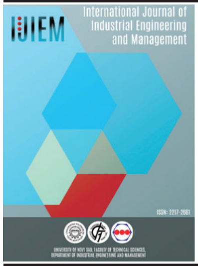
ISSN 2683-345X
journal homepage: http://ijiemjournal.uns.ac.rs/



International Journal of Industrial Engineering and Management

Volume 13 / No 3 / September 2022 / 172 - 185

Original research article

Design of disaster relief logistics network system by combining three data envelopment analysis-based methods

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ABSTRACT

The recent pandemic outbreak and weather-related disasters show that there is no place immune from such emergency events. Thus, it would be essential to provide disaster relief items efficiently through a disaster relief logistics network system (DRLNS). This paper considers a design problem of DRLNS. For this purpose, this study presents a process of combining the multi-objective programming (MOP) model with the three data envelopment analysis (DEA)-based methods. Through a case study, the proposed MOP-DEA design framework would help the decision-makers better evaluate the efficiency of various DRLNS configurations and identify the robust and efficient ones among them.

ARTICLE INFO

Article history:

Received January 26, 2022
Revised May 25, 2022
Accepted June 1, 2022
Published online June 10, 2022

Keywords:
Data envelopment analysis;
Disaster relief supply chain system;
Super efficiency;
Cross efficiency

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1. Introduction

The disaster relief logistics network system (*DRLNS*) plays an essential role in providing relief items such as first aid, drinking water, food, and daily commodities to alleviate people's suffering [1]-[3]. These two terms, *DRLNS* and emergency relief supply chain system, are frequently used interchangeably. In 2017, the US experienced a historic year of weather and climate disasters. The US was seriously affected by 16 separate billion-dollar disaster events, including three tropical cyclones, eight severe storms, two inland floods, a crop freeze, drought, and wildfire. During 2020 and 2021, the US experienced a very active year of weather and climate disasters (see Figure 1), including the COVID-19 pandemic.

The *DRLNS* considered in this study is a two-echelon supply chain system with three distinctive disaster relief facilities (DRFs), as shown in Figure 2. They are (i) Central Warehouses (*CWHs*), where disaster relief commodities are stored, (ii) intermediate response facilities termed Relief Distribution Centers (*RDCs*),

Published by the University of Novi Sad, Faculty of Technical Sciences, Novi Sad, Serbia.

http://doi.org/10.24867/IJIEM-2022-3-310

where people can more effectively gain access to relief goods, and (iii) neighborhood sites (*NBSs*) in need of humanitarian items. The chief objective of the strategic level is to strengthen disaster preparedness as well as to select the most cost/distance-effective location of *CWHs* and *RDCs* among a set of candidate locations, to establish the distribution of disaster supplies throughout the *ERSC*, and to assign *NBSs* to *RDCs* and *RDCs* to *CWHs*. However, traditional cost-based facility location models implicitly assume that all the facilities will always be in service or available and do not consider an associated risk of disruption. Due to natural disasters, accidents, or strikes, all facilities are susceptible to disturbances. Such disorders would be worsened due to a lack of flexibility and interdependency, commonly presented in the general supply chain systems.

Evaluating various *DRLNS* alternatives and identifying the most efficient options would be essential for efficient logistics network planning. The typical multi-objective programming (MOP) model allows the decision-maker to assign weights to the objective function's deviational variables. It would be necessary to reflect on the importance and desirability of deviations from the multiple goals. However, the actual efficiency of the resulting *DRLNS* is not known. No standard procedure is available for assigning values to the weight factors to guarantee we will find the most desirable solution to a MOP problem. Ragsdale [4] suggests that an iterative procedure should be followed, using a particular set of weights, concluding that it is essential for us to repeat this process several times to find the most desirable solution for decision-makers. Thus, it is unavoidable for decision-makers to use some of their subjective judgment. Evaluating various *DRLNS* network schemes objectively, not subjectively, and selecting the most efficient alternatives would be essential for designing *DRLNS*. Hence, it is imperative to answer how to evaluate the efficiency of all alternatives generated by the model and select the most desirable one(s) without any subjective assessments.

Data envelopment analysis (DEA) is one of the methodologies that have been widely used to evaluate the efficiency of decision-making units (DMUs) that have multiple inputs to use and outputs to produce. The classical DEA (C-DEA), proposed by Charnes et al. [5], generates a single, comprehensive performance measure for each DMU. The best ratio would identify the most efficient DMU among all the DMUs. The C-DEA allows each DMU to be evaluated with its most favorable weights due to its nature of self-evaluation. Consequently, the C-DEA model is permitted to ignore unfavorable inputs/outputs to maximize self-efficiency. That would be why it may suffer from a lack of discrimination particularly. The two most popular methods for remedying C-DEA deficiency are the cross-efficiency (CE) DEA and the supers-efficiency (SE) DEA method.

The CE-DEA ranks DMUs with the main idea of peer evaluation rather than DMU's usual pure self-evaluation. Due to its enhanced discriminating pow-

