Research Article

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Benchmarking the efficiency of distribution warehouses using a four-phase integrated PCA-DEA-improved fuzzy SWARA-CoCoSo model for sustainable distribution

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Abstract: In a dynamic market marked by disruptions like pandemics and recessions, organizations face significant challenges in efficiently managing logistics processes and activities. The primary objective of this article is to propose an integrated four-phase model for assessing the efficiency of retail distribution warehouses based on principal component analysis-data envelopment analysis-improved fuzzy step-wise weight assessment ratio analysis-combined compromise solution (PCA-DEA-IMF SWARA-CoCoSo). The model provides a synergistic effect of all positive sides of the considered methods. PCA-DEA methods are used to reduce the number of variables and to identify efficient warehouses. IMF SWARA is applied to determine criteria weights, while the CoCoSo method is employed in the last phase for ranking efficient warehouses. The model incorporates 18 inputs and 3 outputs, derived from both literature and real-world systems. The proposed model identifies the most efficient warehouses, which can serve as benchmarks for improving the performance of less efficient ones. After implementing PCA-DEA, only seven warehouses were identified as efficient. Subsequently, fixed and variable costs are identified as the two most important criteria. Results of the considered case study indicate that warehouse A4 emerges as the best one, whereas A6 is the least preferred warehouse. This research offers valuable insights and practical implications for organizations operating in dynamic markets, assisting them in achieving operational excellence and improving their supply chain performance.

Keywords: distribution, warehouses, efficiency, logistics, performance, four-phase model, MCDM, retail

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1 Introduction

In the context of sustainable distribution, the retail industry, acting as a pivotal intermediary between manufacturers and consumers, plays a crucial role in modern economies. An efficient and effective retail supply chain management (SCM) is essential to ensure the smooth flow of goods from production to consumption. Extending the focus to sustainable practices in SCM becomes paramount, emphasizing the need for not only efficiency and effectiveness but also environmental and social considerations. The retail SC is susceptible to various external factors like pandemics, wars, and recessions, which can disrupt operations and further underscore the importance of building robust and adaptable SCM systems [1].

Within the retail SCM, warehouses represent vital links that facilitate the acquisition of goods from suppliers and their subsequent distribution to retail stores. The efficiency of warehouse operations is very important, as it directly influences not only the price of the final product but also its condition upon arrival at retail stores and its availability on the shelves. Thus, optimizing warehouse efficiency becomes imperative, particularly in the face of external disruptions that emphasize the need for resilience and responsiveness in retail SC [2]. However, the efficiency of warehouse processes has been relatively underexplored in the literature.

This study significantly addresses a notable gap in the existing literature by focusing specifically on measuring the efficiency of warehouses within the retail SC using a comprehensive and practical approach. This research aims to contribute to the existing body of knowledge by providing a robust framework for evaluating and enhancing warehouse performance. The unique contributions of this study include the development of an integrated model, incorporation of a comprehensive set of variables, systematic phases for efficiency assessment, identification of critical criteria, and practical implications for benchmarking and operational excellence in dynamic markets. The identification of critical criteria is another significant aspect of this research. By pinpointing the criteria that substantially impact warehouse efficiency, this study offers valuable insights for decision-makers and practitioners. Such insights provide better strategies for enhancing warehouse performance, thereby contributing to the broader success of the retail SC. The insights gained from this study can be applied not only in the context of Serbia but also in other regions and industries, fostering better warehouse management practices and facilitating the achievement of operational excellence in the retail SC. After the literature review, it has been identified that most of the articles deal with the location selection problem [4–7] and not with measuring the efficiency. Besides that, a small number of articles deal with the problems in retail SCs and none with the measurement of process efficiency [1].

The objective of this article is to develop a comprehensive model for measuring the efficiency of distribution warehouse (DW) operations within the retail SC based on a four-phase integrated model encompassing principal component analysis-data envelopment analysis-improved fuzzy step-wise weight assessment ratio analysis-combined compromise solution (PCA-DEA-IMF SWARA-CoCoSo) methodology. In order to determine the efficient DWs in the first phase, PCA-DEA methods were used in the second phase. Due to the relatively large number of observed indicators and a smaller number of DMUs, the classic DEA model does not yield the best results. For this reason, the PCA-DEA approach was applied, which minimizes the shortcomings of the DEA method [3]. After determining the efficient DWs in the second phase, the IMF SWARA method was applied to determine criteria weights in the third phase. This method is applied since it was easier to evaluate alternatives in accordance with criteria using fuzzy scales. One reason for implementing the IMF SWARA method is that the triangular fuzzy number (TFN) scale used in this method allows for precise and higher-quality determination of the significance of criteria [8]. Another reason for implementing IMF SWARA method instead of some others (such as analytic hierarchy process [AHP], PIvot Pairwise RElative Criteria Importance Assessment [PIPRECIA], PIPRECIA-S, etc.) is reflected in the fact that IMF SWARA has smaller number of pairwise comparisons and it is easy to use (which is especially important when proposing a model that will be used by the managers or other decision-makers that are not so familiar with these methods). SWARA is known for its straightforward and intuitive approach. The step-wise process of assessing criteria weights makes it accessible to decision-makers, even those without extensive expertise in decision analysis. SWARA provides a systematic and transparent way to assess criteria weights. The step-wise nature of the method allows decision-makers to understand and validate the weight assignment process at each stage. This transparency contributes to the credibility of the decision-making process.

Once the criteria weights were established, the CoCoSo method was applied in the fourth phase in order to determine the final ranking of DWs. The main reason why the CoCoSo method was applied in this article is reflected in the fact that this method is reliable and stable. The CoCoSo method is effective in handling conflicting objectives or criteria and seeks a compromise solution that balances the trade-offs between different criteria, providing a more realistic and balanced approach to decision-making. The CoCoSo method offers clarity in how criteria are weighted and combined, making it easier for stakeholders to understand the decision-making outcomes [9]. In order to determine the overall utility of the alternatives, the CoCoSo method uses three aggregation strategies. The developed model contributes twofold: first, it fills a gap in the relatively scarce literature on warehouse process efficiency in the retail sector; second, it provides decision-makers with a quick and efficient means to enhance their warehouse processes.

By creating such a model, the authors aim to provide a practical and standardized approach to assess and improve warehouse performance. The model's primary motivation is to enable simple and efficient measurement of warehouse efficiency, allowing for the identification of areas for enhancement and the implementation of appropriate corrective actions. Through the application of this model, decision-makers can make decisions to enhance the overall efficiency and effectiveness of their retail SCs. Efficiency measurement in the retail sector holds immense significance as it directly influences product pricing, which, in turn, hinges on the effectiveness of logistics processes. The pricing strategy of retailers is intricately tied to the efficiency of their SC operations. Beyond mere cost considerations, enhancements in warehouse processes exert a profound impact on overall SC performance and operational excellence. Improving warehouse processes not only optimizes costs but also has a ripple effect on various facets of SC. For instance, efficient logistics processes play a pivotal role in on-shelf availability, directly influencing sales. By minimizing lead time and delivery time, as well as enhancing service quality and reliability, retailers can ensure that products are readily accessible to consumers, fostering an environment conducive to increased sales and customer satisfaction. Moreover, the efficiency gains achieved in warehouses translate to higher productivity using the same resources. This not only contributes to cost-effectiveness but also reduces the necessity for additional investments, thereby enhancing the overall efficiency of the SC. The optimization of resources, including manpower and equipment, is a direct outcome of efficient processes. This resource utilization efficiency contributes to higher productivity levels, bolstering the retailer's ability to meet demands without escalating operational costs. In a dynamic retail landscape, adaptability is a key differentiator. Efficient warehouses, by design, can swiftly adapt to changing market demands and trends. This adaptability positions retailers to introduce new products seamlessly, respond promptly to seasonal shifts, and stay ahead of competitors, thereby ensuring sustained relevance in the market.

