FACTA UNIVERSITATIS
Series: **Mechanical Engineering**
https://doi.org/10.22190/FUME260305009K

Original scientific paper

MULTI-CRITERIA RANKING OF INDUSTRIAL PRESSES WITH RESPECT TO OPERATIONAL PERFORMANCE USING THE SQUARE-ROOT BASED EVALUATION METHOD (SREM)

Nikola Komatina[1], Nikola Petrović[2], Dragan Pamučar[3,4,5], Vladimir Simić[6,7], Dragan Marinković[8,9,10]

[1]Faculty of Engineering, University of Kragujevac, Kragujevac, Serbia
[2]Faculty of Mechanical Engineering, University of Nis, Serbia
[3]Department of Operations Research and Statistics, Faculty of Organizational Sciences, University of Belgrade, Belgrade, Serbia
[4]UNEC Applied Artificial Intelligence Research Center, Azerbaijan State University of Economics (UNEC), Baku, Azerbaijan
[5]Faculty of Engineering, Dogus University, Istanbul, Türkiye
[6]Yuan Ze University, College of Engineering, Department of Industrial Engineering and Management, Taoyuan City 320315, Taiwan
[7]Vilnius Gediminas Technical University, Lithuanian Maritime Academy, Department of Marine Navigation, Klaipėda, 92123, Lithuania
[8]TU Berlin, Department of Structural Analysis, Berlin, Germany
[9]Institute of Mechanical Science, Vilnius Gediminas Technical University, Lithuania
[10]University College, Korea University, 145 Anam-ro, Seoul, Korea

Abstract. *This paper presents a Multi-Criteria Decision-Making (MCDM) framework for the evaluation and ranking of industrial punch presses based on their operational performance. The case study was conducted in a company engaged in the production of industrial machines and assemblies. For the first time, the Square-Root based Evaluation Method (SREM) is introduced and applied, aiming to overcome certain limitations of MCDM methods based on linear data normalization. The SREM method introduces a combined nonlinear transformation approach based on square and root transformations. Unlike standard approaches, it employs a fusion of these two transformations, thereby enabling decision makers to balance between emphasizing excellent (extreme) alternative values with respect to a given criterion and achieving ranking stability by reducing the influence of such alternatives. The former is achieved through the square transformation, while the latter is attained through the root transformation. The results*

Received: March 05, 2026 / Accepted May 12, 2026
Corresponding authors: Nikola Komatina[a], Dragan Marinković[b]
[a]Faculty of Engineering, University of Kragujevac, Sestre Janjić 6, 34000 Kragujevac, Serbia
[b]TU Berlin, Department of Structural Analysis, Str. d. 17. Juni 135, 10623 Berlin, Germany
E-mail: nkomatina@kg.ac.rs[a], dragan.marinkovic@tu-berlin.de[b]

obtained using the SREM method were compared with those derived from the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) and the Simple Additive Weighting (SAW) methods under three different scenarios, i.e., varying criterion weights. The comparative analysis confirmed the robustness of the SREM method. The results further indicate that SREM provides flexibility and inherently incorporates sensitivity analysis, which can be highly valuable in practice, as problem analysis does not require the application of multiple MCDM methods.

Key words: *MCDM, Punch presses, Operational performance, SREM, Square transformation, Root transformation*

1. INTRODUCTION

Manufacturing companies record and collect a large amount of data from various business processes on a daily basis; however, these data are often misinterpreted or not analyzed at all as potentially useful indicators. Of particular importance are data originating from the production process. Some of these data provide direct insight into the process itself, while others cannot be interpreted independently; nevertheless, when considered together, they can provide a broader picture of process quality, reliability, and productivity. One of the important analytical tasks of operational management that can be addressed through the analysis of available data is the evaluation of the operational performance of production equipment.

In this study, the focus is on a company engaged in the production of industrial machines and assemblies. The company operates several sectors within its production facility, one of the most important being sheet metal punching performed on punch presses. Subsequently, the punched sheet metal parts are used as frames for pumps or cooling units. In fact, punch presses represent one of the more vulnerable segments of the production process due to the demanding setup procedures and the generation of a significant number of defective products. For this reason, the company's management aims to analyze the available data and undertake appropriate measures in order to obtain a realistic assessment of the current state of the process.

A total of five punch presses used in the considered company have identical characteristics and originate from the same manufacturer. Nevertheless, their operational performance differs, which can be readily observed from the available data. However, the data available to the company often exhibit certain inconsistencies. For example, a press that produces a higher average number of conforming parts may simultaneously generate defective products more frequently throughout the year, i.e., over a larger number of working days. In order to compare the operational performance of the punch presses in an adequate and systematic manner, taking into account all relevant data, a combined Multi-Criteria Decision-Making (MCDM) approach is applied in this study. The objective is to identify the punch presses with the best performance and establish them as benchmarks in practice, while special attention is devoted to those with the poorest performance, for which appropriate corrective measures are proposed.

MCDM methods represent a highly useful and effective tool for solving such types of problems. In this study, a new method termed the Square-Root based Evaluation Method (SREM) is developed and applied for the first time. This method is based on the combination of square and root transformations of data and on their balancing (fine tuning).

The basic steps and key characteristics of the SREM method are presented in the following sections.

Two approaches were used in this study to determine the criteria weights, namely the Analytic Hierarchy Process (AHP) [1] method, which is based on the subjective assessments of experts, and the CRiteria Importance Through Intercreteria Correlation (CRITIC) [2] method, which relies on the input data and is therefore considered an objective approach. For the purpose of sensitivity analysis and examination of the obtained results, an additional scenario in which all criteria are assigned equal importance was also considered.

In order to examine the robustness of the results obtained using the SREM method, the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) [3,4] and Simple Additive Weighting (SAW) [4] methods were additionally applied. The obtained results were compared across all three scenarios, i.e., when the criteria weights were determined using the AHP and CRITIC methods, as well as when all criteria were assumed to have equal weights.

The primary objective of the research presented in this paper is, first and foremost, the verification of the proposed SREM method through its application to a real industrial case. The case study is based on data collected by the company over the course of one calendar year. In addition, the objective is to determine which of the considered punch presses exhibit the best operational performance and which represent the most operationally critical ones. The problem is analyzed from multiple perspectives by applying a combination of several MCDM methods in order to ensure that the obtained results are as reliable and relevant as possible.

The key scientific contributions of this study can be summarized as follows: (1) the introduction and validation of a novel MCDM method, (2) the integration of subjective and objective approaches for determining criteria weights, and (3) the solution of a practical industrial problem through the combined application of multiple MCDM methods.

The paper is organized as follows: Section 2 reviews and analyzes the application of MCDM approaches for the evaluation and selection of industrial equipment. Section 3 presents the theoretical background and the motivation for defining the new SREM method. The proposed methodology and the main steps of the SREM method are presented in Section 4. After that, section 5 presents the case study, together with the sensitivity analysis and a discussion of the obtained results. Finally, Section 6 provides the main conclusions of the research.

