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A Hybrid Genetic Algorithm-Ratio DEA Approach for Assessing Sustainable Efficiency in Two-Echelon Supply Chains

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Abstract: Measuring sustainable efficiency is a wide research topic that has gained increased relevance over the course of the years, particularly in the field of supply chain management. In this paper, novel Data Envelopment Analysis—ratio data (DEA-R) models are used to assess sustainable efficiency in two-echelon supply chains based on endogenous factors. Genetic algorithms are employed to determine optimal productive weights for each echelon and the overall supply chain by taking into account the hidden correlation structures among them as expressed in non-linear multi-objective functions. A case study on 20 firefighting stations is presented to illustrate the approach proposed and its accuracy for decision-making, as long as the issues of pseudo inefficiency and over estimation of efficiency scores are mitigated. Results indicate that the method proposed is capable of reducing efficiency estimation biases due to endogenous sustainable factors by yielding overall scores lower than or equal to the product of the efficiencies of the individual stages.

Keywords: sustainability; endogenous factors; two-echelon supply chains; DEA-R; genetic algorithms

1. Introduction

Companies are increasingly focusing on sustainability dimensions such as environmental and social factors with the aim of reducing industrial waste and non-renewable energy sources while observing human rights and occupational safety in the process of delivering goods and services [1]. Most of these dimensions, however, are measured or expressed in terms of ratio data [2]. To this end, DEA-R, a variant of classical non-parametric DEA—Data Envelopment Analysis—models for ratio data, can be used in computing sustainable efficiency levels, thus helping in ranking, modeling, and scoring different Decision-Making Units (DMUs) based on optimizing productive weights [3]. Generally, as an extension to the DEA technique, the research stream of DEA-RA was proposed by Despic et al. in 2007 [2] by combining DEA with Ratio Analysis (RA). In DEA-RA, the data are not inherently ratios, but the DMUs are evaluated based on defined output-to-input ratios (the output-oriented model) or vice versa (the input-oriented model) [4]. Regarding cases in which the DMUs have ratio parameters, some interesting and comprehensive studies have been conducted by Emrouznejad and Amin [5], Olesen et al. [6,7], and more recently by Hatami–Marbini and Toloo [8]. Under more complex productive structures such as supply chains, the optimization of productive weights is not a straightforward task due to the strong endogenous relationships that may exist among their echelons when delivering goods and services [9]. These hidden trade-offs among how resources are used and products transformed in a supply chain are the cornerstones of these endogenous relationships [10].

Yet supply chain management initiatives stand as an excellent example for designing continuous improvement paths in productive structures built upon distinct echelons [11]. In fact, the effective management of the supply chain entails moving further local efficiency improvements towards a more systemic perspective of performance [12].

Performance measurement along a supply chain has been a research objective for almost two decades, although the measurement locus and methods employed have varied substantially from one study to another. For instance, Waters demonstrated the importance and challenges of the supply chain [13]. Shervadi et al. utilized the Analytic Hierarchy Process (AHP) method in assessing the sustainable supply chain in the printing industry [14]. Tseng and Chiu assessed the global supply chain performance in a printed circuit board manufacturer in Taiwan [15]. Azadi et al. while studying 24 bus companies in Tehran, proposed two alternative DEA models to evaluate the performance of the green supply chains [16]. In addition, research on supply chain measurement is also numerous. Balfaqih provides an overview of 83 articles selected out of a total of 374 studies in the area of supply chain performance measurement where two or more echelons were analyzed over the 1998–2015 time frame [17]. More recent studies from this perspective include, for instance, Tavana et al. who used a network DEA model to evaluate a three-echelon supply chain [18]. In turn, Zhong et al. discussed the warehouse-retailer inventory management issue and designed an integrated supply chain network model [19]. Advancing further into inventory issues, Sing and Verma investigated inventory management in the supply chain by considering the inventory as inputs and benefits as outputs [20]. Yoo and Cheong focused on increasing the quality of the supply chain for buyer-supplier beneficial relationships [21]. Lately, supply chain performance measurement has become a research topic attached to big data analytics issues. For instance, Tiwari et al. examined big data analytics and its application in supply chain management within the ambit of different sectors [22]. Singh and Verma analyzed the supply chain of big data in the food industry and then evaluated the meat supply chain in Australia, the USA, and the UK in 2016 [23]. Nguyen reviewed big data analytics studies in the context of supply chain management in the period 2011–2017 [24]. Lastly, Govindan et al. conducted a review of articles published in Scopus about big data analytics and their application to supply chain management and logistics over the period 2012–2018 [25].

Analogously to other research streams, sustainability is an issue of growing importance in supply chain management. A sustainable supply chain is created by feedbacks among sustainability dimensions or factors mainly related to environmental, economic, and social spheres. These interactions have been studied through a diversity of alternative modeling approaches addressing different research loci ranging from industries and specific sectors to cities and managerial styles. Clift analyzed the development of different dimensions of sustainability in industrial sectors and manufacturing companies [26]. Gauthier used the environmental and social factors to evaluate the supply chain management of products [1]. Sustainability of some Italian regions was conducted by Floridi et al. [27]. Büyüközkan and Çifçi used fuzzy multi-criteria decision-making models in assessing the drivers for sustainable supply chains [28]. Azadi and Saen used a Slacks-Based Measure (SBM) model with undesirable outputs to analyze sustainable issues in 20 IT companies in Iran [29]. Eskandarpour et al. reviewed 87 articles in the period 1991–2014 for compiling the different factors involving the building up of sustainable supply chains [30].

Since the majority of metaheuristic algorithms are inspired by natural phenomena, these algorithms can be efficient in solving mathematical models that are in non-linear form. Rajpurohit et al. classified the optimization methods into the categories of deterministic and heuristic ones while also carefully gathering 117 references related to these alternative categories [31]. The need for using metaheuristic methods to solve certain problems has become apparent in recent years due to the application of DEA in organizations and using mathematical models for evaluating DMUs. Therefore, some studies have been conducted on the subject of DEA and metaheuristic algorithms, which are briefly mentioned. Gonzalez et al. presented a model for calculating the minimum distance of the DMU under evaluation to the efficiency frontier, and they used the genetic algorithm for solving it [32]. With regard to the applications of the genetic algorithm and determining suitable benchmarks for inefficient units, Martinez–Moreno et al. proposed an efficient method for obtaining better solutions [33]. In many mathematical models, we are faced with non-deterministic polynomial-time (NP) hardness problems. For solving these problems, Gonzalez et al. used a parallel metaheuristic algorithm to find the optimal solution. They claimed that their proposed method has low computational time and can compete with accurate methods [34]. Although, aside from the genetic algorithm, the ant colony algorithm is also used to solve such problems. In this regard, Liu et al. proposed a hybrid algorithm based on genetic-ant colony optimization for finding and selecting optimal paths. Their proposed algorithm was based on speeding up the convergence rate and improving the efficiency [35]. What is interesting about the use of metaheuristic methods is that recently inverse DEA models have shown a wide range of applications in organizations for merging the DMUs. For solving their non-linear models, Gaijarro et al. proposed the InvDEA-GA model by combining inverse DEA with the genetic algorithm and demonstrated two practical applications of the model in banking affairs and higher education [36].