To evaluate and validate the proposed model, a case study involving 18 DWs operated by a company in Serbia is conducted. By examining a real-world scenario, the authors aimed to ensure the model's applicability and effectiveness in capturing the complexities and challenges faced by DWs in the retail SC. The case study provided valuable insights into the practical implementation of the model, allowing us to identify its strengths and limitations while deriving actionable recommendations for improving warehouse operations.

The article is structured as follows: Section 2 provides an overview of relevant literature on SC efficiency and warehouse management, highlighting gaps in existing research. Section 3 outlines the proposed model for measuring warehouse efficiency in retail SC. Section 4 describes the case study and presents the results. Section 5 analyzes and discusses research implications, exploring potential avenues for future exploration along with sensitivity analysis. Finally, in Section 6, key findings are summarized, emphasizing the significance of the developed model in improving warehouse operations within retail SC.

2 Problem description and literature review

2.1 Problem description

Measuring efficiency in logistics is a subject that has received considerable attention in the literature. Understanding and measuring warehouse efficiency is essential to optimizing logistics operations. There are various models and approaches for measuring logistics process efficiency in particular systems. However, the analysis of warehouse efficiency in trade SCs has not been adequately explored in the literature [1]. In this sense, certain gaps have been identified. The first gap refers to the definition of key indicators that provide the most accurate information about the warehouse's and distribution center's operations. In the literature, a small number of available indicators are often used, which do not describe how the observed system is working in the best way.

The second gap is related to the lack of adequate models for measuring warehouse efficiency. In fact, there are no models in the literature dealing with measuring warehouse efficiency in retail SCs. The third gap that is present in the literature regarding efficiency measurement in logistics is the lack of specific case studies and testing of theoretical models on real examples. Many models proposed in the literature (e.g., network DEA models that are more suitable for simplified networks and do not perform well when considering complex networks) cannot be applied to real logistics systems due to numerous limitations. All previously mentioned gaps are the research subject in this article. A new PCA-DEA-IMF SWARA-CoCoSo model has been proposed for measuring warehouse efficiency in retail SCs. Special emphasis is given to the indicators that describe observed warehouses in the best way. The approach was proposed and tested on a real system (company) and overcomes all limitations of existing models in the literature. A limitation observed in all existing research is the absence of models that comprehensively address the presented problem.

2.2 Literature review

Liu and Li [4] proposed a two-dimensional linguistic similarity-degree-based clustering analysis method, the two-dimensional linguistic partitioned Maclaurin symmetric mean operator, and the two-dimensional linguistic weighted partitioned Maclaurin symmetric mean operator for comprehensive logistics DC location selection. Similarly, a model for location selection for a fruit DC in the southern and eastern regions of Serbia based on an AHP and weighted aggregated sum product assessment methods has been proposed [5]. In order to evaluate potential retail locations for the apparel stores, Burnaz and Topcu [6] developed an approach based on the analytic network process (ANP). For this purpose and in order to obtain the results, the authors observed 23 criteria and 2 alternatives. Kuo [7] implemented a hybrid methodology, integrating fuzzy decision-making trial and evaluation laboratory and AHP-ANP methods, for solving the intricate challenges of international distribution center (IDC) location selection in the context of complex decision-making and uncertain conditions. Ou and Chou [10] addressed a similar problem where the selection of an IDC from a foreign market perspective was resolved through the application of a weighted fuzzy factor rating system. Liao et al. [11] proposed the Pythagorean fuzzy CoCoSo method for selecting a distribution center in a cold chain. In addition to DC selection, a review of existing literature revealed the presence of articles addressing DC location selection. Nong [12] proposed a hybrid model based on ANP and a technique for order preference by similarity to the ideal solution (TOPSIS) for distribution center location selection. The ANP method was used to determine the criteria weights, while the TOPSIS method was used to rank alternatives. Similarly, Hu et al. [13] proposed an algorithm for logistics DC location selection for supply and demand network enterprises. The authors proposed an improved firefly algorithm in order to improve the optimization effectiveness of the traditional methods used in solving the location selection problem. He et al. [14] proposed a new hybrid fuzzy model for the location selection of joint distribution centers, taking into account sustainability. In order to obtain the results, fuzzy AHP (for determining criteria weights) and improved fuzzy TOPSIS (for ranking the alternatives) were used. Özmen and Aydoğan [15] presented a three-stage methodology for logistics center location selection within the framework of Kayseri's logistics development plan. In the first stage, criteria were determined through a literature review and expert interviews. The second stage involved the weighting of identified criteria using the linear Best–Worst method. In the third stage, locations were ranked using the evaluation based on distance from average solution (EDAS) method with various distance measures. Wan et al. [16] developed a model for DC location selection in case of large-scale emergencies based on a bi-objective trapezoidal fuzzy mixed integer linear program. Besides DC location selection, another problem that has been solved in the literature is warehouse location selection. Bairagi [17] proposed a model for warehouse location selection in SCM based on MCDM methods. Ulutaş et al. [18] proposed a new model for warehouse location selection based on an integrated grey MCDM model, encompassing grey preference selection index and grey proximity indexed value, to determine the most suitable warehouse location for a supermarket. Khaengkhan et al. [19] compared three methods, simple additive weighting, AHP, and TOPSIS in order to select the most suitable location for an agricultural products warehouse in Thailand. Amin et al. [20] aimed to efficiently select a warehouse and addressed the warehouse selection problem by applying AHP and TOPSIS methods, preceded by a survey on warehouse selection problems.