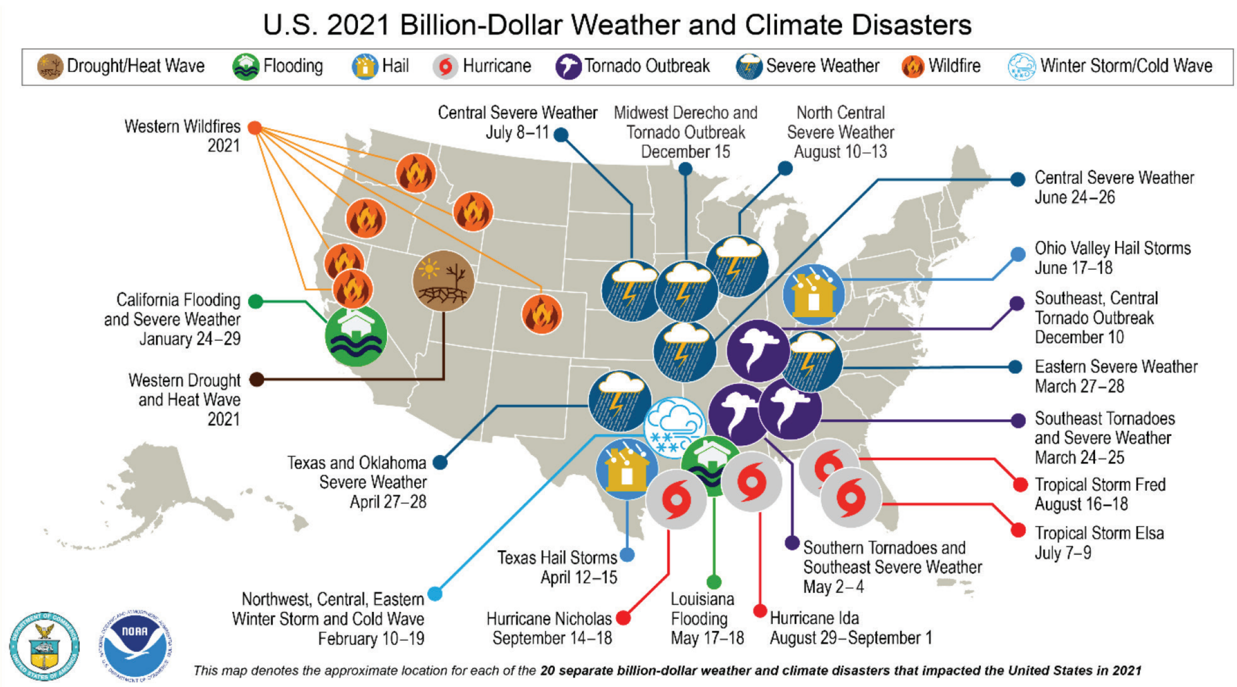

Figure 1. US 2021 billion-dollar weather and climate disasters

er, many applications based on the CE evaluation have been published [6]-[9]. As Doyle and Green [10] note, the primal issue is the non-uniqueness of CE scores due to the often-present multiple optimal DEA weights. The second issue is that the CE method frequently ranks inefficient DMUs ahead of fully efficient DMUs. The idea of super-efficiency (SE), which is mainly developed by Anderson and Peterson [11], is that the C-DEA model is applied, excluding a DMU under evaluation from the reference set of the C-DEA model. Charnes et al. [12] use the SE-DEA model to study the sensitivity of the efficiency classification. But the critical issue of using the model is that the adjacent DMUs decide the SE score (SES) of an efficient DMU, so it would be unreasonable for DMUs to be ranked by the SESs.

This paper might be the first attempt to integrate these three popular DEA methods to eliminate each method's weaknesses and apply the proposed method for designing *DRLNS*. Thus, we can evaluate various *DRLNS* network schemes objectively, not subjectively, and select the most efficient alternatives, which would be essential for planning the *DRLNS* network. Thus, the contribution of this paper is to propose a framework consisting of how to formulate the design problem using a MOP model and how to identify the robust and efficient logistics network systems for disaster relief operations by combing the three DEA evaluation methods.

2. Literature review and research gap

The number of publications on the *DRLNS* or humanitarian logistics design has considerably increased since it has become an important strategic decision due to the significant damage inflicted by several natural disasters [13]. Van Wassenhove [14] emphasizes that since disaster relief is 80% logistics, disaster relief planning should be through efficient and effective logistics operations and, more precisely, supply chain management. Logistics planning in emergencies involves quickly and efficiently distributing disaster supplies from DRFs to the affected areas via supply chains. [15]-[27] consider various problems related to *DRLNS* design and analysis. Several authors also consider the effect of the COVID-19 pandemic on the design of *DRLNS*. Gress et al. [28] present a methodology for designing a *DRLNS* to distribute COVID-19 vaccines in Mexico. Malmir and Zobel [29] propose a sustainable *DRLNS* design model considering the COVID-19 outbreak. Abdul Rahman et al. [30] examine the trend of humanitarian supply chain studies pre, during, and post-COVID-19 pandemic.

Multi-objective programming (MOP) models are applied for designing efficient *DRLNS*. Cao et al. [31] propose multi-objective programming models of relief distribution for sustainable DRLNS. Mansoori et al. [32] consider a robust multi-objective humanitarian relief chain network design for earthquake response. Cheng et al. [33] propose a goal programming (GP) model for distribution problems in humanitarian relief logistics. Mohamadi et al. [34] propose a multi-objective mathematical model to design a humanitarian logistics network under uncertain conditions and employ a robust optimization approach. Saatchi et al. [35] consider a multi-echelon, multi-objective forward and backward relief network and propose a hybrid algorithm.

Hong and Jeong [13] combine MOP models with the C-DEA method to find the efficient DRF location and allocation schemes of humanitarian supplies through DRFs in a humanitarian supply chain system. They [13] formulate the design problem as two MOP models and generate various logistics network schemes for applying various weights assigned to each objective. Then, the C-DEA method is applied to find efficient logistics network schemes, which are considered DMUs in the context of DEA. As mentioned above, C-DEA can only separate efficient DMUs from inefficient DMUs. Thus, these efficient DMUs cannot be ranked by C-DEA, which treats all efficient DMUs the same. Later, Hong [36] applies CE-DEA methods for designing an emergency relief supply chain network model. As mentioned before, the CE-DEA methods are developed to rank DMUs under evaluation but exhibit their critical weaknesses.

There is a gap between finding efficient DMUs from the DMUs under evaluation and ranking DMUs to be rated. The CE- and SE-DEA methods, which have been developed to rank DMUs, exhibit their critical weaknesses, as mentioned before. Thus, the research question for this study is how to combine these three most popular DEA methods, C-, CE-, and SE-DEA methods, to evaluate and rank *DRLNS* schemes generated by the multi-objective programming models. What distinguishes the present paper is that the proposed procedure of integrating the three DEA methods can identify top-rated DRLNS alternatives so that decision-makers can evaluate these ranked logistics networks better than each DEA method. The proposed approach can attract federal and local disaster/emergency response officials to develop more flexible and robust supply chain plans.

3. Formulation of the DRLNS model

We follow the multi-objective model that Hong and Jeong [13] consider.

Sets:

I: index set of candidate locations for $CWHs$ $(i = 1, 2, \omega)$ (1)

N: index set of $NBSs$ n $(n = 1, 2, \ldots, \eta)$ (2)

M: $M = \{N, I\}$, index set of $NBSs$ and $CWHs$ $(m = 1, 2, ..\eta, \eta+1, \ldots, \eta+\omega)$ (3)

J: index set of candidate locations for $RDCs$ $(j = 1, 2, \eta, \eta+1, \ldots, \eta+\omega)$ (4)

Parameters:

f_i: fixed cost for constructing and operating CWH_i (5)

c_j: fixed cost for constructing and operating RDC_j (6)

a_{ij}^1: shipping cost per mile per one unit of demand from CWH_i and RDC_j (7)

a_{im}^2: shipping cost per mile per one unit of demand from CWH_i and NBS_m (8)

d_{ij}: distance between CWH_i and RDC_j (9)

d_{jm}: distance between RDC_j and NBS_m (10)

C^{max}: maximum number of $RDCs$ can be built (11)

CAP_i^{max}: capacity of CWH_i (12)

CAP_j^{max}: capacity of RDC_j (13)

h_m: demand of $NBSm$ (can be either NBS or RDC or CWH) (14)

W^{max}: maximum number of $CWHs$ can be built (15)

k_i: minimum number of $RDCs$ that CWH_i can handle (16)

K_i: maximum number of $RDCs$ that CWH_i can handle (17)

l_j: minimum number of $NBSs$ that RDC_j can cover (18)

L_j: maximum number of $NBSs$ that RDC_j can cover (19)

Decision variables:

C_j: binary variable deciding whether neighborhood j is selected as RDC_j (20)

W_i: binary variable deciding whether a candidate CWH_i is selected (21)

x_{ij}: binary variable deciding whether RDC_j is covered by CWH_i (22)

y_{jm}: binary variable deciding whether location m is covered by RDC_j (23)

z_{ijm}: binary variable deciding whether location m is covered by CWH_i through RDC_j (24)

Assumption (see Figure 2):

(i) All $NBSs$ and potential CWH locations are the candidates for $RDCs$ to be located.