2. Literature Review

Evaluation and selection of machines and equipment represent one of the problems characteristic of many manufacturing enterprises. The characteristics and operational performance of equipment directly affect the generation of undesired costs and the reliability of production processes. Since this problem is inherently complex and multidimensional, often based on the comparison of multiple criteria, MCDM methods have become one of the important analytical tools in this domain [5].

Specifically, in paper [5], the author conducted a review of studies in which the MCDM approach was applied for the selection of handling equipment in logistics. The author concluded that, in the majority of the analyzed studies, the main subject of analysis were conveyors, as for example in [6]. When it comes to a related domain, namely port-based logistics operations, in paper [7] the authors developed a hybrid model based on Fermatean fuzzy logic, as well as on the Method Based on the Removal Effects of Criteria (MEREC) [8] and Alternative Ranking using two-step LOgarithmic Normalization (ARLON) [9] for the selection of forklifts in green ports. In the logistics domain, different MCDM approaches have also been used for the selection of other types of equipment, such as transport robots and automated guided vehicles [10].

When it comes to the selection of equipment used in industrial production processes, it is crucial to establish a balance between efficiency and reliability. In paper [11], an approach based on two MCDM methods was employed. The Best-Worst Method (BWM) [12] was used to determine the weights of criteria, while RAnking based on the Distance And Range (RADAR) [13–15] was applied to rank devices used in the automotive industry. On the other hand, in the domain of plastic manufacturing, the authors in [16] compared multiple MCDM methods in order to examine the reliability of the obtained solution. In addition, their analysis was based on two approaches, i.e., considering criteria weights and not considering criteria weights. In total, two methods for determining criteria weights and four ranking methods were used.

In the domain of construction equipment selection, with a focus on environmental protection, the authors in [17] employed a fuzzy MCDM approach based on the application of the CRITIC method, Step-wise Weight Assessment Ratio Analysis (SWARA) [18], and Evaluation based on Distance from Average Solution (EDAS) [19].

For selecting occupational safety equipment, the authors in [20] employed AHP and the Preference Ranking Organization Method for Enrichment of Evaluations (PROMETHEE) [21].

In the relevant literature, multiple MCDM methods are very often applied in parallel in order to examine the reliability of the obtained results, as well as to evaluate the applicability and usefulness of the methods themselves. Thus, in paper [22], the AHP method was compared with Multi-Attribute Range Evaluations (MARE) [23] and ELimination Et Choix Traduisant la REalité (ELECTRE III) [24] for an equipment selection problem in a chemical manufacturing process. Similarly, in the mining industry domain [25], the authors used TOPSIS and VIKOR (in Serbian: VIšeKriterijumska Optimizacija I Kompromisno Rešenje) [26] for the selection of flotation machines. They found that the application of these two methods produced somewhat different results, which required additional analysis.

Based on the presented review of the relevant literature, it can be concluded that the authors employed various MCDM approaches and combined them with different MCDM methods. In this study, since the analysis is based on precise data obtained from records, it was not necessary to include a fuzzy approach.

In this research, a similar approach to that applied in [16] was adopted. The analysis was performed under two conditions: when criteria have equal weights and when the weights differ. A step further is reflected in the use of two methods for determining criteria weights, one objective (CRITIC) and one subjective (AHP). In addition, this study introduces a new SREM method, whose robustness was tested through its application alongside well-established methods.

3. Theoretical Background of the SREM Method

Although SREM represents a new MCDM approach, it cannot be considered completely unique or original. In fact, it is based on principles and steps that are employed in existing MCDM methods. Primarily, the idea of the SREM method is to overcome the limitations of linear normalization, which preserves proportionality in the data. While this can sometimes be considered "fair" or desirable, in certain situations it is necessary to allow clearer differentiation of alternatives that are at the very top of a measurement scale or within a dataset. Through the introduction of square and root transformations, the SREM method addresses this limitation. In this way, a static linear environment is transformed into a dynamic one that can be adapted to the decision-making strategy. In short, the square transformation emphasizes the advantages of the best alternatives for a given criterion, while the root transformation stabilizes the ranking and reduces the influence of extreme alternative values. Moreover, SREM also allows fine-tuning of these characteristics.

From a theoretical perspective, SREM is most similar to the Weighted Aggregated Sum Product Assessment (WASPAS) method [27]. Both methods use a fusion parameter, i.e., a balancing factor between two approaches. In WASPAS, this parameter is λ, whereas in SREM it is α. The main difference is that the objects of fusion are different. WASPAS fuses two aggregation methods, namely Weighted Sum Model (WSM) (also known in the literature as SAW) and Weighted Product Model (WPM). These two methods employ different aggregation procedures (addition and multiplication). On the other hand, SREM fuses two normalization approaches, i.e., data transformations (square and root), with addition being the sole aggregation procedure.

Therefore, it can be said that SREM is based on balancing/fine-controlling the favoring of dominant alternatives achieved through the square transformation and the solution stability achieved through the root transformation. The model with root transformation is encountered in the Root Assessment Method (RAM) [28], but it focuses solely on solution stability and the reduction of extreme alternative effects. SREM goes one step further, as it not only ensures stability but can also emphasize excellence when needed (through the α parameter), while maintaining a balance between these aspects.

At first glance, SREM may appear similar to TOPSIS due to the squaring. However, TOPSIS uses squaring for a different purpose, i.e., in vector normalization and Euclidean distance calculation, to measure the distance from ideal values. In contrast, SREM uses squaring to highlight the excellence of alternatives.

From the above, it can be concluded that SREM provides decision-makers with flexibility without changing the methodology, and it inherently facilitates sensitivity analysis, making it a suitable tool for solving complex MCDM problems.

To validate the obtained results and verify the robustness of the SREM method, the results were compared with those obtained using two well-known and widely accepted methods – TOPSIS and SAW. TOPSIS was selected because it is based on a different logical approach. Comparison with it provides a strong robustness test, as this method is highly popular and considered the "gold standard" among MCDM methods. On the other hand, SAW was chosen because it relies on linear normalization, whereas SREM introduces both square and root transformations. The aim is to assess how the introduction of these parameters affects ranking stability, as well as potential changes in the ranking compared to linear normalization. Moreover, these two methods were selected because they have demonstrated a high degree of consistency in ranking with different methods in previous studies [11,29–31].

In order to ensure an adequate comparison of the SREM method with TOPSIS and SAW, three scenarios were employed, as already stated in the paper. In the first scenario, the AHP method was used as a representative of methods based on the subjective judgments of decision-makers. AHP was selected as one of the most significant methods in the literature, although other approaches such as BWM or Level Based Weight Assessment (LBWA) [32] also exist today. The second scenario refers to the application of the CRITIC method, which belongs to the group of objective weighting methods. This method is one of the most widely used of its type in the literature [33]; however, it should be noted that some alternative approaches also exist, such as Sequential Identification of Task Weights (SITW) [34] or LOGarithmic normalization and STAndard deviation (LOGSTA) [35]. It should be noted that the literature also includes hybrid approaches that combine subjective and objective methods, i.e., their respective characteristics. One such method is Criteria IMportance ASsessment (CIMAS) [36].The third scenario considers the case in which all criteria have equal importance.