In addition to the problems related to the selection of DC, as well as the location for DCs and warehouses, based on a literature review it was concluded that there are articles dealing with the analysis and improvement of warehouse efficiency. Karim et al. [21] revised the warehouse productivity measurement indicators by conducting a literature review and semi-structured survey. As a result, the authors highlighted the warehouse resources related to the respective activities in the warehouse. Freitas et al. [22] analyzed a bus manufacturing organization in order to improve efficiency in a hybrid warehouse. Warehouse safety and operational efficiency were also addressed by Halawa et al. [23], where authors examined how real-time location system technology can be used to enhance warehouse safety and efficiency. In order to obtain the results, the authors implemented a novel three-phase framework. In order to precisely measure overall warehouse performance, Islam et al. [24] proposed a novel particle swarm optimization-based grey model to predict the warehouse's key performance indicators with less forecasting error. Fuzzy AHP was used by Abdul Rahman et al. [25] to analyze the most important warehouse productivity indicators in order to improve warehouse operation efficiency. The obtained results showed that space stood out as the top-ranked criterion, followed by information systems, labor, and equipment. Pajić et al. [26] in their article proposed an approach based on the DEA-full consistency method (FUCOM)-CoCoSo methodology for supplier selection, where the DEA method was used to separate efficient suppliers from the inefficient. Based on the results of this phase, in the second phase, FUCOM was applied to determine criteria weights. Finally, a CoCoSo method was applied for the final ranking of the alternatives. In order to measure the efficiency of the retail SC, four main groups of models were identified [1]. The main goal of the article was to test different approaches (standard DEA models, efficiency decomposition models, network models, and game-theory-based models) using real data from a company operating in Serbia. Andrejić et al. [3] developed a model for distribution centers' efficiency measuring based on the DEA method in order to facilitate the decision-making process and improve efficiency. Operational, quality, energy, utilization, and equipment warehouse and transport indicators were integrated into the proposed model. Another model based on the DEA method was proposed by Andrejić et al. [27] for measuring distribution centers' efficiency change in time. For this purpose, the Malmquist productivity index was used in order to determine the impact of input and output variable selection on the resulting efficiency in the context of measuring the change in efficiency over time. Istiqomah et al. [28] in their article analyzed how implementation of barcode can affect warehouse efficiency. Namely, by using the qualitative method, the authors determined that barcode should be implemented in order to improve efficiency, minimize human errors, and provide accurate data in a real-time. IMF SWARA was proposed by Vrtagić et al. [8], where authors used it for determining criteria weights in order to rank the road sections. Puška et al. [29] used IMF SWARA in combination with fuzzy Compromise Ranking of Alternatives from Distance to Ideal Solution in order to select DC locations. Conversely, a combination of IMF SWARA and EDAS methods was used by Stević et al. [30] to evaluate the safety of road sections. IMF SWARA was used for determining criteria weights while the EDAS method was used for ranking the road sections. Besides IMF SWARA, there are other methods for determining criteria weights present as well. For instance, Đalić et al. [31] implemented fuzzy PIPRECIA for analyzing the competitiveness to improve logistics performances. In other words, Stanujkic et al. [32] proposed a simplified version of the PIPRECIA method (PIPRECIA-S) for determining criteria weights. IMF SWARA was combined with the fuzzy Bonferroni operator by Moslem et al. [33] in order to improve the service quality of the public transport system in Turkey. Conversely, a parsimonious spherical fuzzy AHP was proposed by Moslem [34] to evaluate sustainable urban transport solutions. The interval valued Fermatean fuzzy SWARA was used by Aytekin and Korucuk [35] in order to determine criteria weights when concerning SC integration. A combination of AHP and MABAC (multi-attributive border approximation area comparison) methods was applied by Đoković and Doljanica [36] to select investment projects.

3 Methodology

The methodology of this article includes four phases, as shown in Figure 1. In the first phase, problem description and literature review were conducted. In the second phase, the PCA-DEA method [37] was implemented to determine the efficiency of the DWs. After implementing these methods, in the third phase, only efficient DWs were taken into consideration. During the third phase, IMF SWARA was implemented to determine the criteria weights that were then used in the CoCoSo method (during the fourth phase) in order to perform the final ranking and evaluation of DWs. In the last step, a sensitivity analysis was conducted.

3.1 PCA-DEA methods

The combination of PCA-DEA methods was used in this article to determine efficient DWs that will be analyzed in the second and in the third phase of the article. The formulation of the PCA-DEA model used in this article is as follows, equation (1) [3,38]:

$$\min_{U_{\mathrm{PC}},V_{\mathrm{PC}}} V_{\mathrm{PC}}X_{\mathrm{PC}}^{a} - v^{a},$$

s.t.

$$\begin{aligned} &V_{\mathrm{PC}}X_{\mathrm{PC}} - U_{\mathrm{PC}}Y_{\mathrm{PC}} - v^{a} \geq 0,\\ &U_{\mathrm{PC}}Y_{\mathrm{PC}}^{a} = 1,\\ &V_{\mathrm{PC}} \geq 0,\\ &U_{\mathrm{PC}} \geq 0,\quad v^{a} \text{ free,} \end{aligned} \tag{1}$$

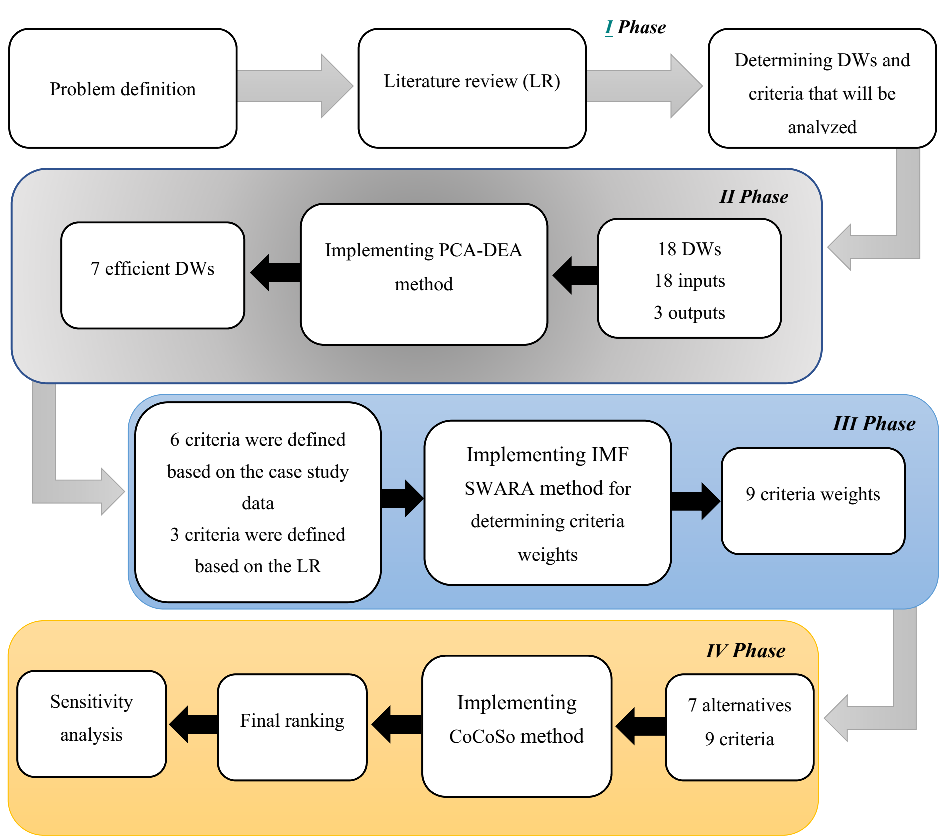

Figure 1: Methodology for benchmarking DWs efficiency.

where V_{PC} and U_{PC} represent vectors of weights assigned to inputs and outputs PCs, v^a is scalar, X_{PC}^a and Y_{PC}^a are input and output column vectors for certain principal components for DMU$_a$.

3.2 IMF SWARA method

In order to obtain criteria weights, the IMF SWARA was applied using the following steps [8]:

Step 1 – First, a set of decision criteria $\{c_1, c_2, \ldots, c_n\}$ must be determined. After that, it is necessary to arrange them in descending order, where the first criterion is the most significant, while the last one is the least significant.

Step 2 – Comparing the criteria. Namely, the relatively smaller significance of the criterion (criterion C_j) was determined in relation to the previous one (C_{j-1}), and this was repeated for each subsequent criterion. In this way, a comparative significance of the average value is obtained ($\overline{s_j}$). The comparison was made using the following scale (Table 1).