(ii) A CWH can be located at one of the candidate CWH locations only due to some realistic requirements.

(iii) An RDC must cover any unselected CWH locations, and for any potential CWH location, both RDC and CWH cannot be located.

(iv) A CWH covers its own demand, and an RDC feeds its own demand and demands from its covered $NBSs$.

(v) When a DRF is disrupted, it cannot satisfy any demand to be expected to cover.

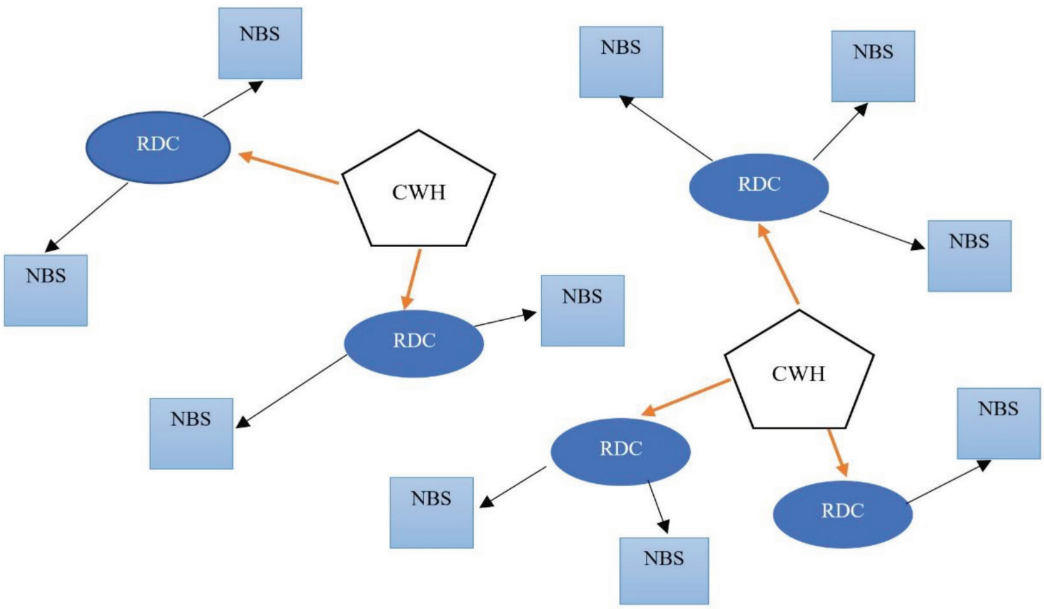

Figure 2. Two-echelon disaster relief logistics network system

The first goal is minimizing the related logistics costs, which is the traditional objective of most facility location allocation models. Given this problem set, the total logistics cost (*TLC*) is given by

$$TLC = \left[\sum_{i\in I} f_i W_i + \sum_{i\in I}\sum_{j\in M}\left(\sum_{m\in M} h_m\right) a_{ij}^1 d_{ij} z_{ijm}\right] + \left[\sum_{j\in M} c_j C_j + \sum_{j\in M}\sum_{m\in M} h_m a_{jm}^2 d_{jm} y_{jm}\right], \tag{25}$$

where

$$z_{ijm} = x_{ij} \cdot y_{jm}. \tag{26}$$

The second goal is to minimize the maximum coverage distance (*MCD*) such that each *NBS* is covered by one of the *RDCs*, and each *RDC* is covered by one of the *CWHs* within the endogenously determined distance. This goal minimizes the longest delivery distance between *CWHs, RDCs*, and *NBSs*. If the *MCD* is too large, it will cause ineffectiveness to the resulting *DRLNS*. Now, *MCD* is given by

$$MCD = Max\{d_{jm} y_{jm,} d_{ij} x_{ij}\}, \forall i, j, and\ m. \tag{27}$$

DRFs should be located at the least likely locations to be disrupted to enhance disaster supply chain resilience. The third goal is to maximize the expected amount of demands covered (*EDC*) by the *DRFs*, which is expressed through several algebraic manipulations as

$$EDC = \sum_{i\in I}\sum_{j\in M}\left[\sum_{m\in M}(1-q_i)(1-p_j)(z_{ijm}h_m)\right] + \sum_{i\in I}(1-q_i)(h_i W_i), \tag{28}$$

where
q_i - the probability that the CWH_i is disrupted (or risk probability).
p_j - the probability that the RDC_j is disrupted (or risk probability);

Deckle et al. [37] consider the condition that each county resident being close to a DRC should be less than a given outset. It implies that each location should be within a certain distance of the nearest DRCs to be served in case of disaster. It would be plausible to claim that the maximum effective coverage distance (*MECD*), denoted by D_c, maybe shorter than the *MCD*. However, it would be desirable to maximize the covered demands within D_c, while minimizing the *MCD*. The next goal is to maximize the covered demands in case of disaster, *CDE*, which is expressed as

$$CDE = \sum_{m\in M}\sum_{j\in J} h_m \kappa_{jm} y_{jm} + \sum_{i\in I} h_i W_i \tag{29}$$

where an indicator parameter, κ_{jm}, is

$$\kappa_{jm} = \begin{cases} 1, & \text{if } d_{jm} \le D_c \\ 0, & \text{otherwise.} \end{cases} \tag{30}$$

Let the nonnegative deviation variables, $\delta_{TLC}^+, \delta_{TLC}^-, \delta_{MCD}^+, \delta_{MCD}^-$, $\delta_{EDC}^-, \delta_{EDC}^+$, δ_{CDE}^-, and δ_{CDE}^+ represent the amounts by which each *TLC, MCD, EDC*, and *CDE* value deviates from the target values. Then, let $\boldsymbol{\alpha} = \{\alpha_1, \alpha_2, \alpha_3, \alpha_4\}$, $\sum_{\kappa=1}^4 \alpha_\kappa = 1$, denote relative weights attached to the corresponding goal. Now, the objective function is minimizing the maximum weighted percentage deviation (WPD), subject to each WPD being less than or equal to the objected value itself. Then, a MOP model is formulated as follows:

$$Min\ Q = Max\left\{\alpha_1 \frac{\delta_{TLC}^+}{TLC_{min}}, \alpha_2 \frac{\delta_{MCD}^+}{MCD_{min}}, \alpha_3 \frac{\delta_{EDC}^-}{EDC_{max}}, \alpha_4 \frac{\delta_{CDE}^-}{CDE_{max}}\right\}, \tag{31}$$