This paper aims at a literature gap in sustainable supply chain performance measurement by designing a hybrid approach capable of simultaneously handling environmental and welfare factors as measured by ratio data. As endogeneity may exist among these factors, which could easily yield to biased weight optimization and pseudo-inefficiency or over-efficient estimates in non-parametric DEA, genetic algorithms were employed for achieving comprehensive unbiased optimal solutions. Precisely, a novel DEA-R model is proposed to measure efficiency scores at each echelon of the supply chain separately, thus helping to mitigate endogeneity. In addition, the overall efficiency score, which is a nonlinear objective function that combines efficiency scores for each echelon, was solved using genetic algorithms. The approach proposed is illustrated in a case study conducted along the supply chains of 20 fire stations in the city of Shiraz, Iran.

The present article is organized as follows: Section 2 reviews the basic concepts of the sustainable supply chain, DEA-R, and the genetic algorithm, while Section 3 presents the hybrid approach for assessing sustainability performance in two-echelon supply chains based on ratio factors and genetic algorithms to handle endogeneity issues. The supply chains of 20 fire stations in Iran are evaluated in Section 4, with the conclusions following in Section 5.

2. Literature Review

The use of alternative DEA approaches is worth noting in the sustainable supply chains research arena. Tajbakhsh and Hassini used Data Envelopment Analysis to calculate the overall efficiency and efficiency of each echelon in the sustainable supply chain and discussed two applied studies of banks and manufacturing companies [37]. Considering the environmental factor, Ding et al. conducted the analysis of sustainability of the supply chain in a case study of the impact of trade on the environment in China [38]. Haghighi et al. utilized a DEA-BCC model in evaluating supply chain models and 40 plastic recycling plants located in Mazandaran and Gilan provinces of Iran [39]. Izadikhah and Saen applied a two-echelon DEA network and negative data from radial and non-radial models for studying 29 medical device companies [40]. Ji et al. used a DEA method for the sustainable supply chain management while taking into account the environmental factor that aims for less resource consumption and pollution emissions, and then evaluated one air-conditioning equipment manufacturer in China [41]. Jauhar regarded the environmental aspects while measuring the efficiency of 19 higher educational centers in India [42].

The causes for the prominence of alternative DEA models in sustainable supply chain research are twofold. First, in a sustainable supply chain, outputs can be divided into two categories: desirable and undesirable. The higher the values of desirable outputs, the higher the efficiency scores, and conversely the higher the values of undesirable outputs yield, the lower the efficiency scores. For instance, wastes, sewage, and CO_2 emissions can have a negative role in assessing the efficiency of productive units [43,44]. Second, economic performance of firms is often based on financial ratios. While DEA-R was first introduced by Despic et al. a handful of different research presented advances in better understanding the impact of using ratio data in non-parametric efficiency measurement [2]. Convexity assumption, pseudo-inefficiency, cost/revenue frontiers, and production possibility sets are issues commonly found in DEA-R models [3,5–7,45]. In DEA, the DMUs are evaluated based on defined input and output parameters, but in DEA-RA the evaluation is carried out based on input-to-output ratios or vice versa. The advantages of DEA-RA models include not using the non-Archimedean number ε, lack of pseudo-inefficiency, and the possibility of using defined ratio factors to evaluate the DMUs more accurately [4,46].

Genetic Algorithm (GA) is a method for solving unconstrained and constrained optimization problems based on the theory of natural selection (i.e., the process that advances the biological evolution). The genetic algorithm was first introduced by Holland [47]. Then Koza et al. used GA to solve and optimize advanced engineering issues [48]. They processed GA into a computer language for the first time and devised a programming language called Genetic Programming (GP). GA modifies a population of unique solutions and randomly chooses individuals as parents from the current generation at each step and uses them to create the next generation of children. The population of solutions over successive generations evolves towards the optimal solution. However, in the genetic algorithm, a set of points is created at each computational echelon and the next-generation population is determined by the computation of random numbers. Dao et al. conducted a review of GA analysis throughout history based on the year of publication, field of research, institutions, and authors [49].

The genetic algorithm can be applied to various optimization problems for which classical optimization algorithms are not able to solve. For instance, we can consider discontinuous, non-derivative, or non-linear objective functions, which are very common in supply chain modelling and optimization. Cichenski et al. referred to minimizing the cost of supply process in charitable organizations using genetic algorithms [50]. González et al. determined the least distance to all dimensions of the efficiency frontier in DEA using the genetic algorithm [32]. Diabat and Deskoores utilized the genetic algorithm in assigning retailers to warehouses and therefore minimizing the cost of operating the supply chain [51]. Garmendia and Anglada applied mathematical models and genetic algorithms for analyzing the temperature in spacecraft and space instruments [52]. Tari and Hashemi used a genetic algorithm to minimize the cost of moving the product of a manufacturing company to warehouses [53]. To incorporate management's views, Ebrahimi et al. assigned weight restrictions in order to measure the efficiency of units using the genetic algorithm [54].

3. Hybrid Genetic Algorithm-Ratio DEA Approach

3.1. DEA-R Background

Assume that n decision making units consuming m inputs $X_j = \left(x_{1j}, x_{2j}, \ldots, x_{mj}\right)$ produce s outputs $Y_j = \left(y_{1j}, y_{2j}, \ldots, y_{sj}\right)$. Also assume that ratios of $Xj > 0$ and $\frac{y_{rj}}{x_{ij}}$ are defined. The output-oriented DEA-R model as presented by [3] with the goal of increasing the output-to-input ratio for the unit under the evaluation $o \in \{1, \ldots, n\}$ is given as below [55]:

$\max \alpha_o$

S.t.

$$\sum_{j=1}^{n} \lambda_j \left(\frac{y_{rj}}{x_{ij}}\right) \geq \alpha_o \left(\frac{y_{ro}}{x_{io}}\right) \; i = 1, \ldots, m, r = 1, \ldots, s, \tag{1}$$

$$\sum_{j=1}^{n} \lambda_j = 1,$$

$$\lambda_j \geq 0 \; j = 1, \ldots, n.$$

Model (1) is a linear programming problem under the constant-returns to scale technology that evaluates the output-oriented DMUo. Also, $(\lambda_1, \lambda_2, \ldots, \lambda_n) \in Rn$ and αo are variables of model (1).