Step 3 – Calculating the fuzzy coefficient $\overline{k_j}$ using equation (2):

$$\overline{k_j} = \begin{cases} \overline{1} & j = 1 \\ \overline{s_j} & j > 1. \end{cases} \tag{2}$$

Step 4 – Determining the calculated weights $\overline{q_j}$ using equation (3):

$$\overline{q_j} = \begin{cases} \overline{1} & j = 1 \\ \dfrac{\overline{q_{j-1}}}{\overline{k_j}} & j > 1. \end{cases} \tag{3}$$

Step 5 – Calculating the fuzzy weight coefficients using equation (4).

$$\overline{w_j} = \frac{\overline{q_j}}{\sum_{j=1}^{m} \overline{q_j}}. \tag{4}$$

3.3 CoCoSo method

The implementation of the CoCoSo method can be divided into five steps [26,39,40].

Step 1 – Determine the initial decision-making matrix with alternatives and criteria.

Step 2 – The criteria normalization is performed using equations (5) and (6) in accordance with the type of criteria:

$$r_{ij} = \frac{x_{ij} - \min_i x_{ij}}{\max_i x_{ij} - \min_i x_{ij}}; \quad \text{for benefit criterion,} \tag{5}$$

Table 1: Linguistic and TFN scale [8]

Linguistic scale	Abbreviation	TFN scale
Absolutely less significant	ALS	(1, 1, 1)
Dominantly less significant	DLS	(1/2, 2/3, 1)
Much less significant	MLS	(2/5, 1/2, 2/3)
Really less significant	RLS	(1/3, 2/5, 1/2)
Less significant	LS	(2/7, 1/3, 2/5)
Moderately less significant	MDLS	(1/4, 2/7, 1/3)
Weakly less significant	WLS	(2/9, 1/4, 2/7)
Equally significant	ES	(0, 0, 0)

$$r_{ij} = \frac{\max_i x_{ij} - x_{ij}}{\max_i x_{ij} - \min_i x_{ij}}; \quad \text{for cost criterion.} \tag{6}$$

Step 3 – In this step, the total of the weighted comparability sequence and the whole of the power weight of comparability sequences for each alternative sum of the weighted comparability sequence and also an amount of the power weight of comparability sequences for each alternative (S_i and P_i), respectively, are determined using equations (7) and (8):

$$S_i = \sum_{j=1}^{n} (w_j r_{ij}), \tag{7}$$

$$P_i = \sum_{j=1}^{n} (r_{ij})^{w_j}. \tag{8}$$

Step 4 – Determining the relative weights of the alternatives by calculating the aggregation strategies using equations (9)–(11):

$$k_{ia} = \frac{P_i + S_i}{\sum_{i=1}^{m}(P_i + S_i)}, \tag{9}$$

$$k_{ib} = \frac{S_i}{\min_i S_i} + \frac{P_i}{\min_i P_i}, \tag{10}$$

$$k_{ic} = \frac{\lambda(S_i) + (1 - \lambda)(P_i)}{(\lambda \max_i S_i + (1 - \lambda)\max_i P_i)}; \quad 0 \leq \lambda \leq 1. \tag{11}$$

In equation (11), λ is chosen by decision-makers and can take a value between 0 and 1.

Step 5 – In the last step, the alternatives are ranked based on the value of k_i (the higher value represents better rank) [equation (12)]:

$$k_i = (k_{ia} k_{ib} k_{ic})^{\frac{1}{3}} + \frac{1}{3}(k_{ia} + k_{ib} + k_{ic}). \tag{12}$$

4 Case study

4.1 Case description

This article presents a case study of a Serbian retail company. The company operates 18 warehouses where perishable goods are procured from suppliers and stored for a designated period, depending on their type. Subsequently, the goods are distributed to various retail stores. Notably, the company follows a distinctive approach by providing its own retail stores with products from nine warehouses (referred to as RW), while also servicing retail stores not owned by the company from the remaining nine warehouses (referred to as WW). It is worth noting that these additional nine warehouses function as wholesale facilities catering to the owners of smaller shops, as indicated in Figure 2.

In the observed system, a greater number of performance indicators are monitored. Most of the indicators are financial, which fully corresponds to the real system. Namely, a company whose main activity is not logistics but trade observes logistics as the cost of placing goods on the market. In addition, the company also monitors certain indicators that are operational-related. So, for example, the number of boxes that the warehouse prepares (after order-picking) and delivers is of particular importance in performance measurement, in addition to turnover. Also, the number of order-picking transactions realized by one warehouse is monitored as a very significant indicator. In order to obtain a pragmatic and reliable scenario of warehouse operations, 21 performance indicators were taken into account in this article, of which 18 are inputs and 3 are outputs. These performance indicators were meticulously chosen through an extensive literature review and subsequent interviews with industry experts possessing substantial experience. All experts involved in the assessment are

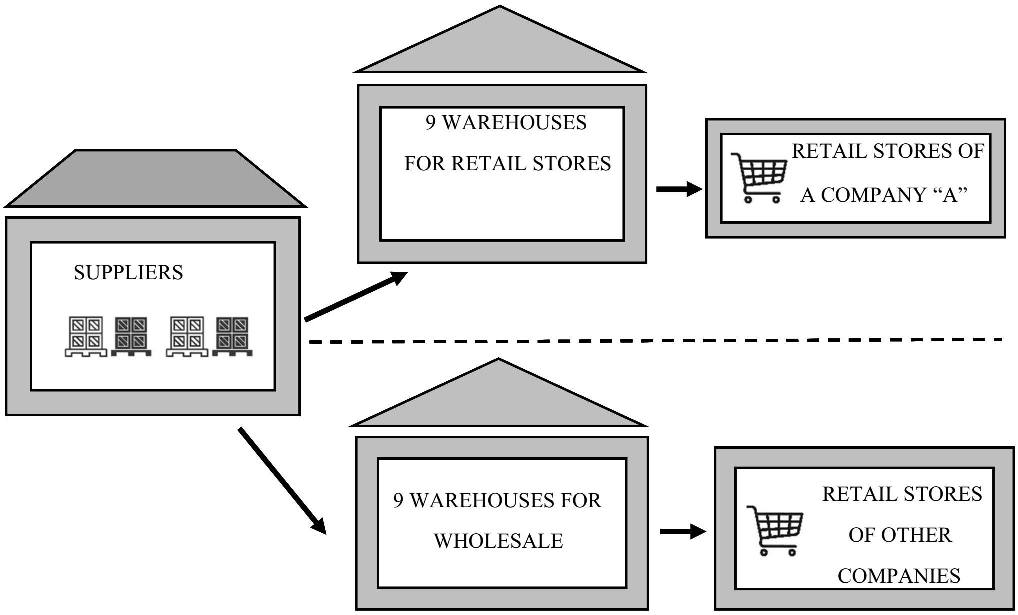

Figure 2: Case study company.

in a higher position (two warehouse managers, one logistics manager, one SC manager, and one reverse logistics manager) in the company and are competent for the observed issue. Their expertise and authority in addressing the observed issue affirm the relevance of the selected indicators, focusing on key financial, operational, and quality aspects [3]. The data used in this case study were collected for the period of 1 year (12 months). The values presented in Table 2 represent average monthly values for the observed period.