4. THE PROPOSED METHODOLOGY

In this study, the objective is to determine which of the five punch presses owned by the considered company exhibits the best operational performance, as well as to identify those that are the most critical in this respect and therefore require special attention. In this case, the punch presses can be considered as alternatives in the MCDM problem and can be formally represented by a set of indices $i, i = 1, \ldots, I$. All punch presses have identical characteristics and were purchased from the same manufacturer.

In collaboration with experts from the considered company who participated in this study, the criteria used to evaluate the operational performance of the punch presses were defined. The experts can be formally represented by a set of indices $e, e = 1, \ldots, E$. These experts include the production manager ($e = 1$), the quality engineer ($e = 2$), and the punch press programmer ($e = 3$). The criteria can be represented by a set of indices $j, j = 1, \ldots, J$, and they are as follows:

- Average number of properly manufactured parts per work shift for each punch press ($j = 1$). This parameter was calculated based on the total annual production records.
- Number of defective products for each considered punch press during the 2025 calendar year ($j = 2$).
- Number of causes leading to the occurrence of defective products for each punch press ($j = 3$). Only those causes that occurred at least 10 times on a given punch press were considered.
- Total number of days on which defective products occurred for each punch press ($j = 4$).

All criteria were defined based on the available data recorded and routinely monitored by the company. The company experts considered these data to be relevant for evaluating the operational performance of the punch presses. Primarily, criteria related to operational efficiency and quality were selected. However, there are also criteria for which the considered company does not maintain records, but which would be interesting to consider and include in the analysis. Such criteria include maintenance costs, downtime, and even electricity consumption. However, in this case, it was not possible to include them.

The first criterion is of the benefit-type, as it refers to the average number of properly manufactured parts. It is desirable to achieve as high a number of such parts as possible. The second criterion relates to the number of defective products; since their quantity should ideally be minimized, this is a cost-type criterion. The third criterion concerns the number of causes leading to the occurrence of defective products, indicating the variety of ways a punch press can malfunction, which is also characterized as a cost-type criterion. Finally, the fourth criterion is also of the cost-type. It refers to the total number of days on which defective products occurred, which indicates the frequency of quality issues on a specific press during the observed period.

In this study, multiple MCDM methods were applied. Two approaches, subjective and objective, were used to determine the criteria weights. The company experts provided subjective assessments to evaluate the relative importance of the criteria, while the final criteria weights were determined using the AHP method. The CRITIC method was employed as an objective approach for determining the criteria weights. Both methods were applied in their original forms. In addition, a third case was considered for the purpose of sensitivity analysis, in which all criteria were assumed to have equal importance.

For the final ranking of alternatives, i.e., for determining which punch presses exhibit the best operational performance, the novel SREM method was applied. TOPSIS and SAW methods, in their original forms, were used for sensitivity analysis and to examine the robustness of the results. Figure 1 illustrates the procedure for applying the proposed methodology to solve the considered problem.

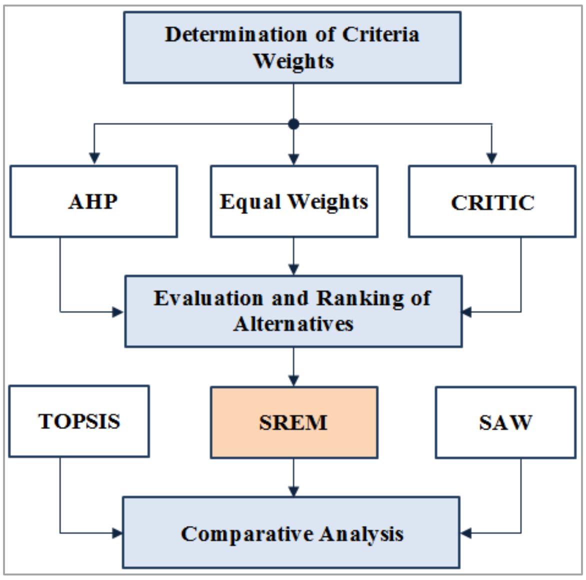


Fig. 1 Workflow of the proposed methodology

A particular emphasis in this study is placed on the novel SREM method and its application to solving the considered MCDM problem. Special attention is devoted to the application procedure of this method and its key characteristics. For this purpose, other MCDM methods were applied to conduct sensitivity analysis and to compare the obtained results with existing approaches.

4.1 Determination of Criteria Weights

Two MCDM methods were employed in this study to determine the criteria weights. The first method is based on the subjective assessments of experts, namely the AHP method, while the second relies on objective data from company records and their intercorrelation relationships, i.e., the CRITIC method. In addition, a third approach was considered, in which all criteria were assigned equal importance.

The AHP and CRITIC methods are well established in the relevant literature, and since their original versions are applied in this study, there is no need to provide extensive explanations. Therefore, only the basic steps of these two methods are presented in the following section in order to ensure that the application procedure is transparent and reproducible.

4.1.1 Determination of Criteria Weights Using the AHP Method

The standard AHP method in this study is implemented through the following key steps:

Step 1. Formation of the pairwise comparison matrix of the relative importance of criteria, $j, j = 1, \dots J$, for each decision-maker, $e, e = 1, \dots E$:

$$\left[W_{jj'}^{e}\right]_{J \times J}, j, j' = 1, \dots, J; j \neq j'; e, e = 1, \dots E \tag{1}$$

The experts expressed their judgments using the classical Saaty 1–9 scale [1].

Step 2. Consistency check of the assessments using the Eigenvector method [1]. The Consistency Ratio (CR) should be less than or equal to 0.1 for the experts' assessments to be considered consistent.

Step 3. Calculation of the criteria weights at the level of each decision-maker, ω_j^e.

Step 4. Aggregation of the criteria weights using the arithmetic mean operator, ω_j.

4.1.2 Determination of Criteria Weights Using the CRITIC Method

The standard CRITIC method in this study is implemented through the following key steps:

Step 1. Start from the decision matrix, $\left[D_{ij}\right]_{I \times J}$.

Step 2. Normalize the values using max normalization:

$$m_{ij} = \frac{d_{ij}}{d_j^{max}} \tag{2}$$

Normalization was performed in the same way for both benefit-type and cost-type criteria.

Step 3. Calculate the standard deviation for each criterion, s_j.

Step 4. Calculate the correlation coefficients between all criteria, $r_{jj'}$.

Step 5. Calculate the unnormalized criteria weight coefficients:

$$W_j = s_j \cdot \sum_{j=1,\ldots,J}\left(1 - r_{jj'}\right) \tag{3}$$

Step 6. Calculate the final normalized criteria weights:

$$\omega_j = \frac{W_j}{\sum_{j=1,\ldots,J} W_j} \tag{4}$$

The steps presented in Sections 4.1.1 and 4.1.2 provide the criteria weights, which serve as input for the application of the SREM method, as well as for the TOPSIS and SAW methods, which are employed to compare the obtained results.