Definition 1. *DMUo is efficient in the output-oriented DEA-R model if* $\alpha_o^* = 1$ [45].

Considering variables Wir and β for the first and second restrictions in finding the duality of model (1), the output-oriented DEA-R multiplier model under constant-returns to scale technology is presented for evaluating DMUo as follows [3]:

$\min \beta_o$

S.t.

$$\sum_{i=1}^{m}\sum_{r=1}^{s} w_{ir}\left(\frac{\frac{y_{rj}}{x_{ij}}}{\frac{y_{ro}}{x_{io}}}\right) \le \beta_o,\ \mathrm{j} = 1,\ldots,\mathrm{n}. \tag{2}$$

$$\sum_{i=1}^{m}\sum_{r=1}^{s} w_{ir} = 1\,,$$

$$w_{ir} \ge 0, i = 1,\ldots,m, r = 1,\ldots,s\,.$$

DEA-R models in the present study offer the following advantages:

(1) In the DEA model, the efficiency is obtained from the ratio of the weighted sum of output to the weighted sum of input, but in the DEA-R model, the efficiency is defined as the weighted sum of the ratio of output-to-input. Therefore, based on the definition of efficiency in DEA-R, there is no need to use the non-Archimedean number ε, but the approach for constructing PPS is different [2].
(2) DEA-R models prevent pseudo inefficiency [3].
(3) The pattern of inefficient units in DEA-R are more realistic and more accessible than inefficient patterns in DEA.
(4) DEA models are not capable of evaluating units when only ratio data exists. On the other hand, DEA-R models are able to evaluate the efficiency of units if data of inputs, outputs, or a proportion of data are available [45,46].

3.2. Modelling Supply Chain Echelon Efficiencies with Ratio Factors

A two-echelon supply chain consists of input vectors $\mathrm{X_j} = \left(\mathrm{x_{1j}}, \mathrm{x_{2j}}, \ldots, \mathrm{x_{mj}}\right)$ and output vectors $\mathrm{Y_j} = \left(\mathrm{y_{1j}}, \mathrm{y_{2j}}, \ldots, \mathrm{y_{sj}}\right)$ and intermediate vectors $\mathrm{Z_j} = \left(\mathrm{z_{1j}}, \mathrm{z_{2j}}, \ldots, \mathrm{z_{tj}}\right)$. The intermediate vectors are considered as the output of the first echelon and the input of the second echelon. In classical DEA models, intermediate vectors do not play any role in calculating the efficiency, and input and output vectors are only used for calculating efficiency scores. However, in network models, intermediate vectors play a significant role in calculating the efficiency of the supply chain due to feedbacks and mutual interactions that may exist between individual solutions and their respective weights. Further, outputs are divided into two categories, namely: desirable $\mathrm{Yg_j} = \left(\mathrm{yg_{1j}}, \mathrm{yg_{2j}}, \ldots, \mathrm{yg_{r2j}}\right)$ and undesirable $\mathrm{Yb_j} = \left(\mathrm{yb_{1j}}, \mathrm{yb_{2j}}, \ldots, \mathrm{yb_{r3j}}\right)$. The general form of the sustainable supply chain is as follows: all Xj and Zj and $\mathrm{Yg_j}$ and $\mathrm{Yb_j}$ vectors in all components are positive (cf. Figure 1).

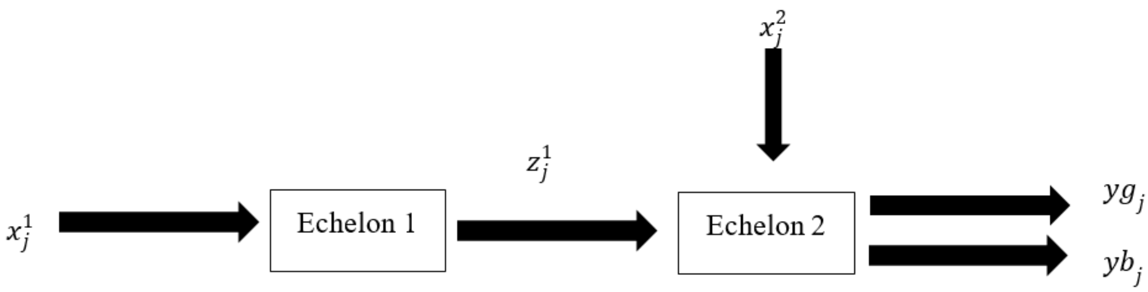

Figure 1. Two-Echelon Sustainable Supply Chain with Undesirable Outputs.

where:

$\mathrm{x_{ij}^1}$: ith input of the first echelon DMUj i $\in \mathrm{I_1}$

$\mathrm{x_{ij}^2}$: ith input of the second echelon DMUj i $\in \mathrm{I_2}$

$\mathrm{yb_{r_3j}^2}$: r3th undesirable output of the second echelon DMUj $\mathrm{r_3} \in \mathrm{R_3}$

$yg^2_{r_2j}$: r2th desirable output of the second echelon DMUj $r_2 \in R_2$

z^1_{tj} : tth intermediate vector DMU_j $t \in T$

Here, I_1 is the set of inputs in the first echelon, I_2 is the set of inputs in the second echelon, R_3 is the set of undesirable outputs in the second echelon, R_2 is the number of desirable outputs in the second echelon, and T is the number of outputs in the first echelon and inputs in the second echelon. Also, $|I_1| = m_1, |I_2| = m_2, |R_2| = s_2, |R_3| = s_3, |T| = k$. The proposed model for calculating the efficiency score in the first echelon is presented as follows:

$E_1{}^* = \max \varphi_1$

S.t.

$$\sum_{j=1}^{n} \lambda_j{}^1 \left(\frac{z^1_{tj}}{x^1_{ij}} \right) \geq \varphi_1 \left(\frac{z^1_{to}}{x^1_{io}} \right) \quad i \in I_1, t \in T, \tag{3}$$

$$\sum_{j=1}^{n} \lambda_j{}^1 = 1,$$

$$\lambda_j{}^1 \geq 0 \; j = 1, \ldots, n.$$

Here, $\left(\lambda_1{}^1, \lambda_2{}^1, \ldots, \lambda_n{}^1\right) \in R^n$ and φ1 are considered as variables of model (3) in evaluating the output oriented DMUo.