Table 2: Descriptive statistics of inputs and outputs

Indicators		Average value	Standard deviation	Type
Inputs	Rent (IP1)	1,934,463	3,479,199	Financial
	Amortization (IP2)	1,148,646	3,298,405	
	Electricity (IP3)	292286.7	318318.1	
	Other energy (IP4)	15132.23	26433.19	
	Forklifts (rental fee – IP5)	73327.4	61921.55	
	Forklifts (maintenance – IP6)	78402.4	66619.88	
	Salaries (IP7)	1632934	1129992	
	Shrinkage (IP8)	365898.2	405072	
	Consumables (IP9)	155542.7	145556.4	
	Other costs (IP10)	471691.6	572332.9	
	Total costs (IP11)	6,152,053	8,602,087	
	Operating costs (including lease – IP12)	5,003,408	5,503,303	
	Costs of operations (without depreciation and lease – IP13)	2,990,542	2,336,421	
	% cost in the turnover (IP14)	0.0241	0.009818	
	Cost of item without lease and amortization (IP15)	1.34898	4.136192	
	Cost of the box without lease and amortization (IP16)	0.029706	0.020891	
	Cost of item with lease (IP17)	2.796056	8.928078	
	Cost of a box with lease (IP18)	0.043876	0.0266	
Outputs	Transaction (OP1)	53897.25	53208.69	Operational
	Box (OP2)	115423.8	137361.7	
	Turnover (OP3)	96,571,842	138288983.2	

Description of the variables (indicators) used in this article are as follows.

INPUT indicators

- Rent (IP1) – the cost of renting the warehouse facilities expressed in monetary units (m.u.).
- Amortization (IP2) – the cost of depreciation of buildings and equipment expressed in m.u.
- Electricity (IP3) – the cost of electricity expressed in m.u. Electricity consumption is a consequence of the need for cooling buildings, lighting the building, as well as charging batteries for electric forklifts.
- Other energy (IP4) – consumption of other energy sources such as gas and similar expressed in m.u.
- Forklifts (rental fee – IP5) – the cost of renting a forklift expressed in m.u. In the observed warehouses, a certain number of forklifts are leased, while the other is owned.
- Forklifts (maintenance – IP6) – the maintenance cost of forklifts regardless of ownership expressed in m.u.
- Salaries (IP7) – fixed and variable earnings, expressed in m.u.
- Shrinkage (IP8) – write-offs, breaks, damaged goods, expired dates, expressed in m.u.
- Consumables (IP9) – the cost of materials used for packing shipments, e.g., foils, cardboard, paper, styrofoam, as well as other consumables, expressed in m.u.
- Other costs (IP10) – tax costs, labor protection costs, cleaning costs, etc., expressed in m.u.
- Total costs (IP11) – represents the sum of all arising costs, expressed in m.u.
- Operating costs (including lease – IP12) – represents the sum of all operating costs including a lease, expressed in m.u.
- Costs of operations (without depreciation and lease – IP13) – costs of operations without depreciation and lease, expressed in m.u.
- % cost in the turnover (IP14) – shows the ratio/participation of costs in the output.
- Cost of item without lease and amortization (IP15) – a partial indicator of the cost of an item without lease and amortization, expressed in m.u.
- Cost of the box without lease and amortization (IP16) – a partial indicator of the cost of the box without lease and amortization, expressed in m.u.
- Cost of an item with lease (IP17) – a partial indicator of the cost of the item with lease and amortization, expressed in m.u.
- Cost of a box with lease (IP18) – a partial indicator of the cost of a box with lease and amortization, expressed in m.u.

OUTPUT indicators

- Transaction (OP1) – total number of transactions, i.e., items on all orders for order picking.
- Box (OP2) – total number of boxes that leave the warehouse.
- Turnover (OP3) – total turnover, expressed in m.u.

In addition to the presented indicators used in the first phase of the proposed methodology, in the second and the third phase a set of evaluation criteria had to be defined. Based on the company data, as well as the literature review, a set of nine criteria was defined. Six criteria have been established based on data from the observed company, including fixed costs (C1), variable costs (C2), and turnover (C3), expressed in m.u., as well as the number of boxes shipped (C4), number of order-picking lines (C5), and shrinkage (C6), which is also expressed in m.u. In this study, fixed costs encompass the aggregate of rent, amortization, and rental fees for the forklifts. Variable costs, in contrast, encompass the total of electricity, other energy, salaries (considering potential variations due to bonuses), consumables, maintenance costs for the forklifts, and miscellaneous expenses. Conversely, the remaining three criteria used in this case study were defined based on the literature review, such as closeness to the market (C7), available space (C8), and expansion possibility (C9). The values for these three criteria were determined based on the evaluation of the five experts from the observed company (average or simple mean value was taken into account). In the context of this research, the terms “inputs,” “outputs,” and “criteria” are central to the proposed integrated model for assessing the efficiency of retail DWs using PCA-DEA-IMF SWARA-CoCoSo method. Inputs are the factors or resources that are consumed or utilized in the process being assessed. In the context of retail DWs, inputs generally include variables such as rental costs, consumables, maintenance costs, electricity and energy consumption, etc. In the PCA-DEA phase (II phase), these inputs are analyzed to reduce the number of variables and identify the most efficient warehouses. The goal is to find a set of inputs that maximizes the efficiency of the warehouse. In a retail DW, outputs are the results or outcomes generated by the process and include variables like the number of boxes shipped, turnover, or any other measurable outcome. PCA-DEA is used to identify the most efficient warehouses based on their ability to produce the desired outputs with the given inputs. In the third phase, IMF SWARA is applied to determine the weights of the criteria. Criteria refer to the factors that are considered in the decision-making process. In this context, criteria could include elements such as fixed costs, variable costs, or any other relevant factors that contribute to the efficiency assessment. The importance or weight of each criterion is determined using the IMF SWARA method.

4.2 Results

The case study analyzed in this article was conducted as follows. After defining the input and output indicators for all warehouses, an initial analysis was performed using the standard DEA approach. In the literature, initial evaluation with basic models is recommended [3,41]. However, the results obtained using this model showed an extremely low discrimination power (third column of Table 3) where the average efficiency was 0.927, where as many as 13 DMUs were efficient. The consequence of such results is a large number of variables (21) and a relatively small number of observed storage units (DMU), 18 of them.

After that, the evaluation using the PCA-DEA approach was conducted with a 95% of degree information retention. A high retention rate is very important when it comes to measuring the effectiveness of real systems. Conversely, the model has a very high discrimination power, which is confirmed by the average efficiency of 0.674 (fourth column Table 3). In the combined set of all 18 DMUs (9 retail and 9 wholesale warehouses), it was established that there are large mutual differences in efficiency. Thus, it was established that the average efficiency of the first group (DMU1–DMU9) is 0.793, while the efficiency of the second group (DMU10–DMU18) is 0.556. This directly indicates that the observed set has certain inhomogeneities (heterogeneity), which can be explained by certain differences in the functioning and realization of logistic processes and activities.

