- Yi, W., Kumar, A., 2007. Ant colony optimization for disaster relief operations. *Transportation Research Part E* 43 (6), 660–672.
- Zhang, X., 2006. Inventory control under temporal demand heteroscedasticity. *European Journal of Operational Research* 18, 127–144.