Definition 2. *DMUo in Model (3) (the first echelon of the supply chain) is efficient if* $E_1{}^* = 1$.

Model (3) is a linear model and E_1^* represents the efficiency score of the first echelon.

Theorem 1. *Model (3) is always feasible and* $\varphi_1{}^* \geq 1$.

Proof. In model (3), considering $\left(\overline{\lambda}_1{}^1, \overline{\lambda}_2{}^1, \ldots, \overline{\lambda}_n{}^1\right) = e_o$ and $\bar{\varphi}_1 = 1$ for the set of first constraints, $\frac{z^1_{to}}{x^1_{io}} = \frac{z^1_{to}}{x^1_{io}}$ holds, and in the constraint of $\sum_{j=1}^{n} \lambda_j{}^1 = 1$, we have 1 = 1. Therefore, model (3) is always feasible. On the other hand, since $\bar{\varphi}_1 = 1$, then model (3) is a type of maximization model, $\varphi_1{}^* \geq 1$. □

In the second echelon, inputs include z^1_{tj} and x^2_{ij} and desirable output is the vector of $yg^2_{r_2j}$ while undesirable output is the vector of $yb^2_{r_3j}$. The proposed model for calculating the efficiency score in the second echelon is presented as follows:

$E_2{}^* = \max \gamma_2$

S.t.

$$\begin{gathered}
\sum_{j=1}^{n} \lambda_j{}^2 \left(\frac{yg^2_{r_2j}}{x^2_{ij}} \right) \geq \gamma_2 \left(\frac{yg^2_{r_2o}}{x^2_{io}} \right) i \in I_2, r_2 \in R_2, \\
\sum_{j=1}^{n} \lambda_j{}^2 \left(\frac{yg^2_{r_2j}}{yb^2_{r_3j}} \right) \geq \gamma_2 \left(\frac{yg^2_{r_2o}}{yb^2_{r_3o}} \right) r_2 \in R_2, r_3 \in R_3, \\
\sum_{j=1}^{n} \lambda_j{}^2 \left(\frac{yg^2_{r_2j}}{z^1_{tj}} \right) \geq \gamma_2 \left(\frac{yg^2_{r_2o}}{z^1_{to}} \right) t \in T, r_2 \in R_2, \\
\sum_{j=1}^{n} \lambda_j{}^2 = 1, \\
\lambda_j{}^2 \geq 0 \; j = 1, \ldots, n.
\end{gathered} \tag{4}$$

Model (4) is a linear programming problem for evaluating DMU_o in the second echelon in which $\left(\lambda_1{}^2, \lambda_2{}^2, \ldots, \lambda_n{}^2\right) \in R^n$ and γ_2 are variables of model (4).

Definition 3. *DMUo in Model (4), the second echelon of the supply chain, is efficient if* $E_2{}^* = 1$.

Theorem 2. *Model (4) is always feasible and* $\gamma_2{}^* \geq 1$.

Proof. Suppose $\left(\overline{\lambda}_1{}^2, \overline{\lambda}_2{}^2, \ldots, \overline{\lambda}_n{}^2\right) = e_o$ and $\overline{\gamma}_2 = 1$ is a feasible solution for which all constraints hold and the objective function is of a maximization type. So $\gamma_2{}^* \geq 1$. □

A key issue in measuring the performance of a DMU that represents a supply chain is calculating the overall efficiency. Suppose the efficiency score of a DMU is 0.9 in one echelon of the supply chain and that in the second echelon the efficiency score is 0.1. Determining the overall status of the DMU is not straightforward like in productive echelons that belong to the same company. Therefore, the overall efficiency score is a more adequate criterion for measuring supply chain performance.

3.3. Using Genetic Algorithms to Assess Overall Supply Chain Performance

When calculating the overall efficiency in a two-echelon supply chain, due to the fact that ratios of $\frac{\text{desirable output}}{\text{undesirable output}}$, $\frac{\text{desirable output}}{\text{input of the second echelon}}$, $\frac{\text{desirable output}}{\text{undesirable output}}$, and $\frac{\text{desirable output}}{\text{intermediate}-\text{vector}}$ are available, the proposed combination of models (3) and (4) is given as follows:

$$
\begin{aligned}
& E_T{}^* = \max(\varphi_1 \times \gamma_2) \\
& \text{S.t.} \\
& \textstyle\sum_{j=1}^{n} \lambda_j{}^1 \left(\frac{z^1_{tj}}{x^1_{ij}}\right) \geq \varphi_1 \left(\frac{z^1_{to}}{x^1_{io}}\right) \quad i \in I_1, t \in T, \\
& \textstyle\sum_{j=1}^{n} \lambda_j{}^1 = 1 \\
& \textstyle\sum_{j=1}^{n} \lambda_j{}^2 \left(\frac{yg^2_{r_2j}}{x^2_{ij}}\right) \geq \gamma_2 \left(\frac{yg^2_{r_2o}}{x^2_{io}}\right) \quad i \in I_2, r_2 \in R_2, \\
& \textstyle\sum_{j=1}^{n} \lambda_j{}^2 \left(\frac{yg^2_{r_2j}}{yb^2_{r_3j}}\right) \geq \gamma_2 \left(\frac{yg^2_{r_2o}}{yb^2_{r_3o}}\right) \quad r_2 \in R_2, r_3 \in R_3, \\
& \textstyle\sum_{j=1}^{n} \lambda_j{}^2 \left(\frac{yg^2_{r_2j}}{z^1_{tj}}\right) \geq \gamma_2 \left(\frac{yg^2_{r_2o}}{z^1_{to}}\right) \quad t \in T, r_2 \in R_2, \\
& \textstyle\sum_{j=1}^{n} \lambda_j{}^2 = 1, \\
& \lambda_j{}^1, \lambda_j{}^2 \geq 0 \quad j = 1, \ldots, n
\end{aligned}
\tag{5}
$$

Model (5) presents a nonlinear objective function that is multiplied by variables φ1 and γ2, but the constraints of model (5) have a linear form. This non-linear objective function not only represents the interaction between individual efficiencies of both echelons, but also hides feedback processes driven by endogenously defined weights during individual optimizations.