It is precisely for this reason that an independent assessment of PCA-DEA efficiency (95%) was performed for nine retail and nine wholesale warehouses. The reason is to obtain more authoritative results. The last

Table 3: PCA-DEA results

DMU	Description	Standard DEA score	PCA-DEA score (95%) for all 18 DMU (merged set)	PCA-DEA score (95%) for two separate sets (nine retail and nine wholesale warehouses)	
DMU 1	RW 1	1.000	0.887	0.739	Set 1
DMU 2	RW 2	1.000	0.754	1.000	
DMU 3	RW 3	1.000	0.549	0.622	
DMU 4	RW 4	0.914	0.401	0.260	
DMU 5	RW 5	1.000	0.614	1.000	
DMU 6	RW 6	1.000	0.931	0.709	
DMU 7	RW 7	1.000	1.000	1.000	
DMU 8	RW 8	1.000	1.000	1.000	
DMU 9	RW 9	1.000	1.000	1.000	
DMU 10	WW 1	1.000	0.746	1.000	Set 2
DMU 11	WW 2	0.723	0.507	0.726	
DMU 12	WW 3	1.000	0.580	0.849	
DMU 13	WW 4	1.000	0.571	0.736	
DMU 14	WW 5	0.783	0.507	0.610	
DMU 15	WW 6	0.677	0.399	0.489	
DMU 16	WW 7	1.000	0.829	1.000	
DMU 17	WW 8	1.000	0.577	0.637	
DMU 18	WW 9	0.596	0.288	0.429	
Average		0.927	0.674	For retail 0.814 For wholesale 0.719	

Table 4: Linguistic scale assessment

Criteria	Description	Linguistic scale
C1	Fixed costs	—
C2	Variable costs	ES
C3	Turnover	WLS
C4	Boxes shipped	WLS
C5	Order picking lines	LS
C6	Shrinkage	MDLS
C7	Closeness to the market	RLS
C8	Available space	MDLS
C9	Expansion possibility	LS

column of Table 3 shows that the average efficiency of retail warehouses is 0.814, where five warehouses are efficient, while in the group of wholesale warehouses, the average efficiency is 0.719 where only two DMUs had an efficiency of 1.

Efficient DMUs were selected as the best representatives and analyzed in the next phase, with the aim of determining the authoritative benchmark for the entire set. Inefficient warehouses in terms of operational business need to emulate exactly that warehouse.

After determining the efficient warehouses, the second phase which included obtaining criteria weights was conducted. A set of nine criteria was defined after which the criteria were sorted in descending order (from the most to the least significant). Fixed costs (C1) were taken as the most significant criterion, while expansion possibility (C9) was taken as the least significant. Since IMF SWARA was used, the results based on the experts' assessment were obtained (Table 4).

Crisp criteria weights were then obtained by applying equations (2)–(4), as given in Table 5.

As already mentioned, nine evaluation criteria and seven alternatives were considered. The initial decision-making matrix (Table 6) was derived from the real data of the company, along with the expert's assessment. Since two types of warehouses were taken into account in this article, it is worth mentioning that the first five alternatives (A1–A5) represent warehouses for retail stores owned by the company, while the remaining two alternatives (A6 and A7) represent warehouses for wholesale.

After developing the initial decision-making matrix, the second step in implementing the CoCoSo method involved normalization through the application of equations (5) and (6), respectively, for benefit and cost criteria, as shown in Table 7. Additionally, this step presented the weights of the criteria obtained using the IMF SWARA method.

S_i and P_i values for each alternative were determined in the next step by applying equations (7) and (8), as presented in Table 8.

Table 5: Obtained criteria weights using IMF SWARA

Criteria		$\overline{s}_j$			$\overline{k}_j$			$\overline{q}_j$			$\overline{w}_j$		w_j (crisp)
C1				1.000	1.000	1.000	1.000	1.000	1.000	0.193	0.203	0.216	0.204
C2	0	0	0	1.000	1.000	1.000	1.000	1.000	1.000	0.193	0.203	0.216	0.204
C3	0.222	0.250	0.286	1.222	1.250	1.286	0.778	0.800	0.818	0.150	0.163	0.177	0.163
C4	0.222	0.250	0.286	1.222	1.250	1.286	0.605	0.640	0.669	0.117	0.130	0.144	0.130
C5	0.286	0.333	0.400	1.286	1.333	1.400	0.432	0.480	0.521	0.083	0.098	0.112	0.098
C6	0.250	0.286	0.333	1.250	1.286	1.333	0.324	0.373	0.417	0.063	0.076	0.090	0.076
C7	0.333	0.400	0.500	1.333	1.400	1.500	0.216	0.267	0.312	0.042	0.054	0.067	0.054
C8	0.250	0.286	0.333	1.250	1.286	1.333	0.162	0.207	0.250	0.031	0.042	0.054	0.042
C9	0.286	0.333	0.400	1.286	1.333	1.400	0.116	0.156	0.194	0.022	0.032	0.042	0.032
						SUM	4.633	4.923	5.181				

Table 6: Initial decision-making matrix

Criteria	**C1**	**C2**	**C3**	**C4**	**C5**	**C6**	**C7**	**C8**	**C9**
Optimal value	**min**	**min**	**min**	**max**	**max**	**Max**	**max**	**min**	**max**
A1	2885491.803	6056575.934	1311964.943	97727.33333	462123.1298	315585935.2	1	3	2
A2	1719200.129	1819587.249	9545.869167	8201.666667	122996.6882	53014480.94	4	3	4
A3	2428152.191	3795464.652	112214.3858	103672.9167	218243.4395	231528250.8	1	2	5
A4	934792.7442	2571844.34	211545.7083	66608.66667	129808.5712	219696529.7	4	4	3
A5	2256568.242	3052794.228	164638.7642	83563.25	136971.1345	332061041.8	1	4	1
A6	3729331.85	5037879.997	1394743.108	124647.4167	124647.4167	5037879.997	3	5	5
A7	510477.3558	1319876.312	100448.0242	34081.41667	34081.41667	1315095.916	1	4	2

Table 7: Normalized decision-making matrix

Criteria	**C1**	**C2**	**C3**	**C4**	**C5**	**C6**	**C7**	**C8**	**C9**
Weight	**0.204**	**0.204**	**0.163**	**0.130**	**0.098**	**0.076**	**0.054**	**0.042**	**0.032**
A1	0.26	0.00	0.06	0.77	1.00	0.95	0.00	0.67	0.25
A2	0.62	0.89	1.00	0.00	0.21	0.16	1.00	0.67	0.75
A3	0.40	0.48	0.93	0.82	0.43	0.70	0.00	1.00	1.00
A4	0.87	0.74	0.85	0.50	0.22	0.66	1.00	0.33	0.50
A5	0.46	0.63	0.89	0.65	0.24	1.00	0.00	0.33	0.00
A6	0.00	0.22	0.00	1.00	0.21	0.01	0.67	0.00	1.00
A7	1.00	1.00	0.93	0.22	0.00	0.00	0.00	0.33	0.25

Finally, in the last step, the values of k_{ia}, k_{ib}, k_{ic}, and k_i were determined (Table 9) by applying equations (9)–(12) in order to obtain the final ranking of the alternatives (warehouses).