4.2 Ranking of Punch Presses Based on Operational Performance Using the SREM Method

The SREM method, based on square and root transformations and their properties, is presented for the first time in this study. In addition to the key steps of the method, their justifications are provided. Considering a set of alternatives $\{1, \ldots, i, \ldots I\}$, whose evaluation is performed based on a predefined set of criteria $\{1, \ldots, j, \ldots J\}$, the steps of the SREM method are as follows:

Step 1. Formation of the decision matrix, $\left[D_{ij}\right]_{I\times J}$.

Step 2. Normalized decision matrix using the percentage normalization method, $\left[M_{ij}\right]_{I\times J}$:

For the benefit-type of criteria:

$$m_{ij} = \frac{d_{ij}}{\sum_{i=1}^{I} d_{ij}} \cdot 100 \tag{5}$$

For the cost-type of criteria:

$$m_{ij} = \frac{\frac{1}{d_{ij}}}{\sum_{i=1}^{I}\frac{1}{d_{ij}}} \cdot 100 \tag{6}$$

<u>Explanation:</u> As with other MCDM methods, normalization is performed with the aim of bringing the values of the decision matrix, expressed in different units of measurement and on different scales, onto a single scale and converting them into dimensionless values to make them comparable. In this case, standard percentage normalization is used. It is suitable because the normalized values are linear and expressed on a scale from 1 to 100, which is practical for subsequent steps, i.e., for the square and root transformations, in order to avoid calculations with very small values.

Step 3. Squared-transformed normalized matrix, $\left[S_{ij}\right]_{I\times J}$:

Here:

$$S_{ij} = \frac{m_{ij}^2}{\sum_{i=1}^{I} m_{ij}^2} \tag{7}$$

<u>Explanation:</u> The purpose of the square transformation is to emphasize alternatives that have higher scores (larger values) for the considered criterion. It is useful in situations

where it is important for the strong characteristics of alternatives to receive additional weight.

Step 4. Root-transformed normalized matrix, $\left[R_{ij}\right]_{I\times J}$:

Here:

$$R_{ij} = \frac{\sqrt{m_{ij}}}{\sum_{i=1}^{I}\sqrt{m_{ij}}} \tag{8}$$

Explanation: The purpose of the root transformation is to reduce the difference between alternatives with higher scores (larger values) and those that are somewhat lower for the considered criterion. It is useful in situations where the goal is to give alternatives with moderate (stable) values a greater chance. Additionally, it ensures that alternatives with low values are not completely disregarded.

In Fig. 2, the behavior of each type of normalization/transformation is shown graphically using values from 1 to 100 as an illustrative example. For the sake of a practical example, percentage normalization without multiplying the values by 100 was used, as well as the square and root transformations. It should be noted that the values obtained using percentage normalization were not multiplied by 100, in order to make them graphically comparable with the other two transformations.

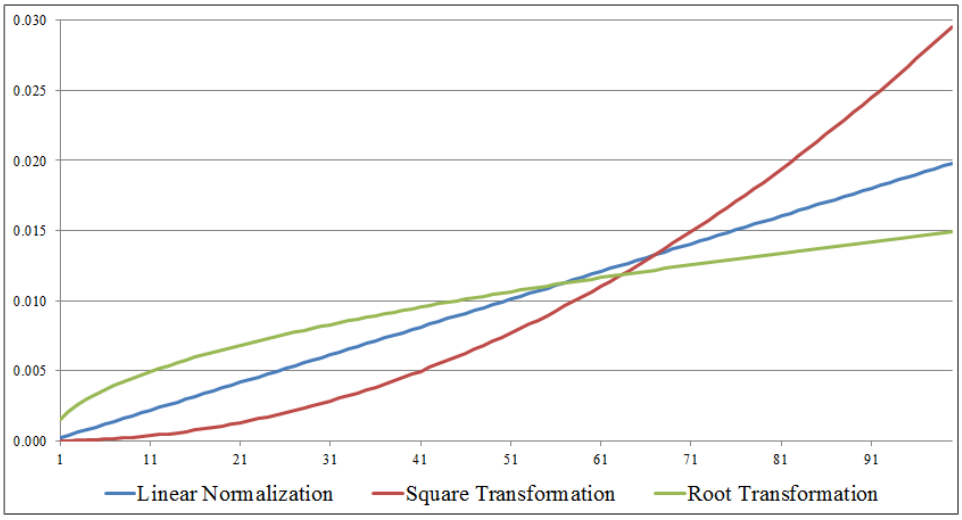


Fig. 2 Comparison of linear, square, and root transformations for values 1-100

In Fig. 2, the characteristics of the square and root transformations are clearly visible in comparison to linear normalization. With the square transformation, alternatives with the highest values for a given criterion become even more favored, increasing their chances of achieving a better position in the final ranking, while the root transformation reduces the influence of alternatives with extreme values.

Step 5. α-fused matrix, $[A_{ij}]_{I\times J}$:

$$a_{ij} = \alpha \cdot S_{ij} + (1-\alpha) \cdot R_{ij} \tag{9}$$

Explanation: The purpose of this step is to adjust the influence of the square and root transformations. A parameter α is introduced, with values ranging from 0 to 1. A value of 1 for this parameter indicates that only the square transformation is considered, while a value of 0 indicates that only the root transformation is considered. Values in between represent a balance between the influences of the two transformations, as illustrated in Fig. 3.

The entire preceding procedure, concluding with this step, is considered a single three-stage normalization process, consisting of linear (percentage) normalization followed by square and root transformations.

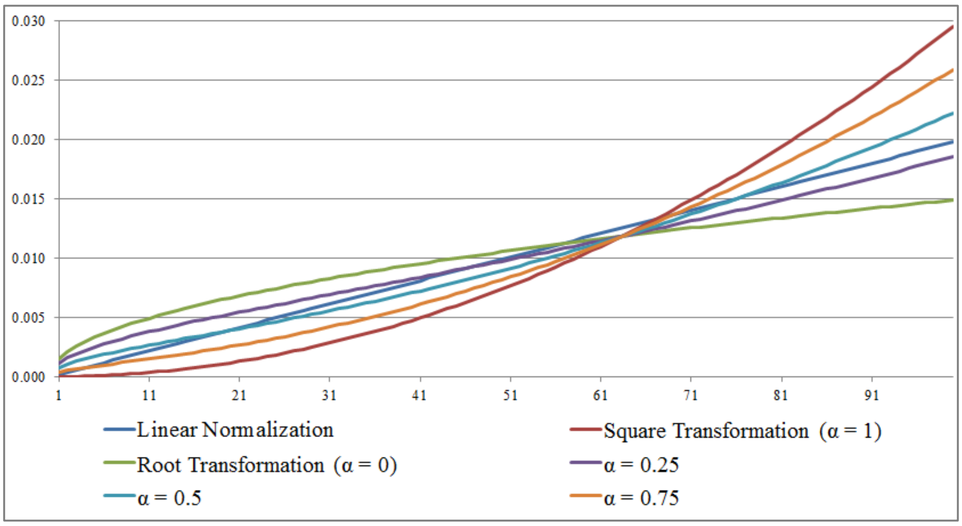


Fig. 3 Effect of changing the parameter α on value transformation

The graph presented in Fig. 3 shows how changes in the α parameter affect value transformation. A middle value of this parameter, 0.5, is actually very close to linear normalization, while slightly favoring alternatives with the lowest and highest values (in a controlled manner). Thus, it slightly allows better alternatives to achieve a higher rank in the final distribution, while giving the worst alternatives a chance to compensate a poor value for one criterion with good values for other criteria.