Definition 4. *DMUo in model (5), the final echelon of the supply chain, is efficient if* $E_T{}^* = 1$.

Theorem 3. *Model (5) is always feasible.*

Proof. Suppose in model (5) $\left(\overline{\lambda}_1{}^1, \overline{\lambda}_2{}^1, \ldots, \overline{\lambda}_n{}^1\right) = e_o$ and $\left(\overline{\lambda}_1{}^2, \overline{\lambda}_2{}^2, \ldots, \overline{\lambda}_n{}^2\right) = e_o$ and $\overline{\varphi}_1 = \overline{\gamma}_2 = 1$. Hence, with the substitution of these terms into the constraints of model (5), it is observed that the solution proposed always holds for the constraints of model (5), Hence, model (5) is always feasible. □

To solve model (5) with the nonlinear objective function, the constraints of model (5) are expressed in the form of matrix AX ≥ b, and the following genetic algorithm is proposed:

Step (1) Constraints of model (5) are presented in the form of AX ≥ b by taking into account the variables of $\left(\lambda_1{}^1, \lambda_2{}^1, \ldots, \lambda_n{}^1\right)$, $\left(\lambda_1{}^2, \lambda_2{}^2, \ldots, \lambda_n{}^2\right)$, γ_2, and φ_1 as follows:

$$A=\begin{bmatrix} \frac{z^1}{x^1} & -1 & & & \\ 1 & 0 & \cdots 0 & & \\ -1 & 0 & & & \\ & & & \frac{yg^2}{x^2} & -1 \\ & & & \frac{yg^2}{yb^2} & -1 \\ 0 & & \cdots & \frac{yg^2}{z^1} & -1 \\ & & & 1 & 0 \\ & & & -1 & 0 \end{bmatrix}, X=\begin{bmatrix} \lambda_1{}^1 \\ \vdots \\ \lambda_n{}^1 \\ \varphi_1 \\ \lambda_1{}^2 \\ \vdots \\ \lambda_n{}^2 \\ \gamma_2 \end{bmatrix},\ b=\begin{bmatrix} 0 \\ \vdots \\ 0 \\ 1 \\ -1 \\ 0 \\ \vdots \\ 0 \\ 1 \\ -1 \end{bmatrix}$$

where $z^1_{k\times n}$, $x^1_{m_1\times n}$, $x^2_{m_2\times n}$, ${yg^2}_{s_2\times n}$, and ${yb^2}_{s_3\times n}$. Also, $|I_1| = m_1, |I_2| = m_2, |R_2| = s_2, |R_3| = s_3, |T| = k$. So matrix A of order $((m_1 \times k) + 2) + ((s_2 \times m_2) + (s_2 \times s_3) + (s_2 \times k) + 2)) \times (2n + 2)$ is considered.

Step (2) Since the objective function of model (5) is in the form of a non-linear product, the initial parameters of the algorithm are determined, which according to the most important parameter is the population size. A random population is created by considering the feasible solutions of the problem. Since X is a vector of order $(2n + 2) \times 1$, then the initial population, which is a set of feasible solutions, is considered as follows:

$$\lambda_j{}^1 = 0, \lambda_j{}^2 = 0,\ j \neq o$$

$$\lambda_o{}^1 = 1, \lambda_o{}^2 = 1$$

$$\varphi_1 = 1, \gamma_2 = 1.$$

So, the initial population are feasible solutions of

$$\overline{X}=\begin{bmatrix} \overline{\lambda}_1{}^1 \\ \vdots \\ \overline{\lambda}_n{}^1 \\ \overline{\varphi}_1 \\ \overline{\lambda}_1{}^2 \\ \vdots \\ \overline{\lambda}_n{}^2 \\ \overline{\gamma}_2 \end{bmatrix}.$$

Step (3) $\overline{X}$ is replaced in the objective function with $E_T{}^* = \varphi_1.\gamma_2$.

Step (4) All feasible solutions of this generation are calculated and stored using the quality assessment function. In model (5), by considering the feasible solutions and putting them into the maximum objective function, we obtain the value of the objective function based on feasible solutions.

Step (5) We determine parents from feasible solutions. The pair of feasible solutions of model (5) is selected as the parent in which the parent selection process is conducted based on the values stored in the evaluation function. Each pair of feasible solutions is combined together and produces one or two child feasible solutions. By using the cross-over operator, parts of the corresponding elements of feasible solutions (parents) are replaced with each other, which makes the children enjoy the characteristics of their parents.

Step (6) By using the mutation operator, we consider some components of feasible solutions and then modify them in order to deviate from the local optimal solution.

Step (7) A number of feasible solutions are selected for being replaced in the new generation, and the rest of the new generation is selected from the previous generation's solutions. Then the new generation substitutes for the previous generation.

Step (8) The value of the objective function $E_T{}^* = \varphi_1.\gamma_2$ is obtained from the feasible solutions of Step (7).

Step (9) The termination condition for the algorithm and the convergence of chromosomes (feasible solutions) to the optimal solution are analyzed. If the termination condition is not fulfilled, the execution of the algorithm restarts from Step (5). Otherwise, the best feasible solution of the current generation is considered as the final solution with the termination of the algorithm being shown. If the termination condition (i.e., the number of repetitions) hold, then the algorithm stops, otherwise we return to Step (4).

The flowchart for computing the efficiency of the first and second echelons and the overall efficiency of the two-echelon supply chain is shown in Figure 2.