subject to

$$TLC\ in\ (25) - \delta_{TLC}^+ = TLC_{min}, \tag{32}$$

$$MCD\ in\ (27) - \delta_{MCD}^+ = MCD_{min}, \tag{33}$$

$$EDC\ in\ (28) + \delta_{EDC}^- = EDC_{max}, \tag{34}$$

$$CDE\ in\ (29) + \delta_{CDE}^- = CDE_{max}. \tag{35}$$

$$\alpha_1 \frac{\delta_{TLC}^+}{TLC_{min}} \le Q, \tag{36}$$

$$\alpha_2 \frac{\delta_{MCD}^+}{MCD_{min}} \le Q, \tag{37}$$

$$\alpha_3 \frac{\delta_{EDC}^-}{EDC_{max}} \le Q, \tag{38}$$

$$\alpha_4 \frac{\delta_{CDE}^-}{CDE_{max}} \le Q. \tag{39}$$

Now, the complete constraints for the *ERSC* design problem are

$$\sum_{i\in I} W_i \le W^{max}, \tag{40}$$

$$W_i + C_{\eta+i} \leq 1, \quad \forall i \in I \tag{41}$$

$$W_i + \sum_{j\in M} y_{j(\eta+i)} = 1, \quad \forall i \in I \tag{42}$$

$$\sum_{j\in M} y_{jn} = 1, \quad \forall n \in N \tag{43}$$

$$W_i\, k_i \leq \sum_{j\in M} x_{ij} \leq W_i K_i, \quad \forall i \in I \tag{44}$$

$$\sum_{i\in I} x_{ij} = C_j, \quad \forall j \in M \tag{45}$$

$$\sum_{j\in M} C_j \leq C^{max}, \tag{46}$$

$$y_{jm} \leq C_j, \quad \forall j \text{ and } \forall m \in M \tag{47}$$

$$C_j \cdot l_j \leq \sum_{m\in M} y_{jm} \leq C_j \cdot L_j, \quad \forall j \in M \tag{48}$$

$$\sum_{m\in M} h_m y_{jm} \leq CAP_j^{max}, \quad \forall j \in M \tag{49}$$

$$\sum_{j\in M}\sum_{m\in M} h_m z_{ijm} + h_i W_i \leq CAP_i^{max}, \quad \forall i \in I \tag{50}$$

$$Max\{0,\, x_{ij} + y_{jm} - 1\} \leq z_{ijm} \leq \frac{x_{ij} + y_{jm}}{2}, \quad \forall i \in I \text{ and } \forall j, \forall m \in M \tag{51}$$

Constraints (40) define the upper bound of the number of *CWH*s that can be built. Here at most W^{max} is allowed. Constraints (41) ensure that the potential *CWH* location will not be selected simultaneously as both *CWH* and *RDC*. Constraints (42) ensure that if a potential *CWH* location i is not selected (i.e.,W_i=0), its demand must be satisfied by an *RDC* or a *CWH*. Constraints (43) make certain that each *NBS* ($n \in N$) is assigned to either an *RDC* or a *CWH*. Constraints (44) limit the minimum and maximum number of *RDC*s to be covered by each *CWH*. Constraints (45) ensure that *CWH*s only supply the selected *RDC*s. Constraints (46) limit the total number of selected *RDC*s to be less than or equal to a user-specified number, C^{max}. Constraints (47) ensure that *NBS*s or unselected *CWH* locations can only be assigned to the selected candidate *RDCs*. Constraints (48) ensure that the selected candidate RDC_j must cover a minimum number of l_j *NBSs* and can only cover a maximum of L_j *NBSs*. Constraints (49) and (50) show the shipping capacity of *RDCs* and *CWHs*, and the amounts, respectively. Constraints (51) show the upper and lower limit of a linearized variable, z_{ijm}, as shown in (26).

Theoretically, the weight assigned to each objective is a continuous variable between 0 and 1. But, for computational purposes, there should be a limitation on the values of the weights. This study considers discrete values for each weight, where each weight alters between 0 and 1 with an increment of 0.1. Solving the above model for a given set of weights generates one DRLNS scheme with a group of optimal four-performance metrics. There will be multiple schemes for various values of the weights. This paper applies DEA by considering these generated schemes.

4. Data envelopment analysis methods

4.1. Classical DEA (C-DEA)

Note that each DMU represents a *DRLNS* scheme generated by solving the MOP model given in (31)-(51) for a given value of each weight. Letting E_{kk} represent the DEA score for DMU_k, we formulate the following mathematical model of C-DEA for DMUs with two inputs, *TLC* and *MCD*, to produce two outputs, *EDC* and *CDE*, as follows:

$$Max\, E_{kk} = u_{1k}EDC_k + u_{2k}CDE_k, \tag{52}$$

subject to

$$v_{1k}TLC_k + v_{2k}MCD_k = 1, \tag{53}$$

$$(u_{1k}EDC_j + u_{2k}CDE_j) - (v_{1k}TLC_j + v_{2k}MCD_j) \leq 0, j = 1, \ldots, N, \tag{54}$$

$$u_{1k}, u_{2k}, v_{1k}, v_{2k} \geq 0.$$

N = number of DMUs under evaluation
i = number of inputs to be used by DMUs
r = number of outputs to be generated by DMUs
u_{rk} = coefficient or weight assigned by DMU_k to output r
v_{ik} = coefficient or weight assigned by DMU_k to input i

DMU_k is said to be efficient only if $E_{kk}^* = 1$. The model given by (52)-(54) is called an input-oriented model, and E_{kk}^* is called CRS efficient score (ES).

4.2. Cross efficiency DEA

The cross-efficiency (CE) method consists of two phases [38]. The first one is the self-evaluation phase, where DEA scores are calculated using the model by (52)-(54). In the second phase, the weights/

multipliers generated in the first phase are applied to all DMUs to get the cross-efficiency score (CES) for each DMU. Now, the CE for DMU_j is given by

$$E_{kj} = \frac{u_{1k}^{*}EDC_k + u_{2k}^{*}CDE_k}{v_{1k}^{*}TLC_k + v_{2k}^{*}MCD_k}, k \text{ and } j = 1, \ldots, N, k \neq j. \quad (55)$$

DMU_j is a rated DMU, whereas DMUk is a rating DMU. By averaging E_{kj} in (55) without the leading diagonal, Doyle and Green [10] propose the CES for DMU_k, which is defined as

$$\bar{E}_{k(p)} = \frac{1}{N-1}\sum_{j\neq k}^{N} E_{jk}. \quad (56)$$

In (56), $'p'$ stands for peer evaluation. In the meantime, Zhu [38] includes self-evaluation value in averaging the appraisals by itself and peers as follows:

$$\bar{E}_{k(s+p)} = \frac{1}{N}\sum_{j=1}^{N} E_{jk}. \quad (57)$$

In (57), $'s'$ stands for self-evaluation. No literature explicitly has suggested the appropriate self-evaluation and peer evaluation proportions in deciding the CE scores. To solve the dilemma between the above two equations, (56) and (57), let β denote the proportion of self-evaluation evaluation. We propose the following equation to combine (56) and (57) and call it the regular CE-DEA model:

$$\bar{E}_{\kappa} = \beta * E_{\kappa\kappa} + \frac{(1-\beta)}{N-1}\sum_{\substack{\omega=1,\\ \omega\neq\kappa}}^{N} E_{\omega\kappa}. \quad (58)$$