From the decision-maker's perspective, the α parameter is a sensitivity coefficient that enables control over the influence of extreme (low and high) values of alternatives within the MCDM process. Therefore, varying this parameter can be interpreted as the decision-maker's stance toward emphasizing or reducing the impact of extreme alternative values. A parameter value approaching 1 favors high alternative values, while a value of 0 reduces the significance of extremely high alternative values.

Step 6. Weighted α-fused matrix, $\left[N_{ij}\right]_{I\times J}$:
with:

$$n_{ij} = a_{ij} \cdot \omega_j \tag{10}$$

where ω_j is the weight of criterion j.

Explanation: A standard MCDM step that takes into account the importance of the considered criteria.

Step 7. Final ranking index:

$$F_i = \sum_{j=1}^{J} n_{ij} \tag{11}$$

The top-ranked alternative is the one assigned the highest value of the index F_i. The opposite also holds.

Explanation: In this step, the final weighted values are summed. The goal is to determine the overall ranking of alternatives in a straightforward manner.

5. The Case Study

The case study was carried out in a company whose main activity is the production of industrial machines and assemblies. The company is located in western Serbia. One of the important stages of the production process in this company is the processing of metal sheets (copper, steel, and aluminum) on punch presses. In the company's production facility, there are a total of five punch presses, on which sheets of different dimensions, as well as shapes that are cut depending on the type of product, are processed.

The standard sheet dimensions are 2500 × 1500 mm, although in certain cases they may also be of somewhat smaller dimensions. On average, between 800 and 1000 sheets are processed daily on all five presses, operating in a total of three work shifts. Therefore, the goal is to maximize the utilization of production capacities. With regard to the number of elements on a sheet or the number of punching operations, it ranges from 20 to 120 depending on the customer's order. Figure 4 shows an example of a sheet before pressing (left) and a correctly cut sheet after pressing (right).

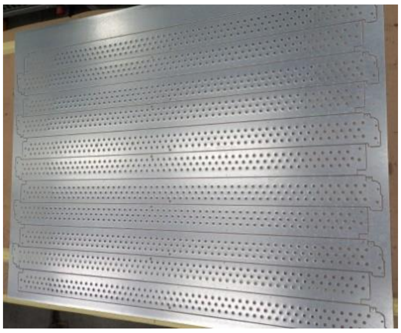
a)  b) 

Fig. 4 Sheet metal specimen; a) before and b) after pressing

During processing on punch presses, various failures occur that affect the occurrence of nonconforming products. Such products are most often scrapped and cannot be used in further production. The defects that occur on the products and are directly related to the operation of the press and the operator are: (1) inclined/skewed holes in the sheet, so-called collars, resulting from improper press operation; (2) damage to the collar, i.e., cracks, indentations, and edge damage; (3) damage to the sheet due to the occurrence of chips during the pressing stage; (4) improper positioning of holes due to inadequate press setup; (5) poor trimming, i.e., uneven edges resulting from improper press operation; (6) non-uniform deformation (sheet bending); and (7) all other defects that occur rarely, i.e., less than three times on an annual basis (thermal influence of the press due to heating, tool displacement during operation, failure to execute the program, etc.). Figure 5 shows some of the defects that occur on the sheets.

Fig. 5 Some of the defects that occur during punch pressing: punches extending beyond the sheet edge (left), poor cutting of parts (uneven edges) (middle), and skewed collars around punched holes (right)

All defects are recorded by operators at each punch press. At the end of each shift, they submit a report to the responsible personnel containing data on the quantity and types of defects. The Quality Engineer is responsible for maintaining the complete defect records. The company most often uses these data for financial analysis (losses resulting from the occurrence of defects).

In collaboration with the company's operations management, criteria were established based on which the operational performance of punch presses will be analyzed. The criteria were defined based on the data that the company diligently and accurately maintains in its records. The data used were extracted from the records for the 2025 calendar year.

5.1 Case Study: Criteria Weighting Using AHP Method

As previously mentioned in Section 4, which describes the proposed methodology, this study involved the production manager ($e = 1$), quality engineer ($e = 2$), and punch press programmer ($e = 3$). The experts are assumed to have equal importance.

The experts first assessed the relative importance of the criteria through pairwise comparisons:

$$\underset{e=1}{\begin{bmatrix} 1 & 2 & 4 & 2 \\ & 1 & 3 & 2 \\ & & 1 & 1/2 \\ & & & 1 \end{bmatrix}} \qquad \underset{e=2}{\begin{bmatrix} 1 & 1/2 & 3 & 1 \\ & 1 & 4 & 2 \\ & & 1 & 1/2 \\ & & & 1 \end{bmatrix}} \qquad \underset{e=3}{\begin{bmatrix} 1 & 1 & 3 & 2 \\ & 1 & 2 & 2 \\ & & 1 & 1/2 \\ & & & 1 \end{bmatrix}}$$

The CR values for the presented pairwise comparison matrices are 0.03, 0.01, and 0.02, respectively. The experts' judgments are considered consistent.

The criteria weights at the level of each expert are:

- Production manager:

$\omega_1^1 = 0.43$ $\omega_2^1 = 0.29$ $\omega_3^1 = 0.10$ $\omega_4^1 = 0.18$

- Quality engineer:

$\omega_1^2 = 0.24$ $\omega_2^2 = 0.44$ $\omega_3^2 = 0.10$ $\omega_4^2 = 0.22$

- Punch press programmer:

$\omega_1^3 = 0.36$ $\omega_2^3 = 0.32$ $\omega_3^3 = 0.13$ $\omega_4^3 = 0.19$

Aggregated criteria weights obtained using the arithmetic mean operator:

$\omega_1 = 0.34$ $\omega_2 = 0.35$ $\omega_3 = 0.11$ $\omega_4 = 0.20$

The obtained weight values represent the result of the experts' subjective assessments and can be considered as the criteria weights from the company's perspective.

5.2 Case Study: Criteria Weighting Using CRITIC Method

The application of the CRITIC method begins with the definition of the decision matrix, which is provided in Table 1.

Table 1 Decision matrix

	$j = 1$	$j = 2$	$j = 3$	$j = 4$
$i = 1$	184	771	5	35
$i = 2$	190	640	1	36
$i = 3$	201	561	6	44
$i = 4$	214	256	7	31
$i = 5$	179	420	2	33

Important parameters for the application of the CRITIC method are the standard deviation of the data at the criterion level and the correlation coefficients between the criteria (Table 2). The standard deviation values are:

$s_1 = 0.066$ $s_2 = 0.258$ $s_3 = 0.370$ $s_4 = 0.113$

Table 2 The correlation coefficients between criteria

	$j = 1$	$j = 2$	$j = 3$	$j = 4$
$j = 1$	1	-0.58	0.73	0.04
$j = 2$	-0.58	1	-0.31	0.43
$j = 3$	0.73	-0.31	1	0.12
$j = 4$	0.04	0.43	0.12	1

The standard deviation and correlation coefficient values were calculated based on the normalized data. The normalization of the decision matrix data was performed using the max normalization procedure.