Based on the obtained results, it can be concluded that alternative 4 (A4) is the best-ranked alternative followed by A2, A3, A5, A7, A1, and A6. The final ranking can also be shown as A4 > A2 > A3 > A5 > A7 > A1 > A6. Besides ranking, the results showed that warehouses for retail stores owned by the company are better ranked (hence more efficient) than warehouses for wholesale. This is an expected result since the company has greater control over its own operations and can manage them better when compared with external management when it comes to wholesale warehouses.

Table 8: S_i and P_i values

Criteria	**C1**	**C2**	**C3**	**C4**	**C5**	**C6**	**C7**	**C8**	**C9**	S_i
A1	0.05	0.00	0.01	0.10	0.10	0.07	0.00	0.03	0.01	0.37
A2	0.13	0.18	0.16	0.00	0.02	0.01	0.05	0.03	0.02	0.61
A3	0.08	0.10	0.15	0.11	0.04	0.05	0.00	0.04	0.03	0.61
A4	0.18	0.15	0.14	0.07	0.02	0.05	0.05	0.01	0.02	0.69
A5	0.09	0.13	0.14	0.08	0.02	0.08	0.00	0.01	0.00	0.56
A6	0.00	0.04	0.00	0.13	0.02	0.00	0.04	0.00	0.03	0.26
A7	0.20	0.20	0.15	0.03	0.00	0.00	0.00	0.01	0.01	0.61
									Σ	**3.71**
										P_i
A1	0.76	0.00	0.63	0.97	1.00	1.00	0.00	0.98	0.96	6.30
A2	0.91	0.98	1.00	0.00	0.86	0.87	1.00	0.98	0.99	7.59
A3	0.83	0.86	0.99	0.97	0.92	0.97	0.00	1.00	1.00	7.55
A4	0.97	0.94	0.97	0.91	0.86	0.97	1.00	0.95	0.98	8.57
A5	0.85	0.91	0.98	0.94	0.87	1.00	0.00	0.95	0.00	6.51
A6	0.00	0.73	0.00	1.00	0.86	0.71	0.98	0.00	1.00	5.28
A7	1.00	1.00	0.99	0.82	0.00	0.00	0.00	0.95	0.96	5.72
									Σ	**47.51**

Table 9: Alternatives ranking

Alternative	K_{ia}	K_{ib}	K_{ic}	K_i	Final rank
A1	0.130	2.593	0.720	1.772	6
A2	0.160	3.754	0.886	2.410	2
A3	0.159	3.729	0.881	2.396	3
A4	0.181	4.230	1.000	2.718	1
A5	0.138	3.377	0.765	2.136	4
A6	0.108	2.000	0.599	1.409	7
A7	0.124	3.400	0.684	2.063	5

5 Discussions

5.1 Theoretical and managerial implications

In accordance with the established gaps, this article has unequivocal practical and theoretical contributions.

From the perspective of practical application, this model was developed and proposed for the needs of a real company. In this sense, it overcomes all the shortcomings of theoretically developed approaches. An integrated model based on four methods overcomes the shortcomings of other approaches and uses all their individual advantages. The evaluation is based on real variables (inputs/outputs and criteria) that provide a real picture of the functioning of a retailer's warehouse. Most of the indicators are financial, which corresponds to the real system and type of company. Since it is a retailing company, and not a logistics one, from the perspective of the company's management, greater emphasis is placed on financial indicators. However, apart from financial ones, operational indicators were also taken into account. Operational indicators in logistics are of crucial importance for measuring the efficiency of the process [3]. The usefulness and reliability of the approach was additionally increased by the inclusion of experts from the observed company during the evaluation of alternatives in accordance with the observed criteria (mainly C7, C8, and C9) and during the ranking of efficient warehouses in the last phase. The proposed approach is easily applicable and easily adaptable, so it can be applied to different logistics systems regardless of primary business activity, size, market, etc. For decision-makers, this model represents an excellent decision support system (DSS) tool with the help of which they can make quick and reliable decisions.

As it was emphasized in Section 2, there are no articles dealing with measuring the efficiency of warehouses in retail chains. But with this research, that gap has been partially filled and an excellent foundation has been laid for further research. The parameters (variables) identified in this article can be useful for the calculation of other warehouse performance indicators of retail chains. The integration of these four approaches into one integrated model has not been used in the literature so far and is very different from all efficiency measurement approaches in the literature. Since there are no articles that deal with the same problem as in this article, obtained results could not be compared with the results of other research. Therefore, the results of this article were compared with the results obtained in [3]. It was concluded that certain inputs/outputs were taken into account in both articles, while the results obtained in [3] confirmed that there is a difference in efficiency scores of large and small DCs. These results are similar to the results presented in the previous section since in this article a difference in efficiency between warehouses for retail stores owned by the company and wholesale warehouses was determined. Another similarity between these two articles is reflected in the fact that the number of efficient warehouses is greater when implementing only the DEA method when compared to PCA-DEA application. In the literature, efficiency is most often evaluated using DEA and Stochastic frontier analysis, while the PCA-DEA approach is used significantly less. By including IMF SWARA and CoCoSo approaches, a completely new model was obtained that has a significantly higher discriminating power than the previously mentioned approaches. The problem of developing theoretical models without the possibility of practical application on real systems was successfully solved with this new model. This is also confirmed by subsequent consultations with experts from the observed company. Namely, the results were presented to the company's experts and they confirmed that the obtained results are in accordance with the actual situation in the company (in terms of warehouse efficiency and a final ranking of the warehouses).

5.2 Sensitivity analysis

In order to conduct a sensitivity analysis and to determine whether the ranking of the alternatives will be different, four scenarios were created. Namely, in the first scenario, experts from the observed company gave their opinion about the significance and criteria weights. Since five experts evaluated each criterion average value of all assessments was taken into account. Those criteria weights were then implemented in the CoCoSo method to rank the alternatives. Based on the results, it can be seen that there is a small change in the final ranking of the alternatives (A2 switched places with A3, and A1 switched places with A7). So, based on the first scenario, ranking can be shown as A4 > A3 > A2 > A5 > A1 > A7 > A6. In the second scenario, it was assessed that all criteria are of the same importance (hence, have equal weights). The ranking in this scenario can be shown as A4 > A3 > A2 > A5 > A1 > A7 > A6. Based on the results, it can be concluded that the results are the same as in scenario 1. In the third scenario, it was assessed that the operational indicators (criteria) should be more important. Hence, the number of orders picking lines, the number of boxes shipped and available space were given the highest values (Table 10). After conducting analysis, it was concluded that the order of the alternatives has changed and is now as follows: A3 > A4 > A1 > A5 > A2 > A6 > A7 (Table 11). Finally, in the last

Table 10: Criteria weights in different scenarios

Criteria	C1	C2	C3	C4	C5	C6	C7	C8	C9
Scenario 1	0.1	0.16	0.14	0.21	0.19	0.02	0.07	0.03	0.08
Scenario 2	0.1111	0.1111	0.1111	0.1111	0.1111	0.1111	0.1111	0.1111	0.1111
Scenario 3	0.0510	0.0595	0.0714	0.1784	0.2761	0.1784	0.0217	0.0446	0.1189
Scenario 4	0.1784	0.1784	0.1189	0.0595	0.0714	0.2761	0.0217	0.0446	0.0510