Wang and Chin [39] develop the neutral CE-DEA model that determines one set of input and output weights for each DMU without being aggressive or benevolent to the others. The model is formulated as follows:

$$Maximize\ w \quad (59)$$

subject to

$$v_{1k}TLC_k + v_{2k}MCD_k = 1, \quad (60)$$

$$u_{1k}EDC_k + u_{2k}CDE_k = E_{kk}^{*}, \quad (61)$$

$$\left(u_{1k}EDC_j + u_{2k}CDE_j\right) - \left(v_{1k}TLC_j + v_{2k}MCD_j\right) \leq 0,$$
$$j = 1, \ldots, N, k \neq j, \quad (62)$$

$$u_{1k}EDC_k \geq w, \quad (63)$$

$$u_{2k}CDE_k \geq w, \quad (64)$$
$$w, u_{1k}, u_{2k}, v_{1k}, v_{2k} \geq 0.$$

4.3. Super efficiency DEA

The super-efficiency score (SES) is obtained from the C-DEA model after a DMU under evaluation is excluded from the reference set. The SES for DMU_k is obtained from

$$Max\ SE_{kk} = u_{1k}EDC_k + u_{2k}CDE_k, \quad (65)$$

subject to

$$v_{1k}TLC_k + v_{2k}MCD_k = 1, \quad (66)$$

$$\left(u_{1k}EDC_j + u_{2k}CDE_j\right) - \left(v_{1k}TLC_j + v_{2k}MCD_j\right) \leq 0, j \neq k, \quad (67)$$

$$u_{1k}, u_{2k}, v_{1k}, v_{2k} \geq 0.$$

In the above SE model, efficient DMUs are not compared to the same standard since the frontier constructed from the remaining DMUs changes for each efficient DMU to be rated. Jeong and Ok [40] and Yu and Hou [41] maintain that the self-evaluation efficiency would not discriminate between efficient DMUs and propose a modified cross-evaluation method using the SES. Now, the cross efficiency of DMU_j based on SES, which is called super-cross efficiency (SCE) in this paper, is given by

$$SCE_{kj} = \frac{u_{1k}^{*}EDC_k + u_{2k}^{*}CDE_k}{v_{1k}^{*}TLC_k + v_{2k}^{*}MCD_k}, \quad (68)$$
$$k \text{ and } j = 1, \ldots, N, k \neq j.$$

Then, the cross-evaluation matrix consists of the self-evaluation value, SE_{kk} in (65), in the leading diagonal and peer evaluation value, SCE_{kj} in (68), in the non-diagonals, as shown in Table 1. As shown in (58), the following equation for the average SCE score for DMU_κ is proposed:

$$\overline{SCE}_{\kappa} = \beta * SE_{\kappa\kappa} + \frac{(1-\beta)}{N-1}\sum_{\substack{\omega=1,\\ \omega\neq\kappa}}^{N} SCE_{\omega\kappa}. \quad (69)$$

Table 1. Super efficiency-based cross-evaluation matrix

		Rated DMU_j			
		1	2	...	N
Rating DMU_k	1	SE_{11}	SE_{12}	...	SE_{1N}
	2	SCE_{21}	SCE_{22}	...	SCE_{2N}
	...	...	...	...	...
	N	SCE_{N1}	SCE_{N2}	...	SCE_{NN}
	Average	$\overline{SCE}_1$	$\overline{SCE}_2$	...	$\overline{SCE}_N$

Now, this study extends the SE-DEA model to the neutral CE-based method. The neutral CE formation based on the SE-DEA can be formulated as shown in (59)-(64) with $k \neq j$ in (62).

5. Case study and observations

The case study applies major disaster declaration records in South Carolina (SC) to illustrate the proposed procedure. Forty-six counties are clustered based on proximity and populations into twenty counties. Then, we choose one city from each clustered county based on a centroid approach, assuming that all population within the grouped county exists in that city. The distance between counties is assumed to be the distance between these cities. The Federal Disaster Management Agency (FEMA) database (FEMA, 2015) provides a list of counties where a major disaster was declared. It is assumed that when a major disaster is declared, the disaster facility in that county is damaged and shut down. Based on the historical record and the assumption, each neighborhood's risk probability is calculated in Table 2. The potential five locations for *CWHs*, listed as the last five locations, are selected based upon population, the proportion of area that each site would potentially cover, and the proximity to Interstate Highways in SC. The numbers of *RDCs* and *CWHs* to be built are pre-specified in most cases. We simplify the *TLC* function given by Eq. (25) by excluding the fixed cost terms for *RDCs* and *CWHs*. Also, the following parameters are pre-determined for our case study. The maximum numbers of *RDCs* and *CWHs* are set to 5 and 2, respectively. The minimum and maximum *RDCs* that a *CWH* must handle are set to 1 and 10, respectively. Each *RDC* must cover at least 2 ($\ell_j = 2$) and at most 7 ($L_j = 7$) *NBSs*. The capacities of *RDCs* and *CWHs* are set to 1,500 K and 2,500 K. We hypothetically set the maximum effective coverage distance in case of disaster, D_c in (30), equal to 35 miles to find CDE_{max}.

The MOP model is formulated and solved for various values of the weight set, α. Each weight alters between 0 and 1 with an increment of 0.1. There are 286 configurations arising out of the combinations of the setting of α under the condition $\sum_{v=1}^{4} \alpha_v = 1$.

Table 2. Data for locations of DRFs

No	City	County	Population (K)	Risk Probability
1	Anderson	Anderson/Oconee/Pickens	373	0.125
2	Beaufort	Beaufort/Jasper	187	0.063
3	Bennettsville	Marlboro/Darlington/Chesterfield	96	0.375
4	Conway	Horry	269	0.375
5	Georgetown	Georgetown/Williamsburg	93	0.438
6	Greenwood	Greenwood/Abbeville	92	0.125
7	Hampton	Hampton/Allendale	33	0.188
8	Lexington	Lexington/Newberry/Saluda	318	0.313
9	McCormick	McCormick/Edgefield	35	0.250
10	Moncks Corner	Berkeley	178	0.313
11	Orangeburg	Orangeburg/Bamberg/Calhoun	123	0.375
12	Rock Hill	York/Chester/Lancaster	321	0.313
13	Spartanburg	Spartanburg/Cherokee/Union	367	0.313
14	Sumter	Sumter/Clarendon/Lee	157	0.375
15	Walterboro	Colleton/Dorchester	135	0.250
16	Aiken†	Aiken/Barnwell	184	0.313
17	Charleston†	Charleston	350	0.250
18	Columbia†	Richland/Fairfield/Kershaw	461	0.375
19	Florence†	Florence/Dillon/Marion	203	0.438
20	Greenville†	Greenville/Laurens	521	0.125

†potential locations for *CWH*

After 286 runs, we reduce these configurations into 148 consolidated schemes after grouping them with the same values of four-performance metrics. Each of the 148 network schemes is considered a DMU, representing the optimal locations of *DRFs* and their supply chain schemes. Considering *TLC* and *MCD* as inputs and *EDC* and *CDE* as outputs, we first apply the C-DEA model in (52)-(54). The thirteen (13) efficient DMUs out of 148 with a perfect ES are called "a best-practice frontier."