The criteria weights determined using the CRITIC method are:

$\omega_1 = 0.08 \qquad \omega_2 = 0.40 \qquad \omega_3 = 0.40 \qquad \omega_4 = 0.12$

Based on the obtained results, it can be clearly concluded that the weights derived using the AHP and CRITIC methods differ significantly. This difference arises from the distinct principles on which these two methods are based. AHP is entirely based on the experts' assessments and directly reflects their perceptions. In contrast, CRITIC relies on the variability of the data in the decision matrix, primarily on the standard deviation and the correlation coefficient. Therefore, criteria with higher standard deviation values can potentially receive higher weights, while in the case of the correlation coefficient, criteria with lower correlation with the others are favored.

Of course, the results obtained using the CRITIC method should not override the decisions of the experts. In this study, greater attention was given to the experts' assessments and the weights obtained using the AHP method, but the CRITIC-based weights will also be used in the sensitivity analysis.

5.3 Case Study: Ranking of Alternatives Using the SREM Method

The main objective of this study is to apply the new SREM method to solve a real MCDM problem, namely the evaluation and ranking of punch presses based on their operational performance. The company uses a total of five punch presses with very similar characteristics, all purchased from the same manufacturer. Figure 6 shows the appearance of one of the considered punch presses.

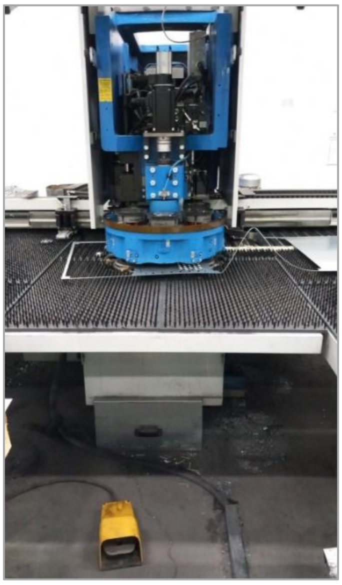


Fig. 6 Example of a punch press considered in the study

The first step in applying the SREM method is constructing the decision matrix, as shown in Table 3.

Table 3 Decision matrix with criteria types

	$j = 1$	$j = 2$	$j = 3$	$j = 4$
$i = 1$	184	771	5	35
$i = 2$	190	640	1	36
$i = 3$	201	561	6	44
$i = 4$	214	256	7	31
$i = 5$	179	420	2	33
Type of criteria	*Benefit*	*Cost*	*Cost*	*Cost*

Then, in the second step of applying the SREM method, the values are normalized using the percentage normalization method (Table 4).

Table 4 Normalized decision matrix

	$j = 1$	$j = 2$	$j = 3$	$j = 4$
$i = 1$	19.008	11.867	9.953	20.172
$i = 2$	19.628	14.296	49.763	19.612
$i = 3$	20.764	16.310	8.294	16.046
$i = 4$	22.107	35.741	7.109	22.775
$i = 5$	18.492	21.785	24.882	21.395

Example of normalization for benefit-type criteria:

$$m_{11} = \frac{184}{184 + 190 + 201 + 214 + 179} \cdot 100 = 19.008$$

Example of normalization for cost-type criteria:

$$m_{12} = \frac{\frac{1}{771}}{\frac{1}{771} + \frac{1}{640} + \frac{1}{561} + \frac{1}{256} + \frac{1}{420}} \cdot 100 = 11.867$$

Step 3 of the SREM method is based on the squared transformation of the values of the normalized decision matrix, resulting in a new squared-transformed normalized matrix (Table 5).

Table 5 Squared-transformed normalized matrix

	$j = 1$	$j = 2$	$j = 3$	$j = 4$
$i = 1$	0.180	0.060	0.030	0.201
$i = 2$	0.192	0.086	0.747	0.190
$i = 3$	0.215	0.113	0.021	0.127
$i = 4$	0.243	0.541	0.015	0.256
$i = 5$	0.170	0.201	0.187	0.226

Example of calculating the first element of the squared-transformed normalized matrix:

$$S_{11} = \frac{19.008^2}{19.008^2 + 19.628^2 + 20.764^2 + 22.107^2 + 18.492^2} = 0.180$$

In the fourth step of the SREM method, the root-transformed normalized matrix is formed, as presented in Table 6.

Table 6 Root-transformed normalized matrix

	$j = 1$	$j = 2$	$j = 3$	$j = 4$
$i = 1$	0.195	0.157	0.152	0.201
$i = 2$	0.198	0.173	0.340	0.198
$i = 3$	0.204	0.184	0.139	0.179
$i = 4$	0.210	0.273	0.129	0.214
$i = 5$	0.192	0.213	0.240	0.207

Example of calculating the first element of the root-transformed normalized matrix:

$$R_{11} = \frac{\sqrt{19.008}}{\sqrt{19.008} + \sqrt{19.628} + \sqrt{20.764} + \sqrt{22.107} + \sqrt{18.492}} = 0.195$$

In the fifth step, the α-fused matrix is formed, as shown in Table 7. The coefficient α is used to slightly adjust the balance between the square- and root-transformed values, as explained in this step of the method. The basic value of the coefficient α was taken as 0.5. This value represents a balance between the application of square and root transformations, that is, between favoring excellence and preserving ranking stability.

Table 7 α-fused matrix, $\alpha = 0.5$

	$j = 1$	$j = 2$	$j = 3$	$j = 4$
$i = 1$	0.187	0.108	0.091	0.201
$i = 2$	0.195	0.130	0.544	0.194
$i = 3$	0.209	0.148	0.080	0.153
$i = 4$	0.227	0.407	0.072	0.235
$i = 5$	0.181	0.207	0.214	0.217

Example of calculating the first element of the α-fused matrix:

$$a_{11} = 0.5 \cdot 0.180 + (1 - 0.5) \cdot 0.195 = 0.187$$

In the sixth step of applying the SREM method, the values are weighted, and the weighted α-fused matrix is formed (Table 8). In this study, the weights obtained using the AHP method were used as the basis.

Table 8 Weighted α-fused matrix

	$j = 1$	$j = 2$	$j = 3$	$j = 4$
$i = 1$	0.064	0.038	0.010	0.040
$i = 2$	0.066	0.045	0.060	0.039
$i = 3$	0.071	0.052	0.009	0.031
$i = 4$	0.077	0.142	0.008	0.047
$i = 5$	0.062	0.072	0.024	0.043

Example of calculating the first element of the weighted α-fused matrix:

$$n_{11} = 0.187 \cdot 0.34 = 0.064$$

In the final, seventh step of applying the SREM method, the alternatives are ranked based on the values of the final ranking index, as shown in Table 9.