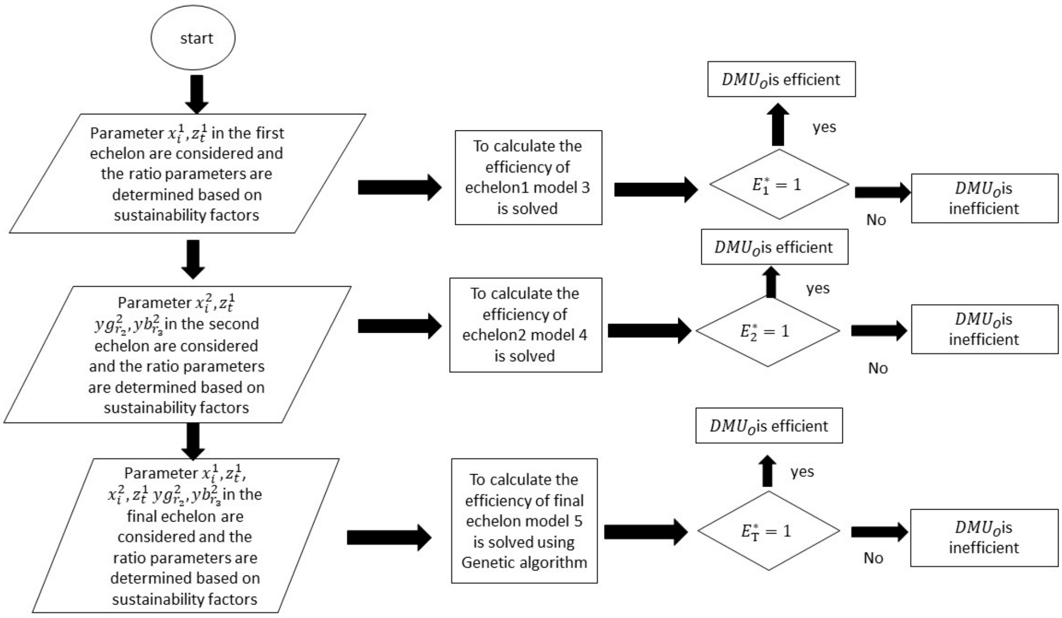

Figure 2. Computational flowchart.

Given that the model proposed for calculating the overall efficiency of supply chains has a non-linear objective function, there are two general methods for calculating the optimal solution in non-linear programming:

I. Classic numerical methods
II. Metaheuristic analytic methods.

In this context, since classic numerical methods are dependent on an initial starting point, some issues arise such as getting stuck at a local point that is not necessarily optimal. Therefore, these methods may be not be efficient enough for evaluating two-echelon supply chains due to the intrinsic endogenous relationships that exist between both echelons.

However, among metaheuristic analytic methods, the genetic algorithm is a simple and basic method for solving the model proposed compared with algorithms such as ant colony or grey wolf algorithms. Although there are issues such as computational complexity in metaheuristic algorithms, they are not as relevant in the case of the genetic algorithm in comparison to alternative approaches.

4. Case Study: Supply Chain Sustainability of Fire Stations

In this section, the efficiency of the two-echelon supply chain related to 20 fire stations in the city of Shiraz, Iran is evaluated based upon environmental, social, and economic factors measured as ratio factors. Fire department services are divided into two categories: firefighting and rescue services. The models proposed in the current study are used to evaluate these two service categories as supply chain echelons. In this context, DEA-RA with ratio sustainability factors being taken into account was chosen as the cornerstone method.

In the firefighting operation, either foam, water, and/or other portable extinguishers are utilized depending on the type of fire. After each operation, the fire engines used for firefighting are refilled by the hydrant valves connected to the tanker and are prepared for the next operation. On the other hand, for the rescue operations, the goal is to save people in situations of risk such as being stuck in elevators, injuries from road accidents, falling into wells, or getting involved in wildlife emergencies. Firefighters use equipment such as toolboxes and air jacks to rescue people and the equipment mix may vary depending on the operational district of stations. Here, the number of toolboxes indicates how well-equipped a station is in its firefighting and accident operations.

Accordingly, fire stations are considered as a two-echelon supply chain in which the apparatus utilized in firefighting and accident operations including water and toolboxes are regarded in the first echelon. Also, the apparatus required such as toolboxes can be considered as an economic factor and water consumption can be considered as an environmental factor due to the water crisis in Iran. The actions taken by the firefighters during the operation are considered in the second echelon. In this echelon, the welfare services provided for citizens and the number of fatalities and survivors in firefighting and the accident operations are considered as the social factors. Figure 3 shows the inputs and outputs of the first and second echelons of the fire station supply chain. Table 1 presents the input and output data of 20 fire stations in the city of Shiraz in 2017:

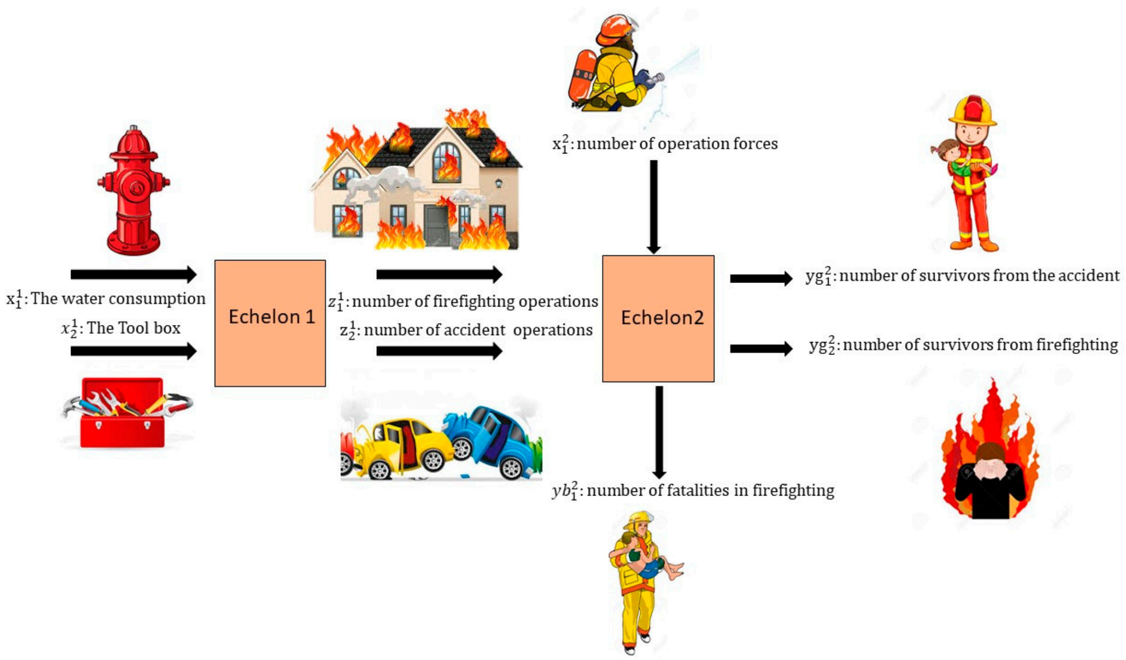

Figure 3. Firefighting supply chain.

Table 1. Inputs and outputs of fire stations.