In Table 3, we present all 13 efficient DMUs, each performance metric's value, ES for C-DEA, and cross-efficiency scores (CESs) for Regular and Neutral models. Similarly, super-cross efficiency scores (SCESs) for Regular and Neutral models for these efficient DMUs are also reported. The DMUs with the top three greatest CESs/SCESs are denoted by '* * *', '* *', and '*,' respectively. From Table 3, we observe that the Regular CES finds DMU #57 as the most efficient DMU, whereas the Neutral CES ranks DMU #53 as #1. In contrast, DMU #58 is ranked #1, DMU #57 is ranked second, and DMU #53 is ranked third by both SCESs. Note that DMU #57 and DMU #58 yield almost identical inputs and outputs, while DMU #57 yields slightly less TLC and EDC than DMU #58. DMU #53 results in fewer inputs, TCL and MCD, and fewer outputs, EDC and CDE, than DMU #57 or DMU #58. In other words, DMU #53 is more efficient in terms of inputs but less efficient in terms of outputs than DMU #57 or DMU #58. From Table 4 showing the effect of self-evaluation proportion, β, we observe that the increase in self-evaluation does not affect the top three DMUs ranked by both CE DEA methods. On the contrary, the effect of β seems to be significant for both SE-DEA models. As β increases, DMU #53, ranked as the top DMU by the CE neutral model, emerges as the top DMU, and DMUs #59, #60, and #142, which are not ranked as the top three by any methods, begin to be ranked by the SE DEA models. Based on these results from Tables 3 and 4, we depict the four highly-ranked DMUs, DMUs #53, #57, #58, and #142, in Figures 3-1 and 3-2.

As shown in Figures 3-1 and 3-2, two sites, {Greenville, Columbia}, are selected as the CWH locations by DMU #53. Three RDC sites, {Anderson, Greenwood, Spartanburg}, are covered by the CWH{Greenville}, while the CWH {Columbia} covers RDCs {Orangeburg, Sumter}. The RDCs {Anderson, Greenwood, Spartanburg} cover the NBSs {McCormick, Aiken, Lexington}, respectively, whereas the RDC {Orangeburg} covers {Hampton, Beaufort, Walterboro, Charleston, Monks Corner} and the RDC {Sumter} covers {Bennettsville, Conway, Georgetown, Florence}. In contrast, in DMU #57, two sites, {Greenville, Charleston}, are selected as the

Table 3. Efficient DMUs, their performance metrics, and efficient scores

No	DMU #	TLC($) Input	MCD (miles) Input	EDC (K) Output	CDE (K) Output	ES	CES (R)	CES (N)	SES (R)	SES (N)
1	25	397,904	100.9	2119	3361	1.0000	0.8566	0.8812	0.8494	0.8501
2	26	338,510	85.5	2754	2139	1.0000	0.8406	0.8840	0.8611	0.8613
3	53	294,084	83.9	2637	2094	1.0000	0.8837*	0.9157***	0.8989*	0.8991*
4	56	329,360	130.0	2411	3040	1.0000	0.8205	0.8041	0.8075	0.8077
5	57	300,062	116.0	2862	2736	1.0000	0.9079***	0.9001*	0.9023**	0.9023**
6	58	300,608	116.0	2868	2736	1.0000	0.9078**	0.9002**	0.9024***	0.9024***
7	59	308,864	116.0	2996	2049	1.0000	0.7782	0.7830	0.7837	0.7834
8	60	335,001	93.9	3031	2057	1.0000	0.8283	0.8645	0.8493	0.8493
9	62	293,234	176.0	2600	2725	1.0000	0.7417	0.6909	0.7165	0.7161
10	78	425,988	100.9	2094	3361	1.0000	0.8248	0.8548	0.8189	0.8197
11	79	434,507	100.9	2090	3361	1.0000	0.8163	0.8478	0.8108	0.8116
12	95	363,088	94.0	3075	2038	1.0000	0.7964	0.8394	0.8209	0.8210
13	142	388,104	100.9	2115	3361	1.0000	0.8670	0.8893	0.8591	0.8599

ES: Efficiency Score, **CES:** Cross-Efficiency Score, **SES:** Super-Efficiency Score, **R:** Regular Model, **N:** Neutral Model
***: Ranked First, **: Ranked Second, *: Ranked Third

Table 4. The effect of self-evaluation proportion on the cross-efficiency score and super efficiency score

		DMU #												
β	Model	25	26	53	56	57	58	59	60	62	78	79	95	142
1	C	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
	SE	1.0006	1.0195	1.0411***	1.0115	1.0017	1.0006	1.0219**	1.0197	1.0147	1.0000	1.0000	1.0134	1.0210*
0.8	CE-R	0.9689	0.9655	0.9748*	0.9611	0.9800***	0.9800**	0.9519	0.9628	0.9440	0.9620	0.9602	0.9559	0.9712
	CE-N	0.9743	0.9749	0.9818***	0.9576	0.9783*	0.9784**	0.9530	0.9707	0.9330	0.9686	0.9670	0.9652	0.9760
	SE-R	0.9678	0.9852	1.0103***	0.9673	0.9801	0.9793	0.9703	0.9828*	0.9501	0.9608	0.9590	0.9717	0.9859**
	SE-N	0.9680	0.9852	1.0103***	0.9674	0.9801	0.9793	0.9702	0.9828*	0.9500	0.9609	0.9592	0.9717	0.9861**
0.5	CE-R	0.9223	0.9137	0.9370*	0.9028	0.9501***	0.9500**	0.8798	0.9070	0.8601	0.9051	0.9005	0.8897	0.9280
	CE-N	0.9357	0.9372	0.9544***	0.8939	0.9459*	0.9460**	0.8825	0.9266	0.8326	0.9214	0.9176	0.9130	0.9401
	SE-R	0.9187	0.9337	0.9641***	0.9010	0.9479**	0.9474*	0.8928	0.9274	0.8532	0.9019	0.8975	0.9091	0.9333
	SE-N	0.9191	0.9338	0.9642***	0.9011	0.9479**	0.9474*	0.8927	0.9274	0.8529	0.9023	0.8979	0.9092	0.9337
0.3	CE-R	0.8912	0.8791	0.9118*	0.8639	0.9302***	0.9301**	0.8318	0.8698	0.8041	0.8672	0.8607	0.8456	0.8992
	CE-N	0.9099	0.9121	0.9361***	0.8515	0.9242*	0.9244**	0.8355	0.8973	0.7656	0.8900	0.8846	0.8783	0.9161
	SE-R	0.8859	0.8994	0.9333***	0.8568	0.9263**	0.9261*	0.8412	0.8905	0.7885	0.8627	0.8565	0.8674	0.8982
	SE-N	0.8865	0.8996	0.9334***	0.8570	0.9263**	0.9261*	0.8410	0.8905	0.7882	0.8633	0.8571	0.8675	0.8988
0.0	CE-R	0.8446	0.8273	0.8740*	0.8056	0.9002***	0.9001**	0.7597	0.8140	0.7202	0.8102	0.8010	0.7794	0.8559
	CE-N	0.8714	0.8744	0.9088***	0.7878	0.8918*	0.8919**	0.7650	0.8533	0.6652	0.8428	0.8352	0.8261	0.8802
	SE-R	0.8368	0.8479	0.8871*	0.7905	0.8941**	0.8942***	0.7638	0.8351	0.6916	0.8038	0.7950	0.8049	0.8456
	SE-N	0.8376	0.8482	0.8873*	0.7907	0.8941**	0.8942***	0.7635	0.8351	0.6912	0.8047	0.7959	0.8050	0.8464