Table 9 Final ranking of alternatives

	F_i	Rank
$i = 1$	0.152	5
$i = 2$	0.210	2
$i = 3$	0.163	4
$i = 4$	0.274	1
$i = 5$	0.201	3

Example of calculating the final ranking index for the first alternative:

$$F_i = 0.064 + 0.038 + 0.010 + 0.040 = 0.152$$

Based on the obtained results, it can be clearly concluded that the punch press labeled as alternative $i = 4$ ranks first, i.e., it exhibits the best operational performance. If this alternative were analyzed for each criterion individually, it can be observed that it ranks first for the three most important criteria, while it ranks last for criterion $j = 3$, which has an almost negligible importance. The punch press labeled as alternative $i = 1$ ranks last overall. This alternative is last according to the most important criterion $(j = 1)$ and second-to-last according to the second most important criterion $(j = 2)$. For the remaining two criteria, it occupies the third position.

For a more detailed examination of the results, a sensitivity analysis was conducted, which is presented in Section 5.4.

5.4 Sensitivity Analysis of Ranking Results

Within the sensitivity analysis, the results obtained using the SREM method were compared with those obtained on the same data using the TOPSIS and SAW methods. Three scenarios were considered: 1) when the criteria weights are derived using the AHP method, 2) when the criteria weights are derived using the CRITIC method, and 3) when all criteria are considered equally important.

5.4.1 Sensitivity Analysis Using AHP-Derived Criteria Weights

In the first scenario, the criteria weights obtained using the AHP method were considered: $\omega_1 = 0.34$, $\omega_2 = 0.35$, $\omega_3 = 0.11$, and $\omega_4 = 0.20$. Table 10 presents the ranking of alternatives using the SREM method for the values of parameter α: 0, 0.25, 0.5, 0.75, and 1, as well as the ranks obtained using the TOPSIS and SAW methods. It is evident that the ranking across the considered approaches overlaps in all cases, except when $\alpha = 0$. In this case, only the root transformation is considered. Although alternative $i = 4$ still remains firmly in first place, and the fourth and fifth alternatives do not change their positions, a swap occurs between alternatives $i = 2$ and $i = 5$. Alternative $i = 2$, which occupies second place in all other cases, now drops to third place because it loses the advantage it previously had over alternative $i = 5$, which existed due to the large advance in criterion $j = 3$, as well as the poor performance of $i = 5$ on the first criterion. The root transformation has mitigated this effect to some extent.

Table 10 Ranking of alternatives using SREM, TOPSIS, and SAW with AHP-derived criteria weights

	SREM ($\alpha = 0$)	SREM ($\alpha = 0.25$)	**SREM ($\boldsymbol{\alpha = 0.5}$)**	SREM ($\alpha = 0.75$)	SREM ($\alpha = 1$)	**TOPSIS**	**SAW**
$i = 1$	5	5	**5**	5	5	**5**	**5**
$i = 2$	3	2	**2**	2	2	**2**	**2**
$i = 3$	4	4	**4**	4	4	**4**	**4**
$i = 4$	1	1	**1**	1	1	**1**	**1**
$i = 5$	2	3	**3**	3	3	**3**	**3**

5.4.2 Sensitivity Analysis Using CRITIC-Derived Criteria Weights

In the second scenario, the criteria weights obtained using the CRITIC method were considered: $\omega_1 = 0.08$, $\omega_2 = 0.40$, $\omega_3 = 0.40$, and $\omega_4 = 0.12$, and the ranking is shown in Table 11.

Table 11 Ranking of alternatives using SREM, TOPSIS, and SAW with CRITIC-derived criteria weights

	SREM ($\alpha = 0$)	SREM ($\alpha = 0.25$)	**SREM ($\boldsymbol{\alpha = 0.5}$)**	SREM ($\alpha = 0.75$)	SREM ($\alpha = 1$)	**TOPSIS**	**SAW**
$i = 1$	5	5	**5**	5	5	**5**	**5**
$i = 2$	1	1	**1**	1	1	**1**	**1**
$i = 3$	4	4	**4**	4	4	**4**	**4**
$i = 4$	3	2	**2**	2	2	**3**	**3**
$i = 5$	2	3	**3**	3	3	**2**	**2**

In the second scenario, there is a very small difference in the ranking of alternatives when applying the different approaches. TOPSIS, SAW, and SREM with $\alpha = 0$ have identical rankings. For the other values of α, a change occurs in the ranking between alternatives $i = 4$ and $i = 5$. In this case, the square transformation emphasizes the strong performance of alternative $i = 4$ across three criteria. This alternative is the best according to three criteria, while for one of the two criteria with the highest weights, it ranks last. In this case, its top position according to the other three criteria prevailed. Nevertheless, even here, the differences in ranking can be considered minor, almost negligible.

5.4.3 Sensitivity Analysis with Equal Criteria Weights

In the final, third scenario, the case where all criteria have equal importance is considered. Table 12 presents the ranking of the alternatives. As can be seen in Table 12, the ranking of the alternatives is completely identical in all the considered cases. It is clear that alternative $i = 2$ occupies the first place in the ranking, while alternative $i = 1$ stands out as the punch press with the worst operational performance.

Table 12 Ranking of alternatives using SREM, TOPSIS, and SAW with equal criteria weights

	SREM ($\alpha = 0$)	SREM ($\alpha = 0.25$)	**SREM ($\boldsymbol{\alpha = 0.5}$)**	SREM ($\alpha = 0.75$)	SREM ($\alpha = 1$)	**TOPSIS**	**SAW**
$i = 1$	5	5	**5**	5	5	**5**	**5**
$i = 2$	1	1	**1**	1	1	**1**	**1**
$i = 3$	4	4	**4**	4	4	**4**	**4**
$i = 4$	2	2	**2**	2	2	**2**	**2**
$i = 5$	3	3	**3**	3	3	**3**	**3**

5.5 Discussion

Based on the results presented in Sections 5.3 and 5.4, several conclusions can be drawn regarding the considered case study as well as the characteristics of the proposed SREM method. Based on the main case study, in which a combination of the AHP method for determining criteria weights and the novel SREM method for ranking alternatives was applied, it was concluded that the alternative denoted as $i = 4$ achieved the highest rank, followed by the alternative $i = 2$ in the second position. The lowest-ranked alternative is $i = 5$, which simultaneously exhibits the weakest operational performance.

When the sensitivity analysis of the results is taken into account, it can be concluded that the SREM method is highly stable and demonstrates a high level of consistency in comparison with the TOPSIS and SAW methods. In the first scenario, the differences between the rankings obtained using the SREM method and those produced by the other two methods are minimal. For the intermediate value of the parameter $\alpha = 0.5$, the obtained ranking is completely identical, while deviations occur only in the extreme case when $\alpha = 0$, i.e., when only the root transformation is considered.

In the second scenario, the TOPSIS and SAW methods yield a slightly different ranking compared to the SREM method for $\alpha = 0.5$, with changes occurring only in the positions of the fourth and fifth alternatives, corresponding to the second and third ranks. All other variants of the SREM method coincide with the ranking obtained for $\alpha = 0.5$, except in the case when $\alpha = 0$, i.e., when only the root transformation is applied. In this case, the resulting ranking is identical to that obtained using the TOPSIS and SAW methods.