Table 11: Results of sensitivity analysis

Scenario 1	Alternative	K_{ia}	K_{ib}	K_{ic}	K_i	Final rank	Scenario 2	Alternative	K_{ia}	K_{ib}	K_{ic}	K_i	Final rank
	A1	0.154	2.260	0.753	1.696	5		A1	0.154	2.489	0.748	1.790	5
	A2	0.184	2.713	0.899	2.031	3		A2	0.184	3.139	0.889	2.204	3
	A3	0.186	2.920	0.907	2.127	2		A3	0.188	3.314	0.912	2.300	2
	A4	0.204	3.030	0.998	2.262	1		A4	0.206	3.443	0.999	2.441	1
	A5	0.157	2.371	0.768	1.759	4		A5	0.159	2.600	0.770	1.859	4
	A6	0.132	2.000	0.643	1.478	7		A6	0.127	2.000	0.614	1.451	7
	A7	0.137	2.167	0.668	1.573	6		A7	0.136	2.268	0.658	1.608	6
Scenario 3	**Alternative**	K_{ia}	K_{ib}	K_{ic}	K_i	**Final rank**	**Scenario 4**	**Alternative**	K_{ia}	K_{ib}	K_{ic}	K_i	**Final rank**
	A1	0.167	3.829	0.800	2.399	3		A1	0.156	3.916	0.742	2.373	5
	A2	0.179	2.918	0.854	2.080	5		A2	0.179	4.453	0.854	2.709	4
	A3	0.193	4.074	0.921	2.627	1		A3	0.186	5.027	0.885	2.972	2
	A4	0.205	3.627	0.983	2.507	2		A4	0.210	5.471	1.000	3.275	1
	A5	0.162	3.206	0.777	2.121	4		A5	0.165	4.904	0.784	2.810	3
	A6	0.125	2.473	0.600	1.637	6		A6	0.116	2.000	0.553	1.395	7
	A7	0.136	2.111	0.648	1.535	7		A7	0.143	3.976	0.681	2.329	6

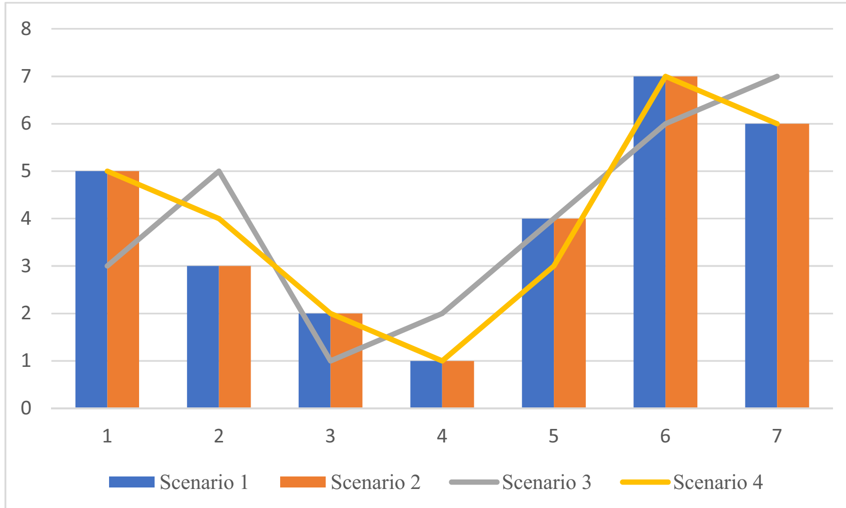

Figure 3: Sensitivity analysis for different scenarios.

scenario, financial indicators (criteria) were considered as the most important, hence, fixed costs, variable costs, turnover, and shrinkage had the highest values. Alternatives changed places in this scenario as well. The final ranking according to this scenario is as follows: A4 > A3 > A5 > A2 > A1 > A7 > A6.

Based on the results of the sensitivity analysis, it can be concluded that the solution is pretty stable (since minor changes in the ranking occurred in different scenarios) and that the criteria weights can affect the results (Figure 3).

6 Conclusions

The conducted research and the proposed model fill the identified gaps determined at the beginning of the article. The model is completely based on indicators from a real system (company) and perfectly describes the functioning of the observed company. The model is originally intended for the efficiency measurement of DWs in retail chains, and there is nothing similar in the literature. It is based on several approaches using the best elements of each of them. The results of testing on a real case study unequivocally prove that this approach can overcome the problem of most approaches in the literature, which is the impossibility of practical application of theoretical models. The research emphasizes the practical significance of its findings by suggesting that the highly efficient warehouses identified can serve as benchmarks for improving the performance of less efficient ones. This benchmarking aspect offers valuable insights for organizations operating in dynamic markets, assisting them in achieving operational excellence and enhancing overall SC performance. The proposed methodology contributes to both research by serving as a foundation for future studies and addressing established gaps in the literature. It also provides practical applications by offering a model that can be easily utilized by managers to enhance efficiency. The practical and scientific contributions of this research are described in detail in the previous section.

To evaluate DW efficiency, this article proposes an approach that integrates PCA-DEA-IMF SWARA-CoCoSo methods. The framework offers a comprehensive way to assess and improve warehouse performance. The combination of PCA-DEA methods was used to determine and separate efficient warehouses from inefficient ones since only efficient warehouses were taken into account in the next phase of the proposed methodology. After conducting the first phase, it was determined that only 7 warehouses, out of 18, were efficient. In the second phase, evaluation criteria were determined based on a literature review and data from a company. Based on this, nine evaluation criteria were observed in this article, fixed costs (C1), variable costs (C2), turnover (C3), the number of boxes shipped (C4), the number of order-picking lines (C5), shrinkage (C6), closeness to the market (C7), available space (C8), and expansion possibility (C9). When implementing the IMF SWARA method, it is required to determine the most and the least significant criterion; hence, as the most significant criterion, fixed costs were determined while expansion possibility was determined as the least significant criterion. The criteria weights, used in the next phase of the proposed methodology, were obtained after implementing the IMF SWARA method. In the last phase, a CoCoSo method was applied in order to rank the alternatives (warehouses). Based on the results, it was concluded that warehouses for retail stores owned by the company are ranked better and are more efficient when compared to wholesale warehouses.

This article has no major limitations. The only limitation that can be stated is the testing of the model on one real system (company). This also represents the first direction of future research. In future research, it is necessary to test the model on other real systems operating in different markets. The next direction of future research is the application of other methods and the testing of new models. In future models, it is desirable to include other types of indicators, primarily quality indicators (claims, user complaints, etc.), and to connect the efficiency of operations with the satisfaction of end-users. Another direction of future research is the simulation of certain scenarios when designing or reengineering logistics systems. Since the case study in this article took into account only perishable goods, in future research it would be useful to implement the proposed methodology on other types of goods as well. Finally, implementation of the proposed methodology in other industries and on other examples stands out as one of the future research directions as well. The findings of this study shall contribute toward sustainable manufacturing which is one of the highlights of the United Nation's 9th Sustainable Development Goals – Industry, Innovation, and Infrastructure. The model can also be extended to incorporate sustainability metrics and evaluate the environmental impact of warehouse operations, considering energy efficiency, waste reduction, and eco-friendly practices. Incorporation of risk management elements into the model is also a future research direction to assess how the model can account for risks associated with external disruptions like pandemics, or economic downturns, to enhance warehouse resiliency. Therefore, imperative toward a sustainable future for all.

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