DMU	Water Consumption	Tool Boxes	Fire Fighting Operations	Accident Operations	Operational Force	Fatalities in Firefighting	Survivors from Accidents	Survivors from Firefighting
1	110,710	118	195	274	21	1	116	100
2	168,196	200	270	524	25	6	92	150
3	321,315	115	240	211	24	6	86	60
4	356,520	314	306	479	24	3	300	95
5	380,331	208	311	518	21	5	368	103
6	122,911	187	276	485	23	4	218	190
7	197,134	132	205	217	20	1	127	28
8	228,352	204	300	324	22	10	186	44
9	419,440	114	242	285	22	6	131	122
10	152,810	50	183	117	19	1	58	20
11	18,330	67	283	214	20	1	56	55
12	73,180	50	113	123	22	1	49	12
13	258,830	22	123	56	20	5	13	14
14	339,980	117	150	204	25	7	86	48
15	192,030	81	116	120	20	1	27	30
16	117,200	6	85	23	10	3	3	2
17	305,280	136	250	218	21	7	67	43
18	252,870	48	171	67	21	4	7	4
19	126,145	118	167	152	21	1	38	32
20	390,932	69	264	133	22	1	42	20

As can be observed in Table 1, fire stations 9 and 11 have the highest and lowest water consumptions, respectively. Meanwhile, station 9 had 6 fatalities in firefighting while station 11 had only one fatality. With regard to the number of survivors from accidents and from firefighting, stations 5 and 6 have the highest numbers, in that order. On the other hand, station 16 had the lowest number of survivors from both accidents and firefighting with 3 and 2 survivors, respectively. Moreover, station 2 with 524 accident operations and station 5 with 311 firefighting operations had the highest number of operations in these two categories. DEA models can evaluate the fire stations based on the parameters presented in Table 1. However, in this section, we evaluate the stations using the DEA-RA models proposed based on the defined ratios provided in Table 2.

Table 2. Ratio of inputs and outputs of fire stations.

Parameters	Definition	Factor Type
$\frac{z_1^1}{x_1^1}$	$\frac{\text{number of firefighting operations}}{\text{water consumption}}$	environmental
$\frac{z_2^1}{x_2^1}$	$\frac{\text{number of accident operations}}{\text{number of toolboxes}}$	economic
$\frac{yg_2^2}{yb_1^2}$	$\frac{\text{number of survivors from firefighting}}{\text{number of fatalities from firefighting}}$	social
$\frac{yg_1^2}{x_1^2}$	$\frac{\text{number of survivors from accidents}}{\text{number of operational forces}}$	social
$\frac{yg_2^2}{x_1^2}$	$\frac{\text{number of survivors from firefighting}}{\text{number of operational forces}}$	social
$\frac{yg_1^2}{z_2^1}$	$\frac{\text{number of survivors from accidents}}{\text{number of accident operations}}$	social

Based on the models presented in Section 3, the ratios of outputs to inputs are defined in Table 2. Firefighting operations may involve several accidents and fire extinguishing simultaneously and the rescue team may conduct several firefighting and accident operations. On the other side, the activity of the operation team is considered useful if the ratio of $\frac{\text{number of survivors from firefighting}}{\text{number of fatalities in firefighting}}$ is at its maximum level, which reduces the number of fatalities and increases the number of survivors. Similarly, for the accident operation, the ratio of $\frac{\text{number of survivors from accidents}}{\text{number of accident operations}}$ is also available.

It is clear that if the number of accidents is low and the number of survivors is high, then the team enjoys an effective performance. The performance improvement of the operational team can be observed by increasing the ratio of the number of survivors from the firefighting or accident operations compared to the number of operational forces, i.e., the ratios of $\frac{\text{number of survivors from accidents}}{\text{number of operational force}}$ and $\frac{\text{number of survivors from firefighting}}{\text{number of operational force}}$.

The second column of Table 3 shows the efficiency scores of the first echelon obtained by solving model 3 and the third column presents the efficiency scores of the second echelon provided by solving model 4. Given that the objective function of model 5 is nonlinear, the overall efficiency scores are presented in the fifth column of Table 3 using the genetic algorithm. The overall efficiency scores have been calculated using Toolbox in MATLab software. It is interesting to note that due to hidden endogenous effects, overall efficiency may not simply be the product of individual efficiencies in some supply chains. While taking into account interactions between echelons and their hidden correlation structures, the non-linear optimization proposed yields unbiased overall scores with higher discriminatory power.

Table 3. Efficiency Scores in Echelons 1 and 2 and Overall Efficiency Scores of Fire Stations.

DMU	Echelon 1 DEA	Echelon 1 DEA-RA	Echelon 2 DEA	Echelon 2 DEA-RA	Echelon 1 × Echelon 2 DEA-RA	Overall.
1	0.722	0.6399	1	1	0.6399	0.6071
2	0.8155	0.7267	0.807	0.807	0.5864	0.4788
3	0.5598	0.4868	0.7745	0.7745	0.3770	0.2617
4	0.4734	0.4163	1	1	0.4163	0.1732
5	0.7673	0.6676	1	1	0.6676	0.2052
6	0.8088	0.7318	1	1	0.7318	0.388
7	0.5082	0.4436	1	1	0.4436	0.3063
8	0.4929	0.4337	0.8081	0.8081	0.3505	0.2577
9	0.756	0.6602	1	1	0.6602	0.5143
10	0.712	0.6198	0.7519	0.7472	0.4631	0.43
11	1	1	0.6929	0.6767	0.6767	0.4027
12	0.7608	0.6643	0.5922	0.5813	0.3862	0.3618
13	0.7119	0.6653	0.584	0.584	0.3885	0.2165
14	0.5314	0.4622	0.7317	0.7341	0.3393	0.2588
15	0.4539	0.3944	0.6378	0.6163	0.2431	0.2207
16	1	1	0.2431	0.2431	0.2431	0.0914
17	0.4918	0.4273	0.5637	0.5637	0.2409	0.1766
18	0.5237	0.3688	0.183	0.183	0.0675	0.0636
19	0.4	0.3525	0.5592	0.5473	0.1929	0.138
20	0.5715	0.5063	0.5413	0.5354	0.2711	0.2488

It should be noted that the data used in the article are non-ratio data, but DEA-RA models evaluate the DMUs based on defined ratios.