C: Classical DEA, **CE:** Cross-Efficiency DEA, **SE:** Super-Efficiency DEA, **R:** Regular Model, **N:** Neutral Model ,
***: Ranked First, **: Ranked Second, *: Ranked Third

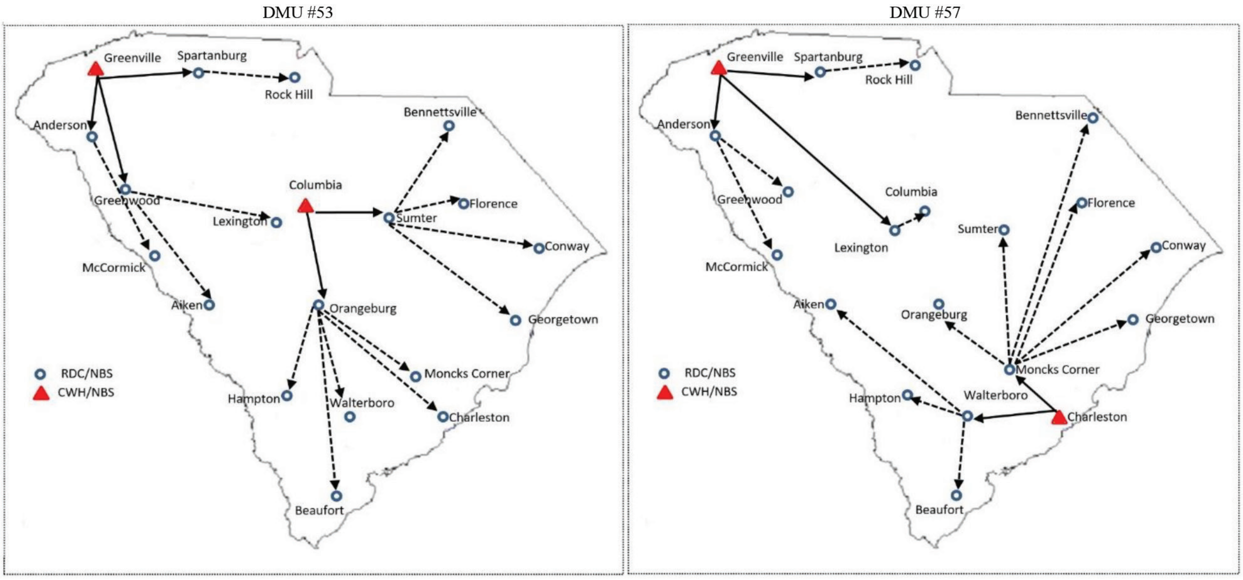

Figure 3-1. Most efficient disaster relief logistics network schemes

CWH locations. Contrary to DMU #53's CWH {Columbia}, DMU #57's CWH {Charleston} covers two RDCs {Walterboro, Moncks Corner}, which cover most of the NBSs located in the Walterboro area. We see that DMU #58 selects the same CWH and RDCs locations as DMU #57. The only difference between DMU #57 and #58 is caused by the RDC covering the NBS {Orangeburg}. In DMU #57, the RDC {Moncks Corner} covers {Orangeburg}, whereas the RDC {Walterboro} covers it in DMU #58.

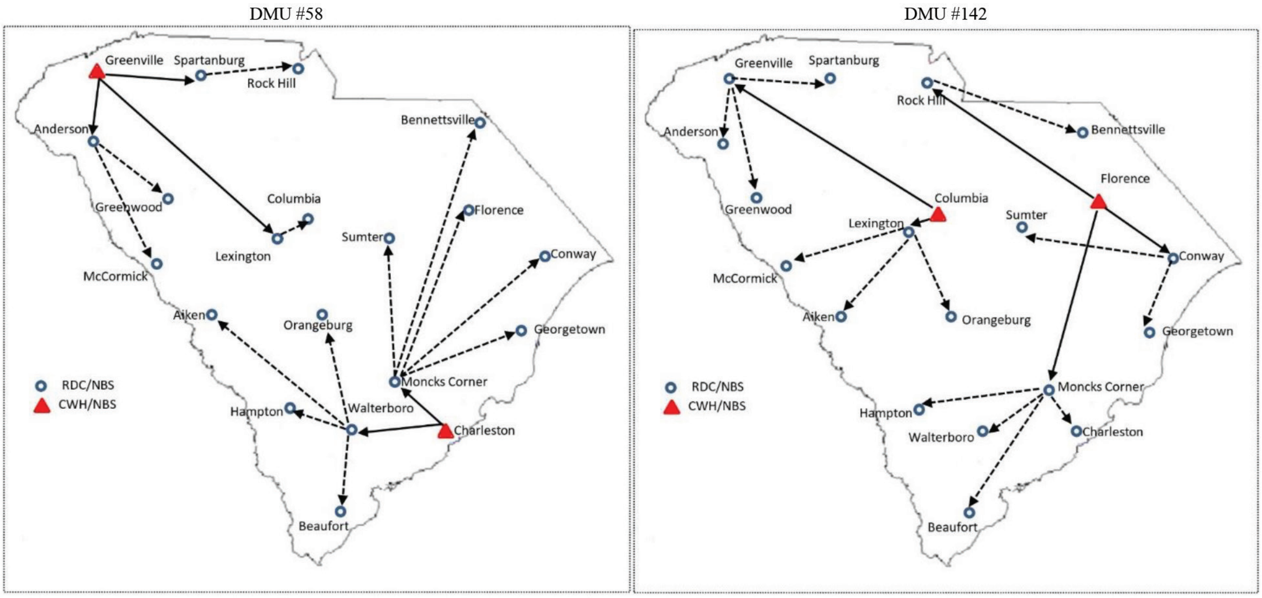

Figure 3-2. Most efficient disaster relief logistics network schemes

DMU #142 locates two CWH sites in SC's middle area, {Columbia, Florence}. Contrary to the allocation of CWH {Columbia} covering the eastern and southeastern areas of SC, the CWH {Columbia} in DMU #142 covers the western and northwestern areas of SC.