The second and third columns of Table 3 show the efficiency scores produced by the output-oriented envelopment model in DEA-RA (Model 3) and by the similar model in DEA under CRS assumption. Stations 11 and 16 are efficient in both DEA and DEA-RA. The DEA and DEA-RA models show a similar behavior in Table 3 (see Wei [3]). Although the difference between DEA and DEA-RA models with m inputs and s outputs lies in the weights corresponding to their multiplicative models, which are m + n and m × n, respectively, this matter has room for further discussion. Based on the fourth and fifth columns of Table 3, fire stations 1, 4, 5, 6, 7, and 9 are efficient.

Generally, our evaluation of the two-echelon supply chains of the fire stations shows that only 2 stations are efficient in the first echelon and 6 stations are efficient in the second echelon. This means that in the first echelon, it is only in two stations that the environmental and economic factors are in relatively suitable conditions (station 11 with the lowest water consumption and station 16 with the lowest number of toolboxes are considered efficient in comparison with other stations). The social factor is not taken into account in the first echelon, as it is not discussable under such conditions. It can be observed that there are more efficient units in the second echelon of the supply chains than there are in the first echelon, and the second echelon is focused on the social factor, which is extremely important. As an example, the efficient stations 1, 5, and 6 are briefly analyzed in the second echelon.

In the second echelon, station 1 is efficient because it has 100 survivors from the firefighting efforts and only 1 fatality from them as can be observed in Table 3. In station 5 there are 368 survivors from accidents with 21 operational forces resulting in a ratio of 17.5238, which is the highest ratio in Table 4. This indicates the capability and efficiency of the managerial team in station 5. In station 6 there are 190 survivors from firefighting efforts with 23 operational forces resulting in a ratio of 8.2609, which is the highest ratio in Table 4. This indicates the capability and efficiency of the support team in improving the social factor.

Table 4. Ratio factors of Fire Stations.

DMU	$\frac{z_1^1}{x_1^1}$	$\frac{z_2^1}{x_2^1}$	$\frac{yg_2^2}{yb_1^2}$	$\frac{yg_1^2}{x_1^2}$	$\frac{yg_2^2}{x_1^2}$	$\frac{yg_1^2}{z_2^1}$
1	0.0018	2.3220	100.00	5.5238	4.7619	0.4234
2	0.0016	2.6200	25.00	3.6800	6.0000	0.1756
3	0.0007	1.8348	10.00	3.5833	2.5000	0.4076
4	0.0009	1.5255	31.6667	12.5000	3.9583	0.6263
5	0.0008	2.4904	20.6000	17.5238	4.9048	0.7104
6	0.0022	2.5936	47.5000	9.4783	8.2609	0.4495
7	0.0010	1.6439	28.0000	6.3500	1.4000	0.5853
8	0.0013	1.5882	4.4000	8.4545	2.0000	0.5741
9	0.0006	2.5000	20.3333	5.9545	5.5455	0.4596
10	0.0012	2.3400	20.0000	3.0526	1.0526	0.4957
11	0.0154	3.1940	55.0000	2.8000	2.7500	0.2617
12	0.0015	2.4600	12.0000	2.2273	0.5455	0.3984
13	0.0005	2.5455	2.8000	0.6500	0.7000	0.2321
14	0.0004	1.7436	6.8571	3.4400	1.9200	0.4216
15	0.0006	1.4815	30.00	1.3500	1.5000	0.2250
16	0.0007	3.8333	0.6667	0.3000	0.2000	0.1304
17	0.0008	1.6029	6.1429	3.1905	2.0476	0.3073
18	0.0007	1.3958	1.0000	0.3333	0.1905	0.1045
19	0.0013	1.2881	32.00	1.8095	1.5238	0.2500
20	0.0007	1.9275	20.00	1.9091	0.9091	0.3158

Generally, more attention has been paid to the social factor in the second echelon because the number of efficient units has tripled in the second echelon as compared with the first echelon. People's intrinsic motivation to save the lives of others can be considered as a reason for this result. In contrast to the first and second echelons of the fire station supply chains, it is observed in the last column of Table 3 (overall efficiency) that none of the fire stations are efficient. Generally solving model (5) through a genetic algorithm shows that the fire station supply chains did not have a suitable performance. The reason for this lies in the inefficiency of stations in the first (90%) and second (30%) echelons.

5. Conclusions

In this study, a hybrid genetic algorithm/DEA-R approach is proposed to handle endogeneity issues in efficiency computation that may arise from sustainability factors such as environmental, social, and economic along supply chains. As a direct consequence of bias removal in weight optimization, the overall efficiency value is always smaller or equal to the efficiency value in the first and second echelons, yielding higher discriminatory power when compared to traditional network DEA approaches where one echelon is sacrificed to the detriment of the other for achieving maximal overall efficiency.

The strength of the DEA-RA models proposed in comparison with corresponding DEA models, in addition to the abovementioned advantages, lies in using the definition of efficiency as a weighted set of input-to-output ratios or vice versa. The proposed models also have similar behavior to DEA models, such as producing efficiency scores between zero and one and finding targets for inefficient units.

Since in the study of the supply chain of fire stations with ratio factors we are dealing with a two-echelon supply chain and the objective is to determine the state of efficiency for echelon 1 and echelon 2, it is of utmost importance to calculate the efficiency scores in the first and second echelons. On the other hand, since calculating the overall efficiency is not dependent on a linear model, it is recommended to use metaheuristic methods to solve the model. The algorithm proposed for evaluating two-echelon supply chains generally aims to identify the efficient and inefficient fire stations and achieve a more accurate evaluation based on sustainability factors.

In our evaluation of the supply chains of fire stations, it is observed that 90% of the stations are not efficient in the first echelon based on environmental and economic factors and 70% of the stations are inefficient in the second echelon based on the social factor. The inefficiency in the first echelon can be explained by the large number of firefighting and accident operations, which would also result in a shortage of operational forces. Furthermore, the issues in the second echelon can be explained by the shortage of operational forces and the increased number of fatalities.

Overall, 10% of the stations were found to be efficient in the first echelon of the supply chain and 30% were deemed inefficient in the second echelon. However, none of the fire stations are efficient based on the overall efficiency scores, which means that both in the first and second echelons of the supply chain, it is necessary to increase and decrease the input and output parameters, respectively.

Finally, according to the overall efficiency scores based on the genetic algorithm, none of the stations are efficient. The results produced by the genetic algorithm indicate that the number of accident and firefighting survivors and the reduced number of fatalities (social factor) alone cannot be proper criteria for evaluation, since improvements in environmental and economic factors are also important in the overall evaluation of fire stations.

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