From the above analysis, there are some interesting managerial implications for decision-makers. Each of these top-four configurations has its advantages and disadvantages that the decision-makers would like to consider before making the final decision. DMU #142 has the highest CDE as its advantage, but the highest TLC and the lowest EDC can be considered a disadvantage. DMUs #57 and #58, ranked as #1 more than the other two DMUs, have similar configuration and performance measures. With the top priority of the total cost and coverage distance, DMU #53 has an advantage over the other top DMUs. However, the disadvantage comes from the lowest expected demand covered (EDC) and covered demand in case of disaster (CDE).

We observe that DMU #53 shows CWH {Greenwood}, rather than CWH {Columbia}, covers NBS {Lexington} through RDC {Greenwood}. The distance between {Greenwood} and {Lexington} is 61 miles, whereas the distance between RDC {Orangeburg} and {Lexington} is only 45 miles and between {Columbia} and {Lexington} is only 15 miles. The main reason that {Columbia} or {Orangeburg} does not cover {Lexington} is that the limited storage capacity of {Columbia} and relatively high disruption probabilities for {Columbia} and {Orangeburg}. If the current capacity of {Columbia} is increased by 103K, it could cover the demand of {Lexington} via RDC {Orangeburg}, which is called Scenario 1, or directly, Scenario 2. Now, Table 5 displays each performance metric's value for each scenario and the original scheme. We observe no difference in rankings between Scenario 1 and the original scheme, but the modified DMU #53 with Scenario 2, depicted in Figure 4, ranks #1 regardless of the evaluation models. Thus, if there are no particular guidelines, DMUs #57 and #58 would be candidates for the decision-makers to select as the final ones. As for Scenario 2, the decision-makers could select DMU #53 to implement as the most efficient DRLNS configuration with some flexibility.

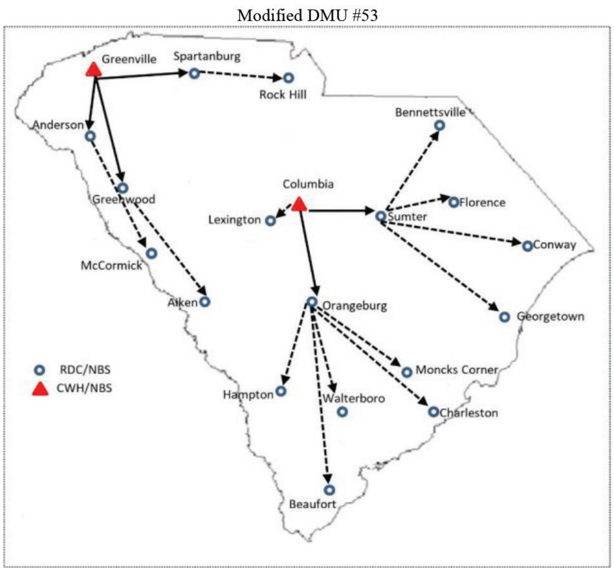

Figure 4. Modified disaster relief logistics network scheme (DMU #53)

Table 5. Performance metrics and efficient scores for DMU #53

Scenario	TLC($)	MCD (miles)	EDC (K)	CDE (K)	ES	CES (R)	CES (N)	SES (R)	SES (N)
	Input	Input	Output	Output					
Original	294,084	83.9	2637	2094	1.0000	0.8837*	0.9157***	0.8989*	0.8991*
1	285,749	83.9	2517	2094	1.0000	0.8697*	0.9150***	0.8958*	0.8958*
2	263,371	83.9	2592	2412	1.0000	0.9634***	0.9789***	0.9874***	0.9874***

Scenario 1: CWH {Columbia} -> RDC (Orangeburg)-> NBS {Lexington}, **Scenario 2:** CWH {Columbia} -> NBS {Lexington}

6. Summary and conclusions

The design of the disaster relief supply chain system (DRLNS) has become an important strategic decision due to the significant damage inflicted by recent natural or human-made disaster events, including the Covid-19 pandemic. This study deals with designing efficient and resilient *DRLNS* so that DRFs can deliver relief items to more affected sites at the right time with the right amount of items. For planning more balanced *DRLNS* configurations, multi-objective programming (MOP) is applied to generate various network alternatives. Three data envelopment analysis (DEA) methods are used to evaluate these alternatives and identify the most efficient one, considering each network scheme as a decision-making unit (DMU).

The classical DEA (C-DEA) estimates DMUs regarding self-evaluation only, allowing each DMU to rate its efficiency score with the most favorable weights. Consequently, problems related to weak discriminating power have arisen because multiple DMUs frequently become efficient. The cross-efficiency (CE) evaluation was introduced to increase the discrimination power. The two models, Regular and Neutral, were introduced a long time ago to compensate for the critical weaknesses of CE-DEA. But only a few references have applied these methods to show the increased discriminating power. Also, no literature explicitly has suggested the appropriate proportions of self-evaluation and peer evaluation in deciding the CE scores. The super-efficiency DEA (SE-DEA) method was developed to enhance the discrimination power. This paper might be the first attempt to combine C-, CE-, into SE-DEA methods for designing *DRLNS*, using the two models, Regular and Neutral, integrated into this cross-evaluation method based on the super efficiency scores. This paper also considers the effects of self-evaluation proportion on the various ESs generated by each DEA method.

Using the actual data available for South Carolina, this paper demonstrates the proposed methods to evaluate various *DRLNS* configurations generated by the MOP model. Surprisingly, the proposed methods reveal some hidden efficient network configurations that the regular CE model alone can't identify. We observe that the proposed approach can be an essential tool for designing DRLNS and other supply chain network systems with multiple inputs and multiple outputs. In addition, if some flexibility is added to the efficient network configurations designed by the proposed method, the performance of such networks could be enhanced.

The limitation of this study comes from the assumption that if a DRF, either *CWH* or *RDC*, is disrupted and shut down, the sites, either *NBSs* or *RDCs*, allocated to this DRF won't be covered. For example, if a *CWH* is disrupted, all *RDCs* assigned to this *CWH* and subsequent *NBSs* won't be covered. Future research will enhance this study if the concept of backup operation in the case of facility shutdown is considered. Another limitation of this study assumes that only facilities are subject to disruptions, but disruption can block the flow of relief items due to the trouble of the routes. Thus, it would significantly enhance this study if an emergency backup routing plan is considered for future research.

Acknowledgements

The authors are grateful for the valuable comments from two anonymous reviewers.

Funding

This work was supported by U.S. Department of Education, Grant No. P382G170106.

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