In the final analyzed case, where all criteria were assigned equal weights, an absolutely identical ranking of alternatives was obtained for all considered methods.

Considering all three scenarios, it is evident that the punch press denoted as alternative $i = 1$ exhibits the poorest operational performance. For this press, it is necessary to undertake specific actions in order to improve its performance. At present, this press represents a highly vulnerable point in this segment of the production process.

Overall, it can be concluded that the SREM method provides a highly stable and reliable ranking, which largely corresponds to the results obtained using standard and widely accepted MCDM methods. At the same time, the SREM method enables fine-tuning and balancing between emphasizing and reducing the influence of alternatives with high values for a given criterion, depending on decision-making needs. In this way, decision makers are provided with a broader and more informative perspective on the considered problem.

In addition to the theoretical contribution of the research, which relates to the development and application of a new MCDM method, the practical significance of the obtained results should also be emphasized in the context of the considered company and its managers. This ranking of punch presses enables the identification of those with the best operational performance, which can serve as benchmarks, i.e., a basis for improving the performance of the remaining presses.

Furthermore, low-ranked presses can be identified as critical points in production where certain actions need to be implemented to improve their performance. It should be taken into account that this type of ranking is relative, as it does not indicate the absolute performance level of a press, but rather establishes a ranking based on a limited set of alternatives. However, operational management can use the values of the criteria for each considered punch press as indicators for analyzing press performance. In other words, they can define clear target values for each indicator to be achieved. The ranking of presses will help determine the priority in which these actions should be implemented.

6. CONCLUSION

In this paper, a new MCDM method called SREM is presented for the first time, applied to a practical case study involving the evaluation and ranking of industrial punch presses based on their operational performance. The main motivation for developing the SREM method stems from the desire to overcome the "rigidity" of linear normalization, which is very frequently used in MCDM approaches. The SREM method introduces nonlinear transformations, namely square and root transformations, enabling decision makers to balance between rewarding excellent alternatives with respect to the considered criteria and achieving ranking stability.

The paper explains that the SREM method relies on principles and mathematical formulations that already exist in various MCDM approaches. It should be emphasized that the method shows the greatest similarity to the WASPAS (as well as SAW) and RAM methods. As a key advantage of the SREM method compared to other approaches, the introduction of the control parameter α can be highlighted, which allows the method to be adapted to the specific requirements of the decision environment. In other words, by varying the parameter α, the SREM method can independently perform sensitivity analysis of the obtained results.

The results obtained in the case study showed that SAW and TOPSIS exhibit a high degree of consistency in ranking, which has also been reported in previous studies. Across all analyzed scenarios, the SREM method proved to be stable, while at the same time providing clearer differentiation among alternatives with similar performance. As a result, rank changes occurred only in a limited number of cases.

Based on the above, the key advantages of the SREM method can be summarized as follows: (1) flexibility through the use of the α parameter, (2) enhanced differentiation among alternatives through the square transformation, (3) increased robustness to extreme values through the root transformation, and (4) intuitive applicability for decision makers.

If some key limitations of the SREM method are to be highlighted, they include: (1) higher computational complexity compared to SAW, and (2) reliance of the α parameter on the subjectivity of decision makers. From a theoretical perspective, future research directions may focus on extending the SREM method through the application of fuzzy set theory, its hybridization with other MCDM approaches, and its application in different industrial domains. On the other hand, from a practical perspective, such problem formulation and the SREM method itself are highly adaptable and subject to modifications, which enables the application of this approach to other types of industrial equipment, such as CNC machines, robots, and other machining systems. It is only necessary to define the criteria relevant to the specific machine, as well as their corresponding weights. For this reason, future research directions will also be oriented toward the application of this approach to other machines and industrial problems.

REFERENCES

1. Saaty, T.L., 2013, *The modern science of multicriteria decision making and its practical applications: the AHP/ANP approach*, Operations Research, 61(5), pp. 1101-1118.
2. Diakoulaki, D., Mavrotas, G., Papayannakis, L., 1995, *Determining objective weights in multiple criteria problems: the critic method*, Computers & Operations Research, 22(7), pp. 763-770.
3. Çelikbilek, Y., Tüysüz, F., 2020, *An in-depth review of theory of the TOPSIS method: an experimental analysis*, Journal of Management Analytics, 7(2), pp. 281-300.
4. Ciardiello, F., Genovese, A., 2023, *A comparison between TOPSIS and SAW methods*, Annals of Operations Research, 325, pp. 967-994.
5. Jusufbašić, A., 2023, *MCDM methods for selection of handling equipment in logistics: a brief review*, Spectrum of Engineering and Management Sciences, 1(1), pp. 13-25.
6. Nguyen, H.T., Md Dawal, S.Z., Nukman, Y., Rifai, A.P., Aoyama, H., 2016, *An integrated MCDM model for conveyor equipment evaluation and selection in an FMC based on a fuzzy AHP and fuzzy ARAS in the presence of vagueness*, PLOS ONE, 11(4), e0153222.
7. Yalçın, G.C., Kara, K., Gürol, P., Babič, M., 2025, *A fermatean fuzzy MCDM framework for green port transformation and heavy-duty forklift selection*, Journal of Engineering Management and Systems Engineering, 4(4), pp. 269-283.
8. Keshavarz-Ghorabaee, M., Amiri, M., Zavadskas, E.K., Turskis, Z., Antucheviciene, J., 2021, *Determination of objective weights using a new method based on the removal effects of criteria (MEREC)*, Symmetry, 13(4), 525.
9. Kara, K., Yalçın, G.C., Simic, V., Baysal, Z., Pamucar, D., 2024, *The alternative ranking using two-step logarithmic normalization method for benchmarking the supply chain performance of countries*, Socio-Economic Planning Sciences, 92, 101822.
10. Goswami, S.S., Behera, D.K., 2021, *Solving material handling equipment selection problems in an industry with the help of entropy integrated COPRAS and ARAS MCDM techniques*, Process Integration and Optimization for Sustainability, 5(4), pp. 947-973.
11. Komatina, N., 2025, *A novel BWM-RADAR approach for multi-attribute selection of equipment in the automotive industry*, Spectrum of Mechanical Engineering and Operational Research, 2(1), pp. 104-120.
12. Rezaei, J., 2015, *Best-worst multi-criteria decision-making method*, Omega, 53, pp. 49-57.
13. Komatina, N., 2024, *A compromise-based MADM approach for prioritizing failures: integrating the RADAR method within the FMEA framework*, Jurnal Sistem dan Manajemen Industri, 8(2), pp. 73-88.
14. Komatina, N., Marinkovic, D., Babič, M., 2026, *Fundamental characteristics and applicability of the RADAR method: proof of ranking consistency*, Spectrum of Operational Research, 3(1), pp. 63-80.
15. Komatina, N., Marinković, D., Tadić, D., Pamučar, D., 2025, *Advancing PFMEA decision-making: FRADAR based prioritization of failure modes using AP, RPN, and multi-attribute assessment in the automotive industry*, Tehnički Glasnik, 19(3), pp. 442-451.
16. Trung, D.D., Dudić, B., Duc, D.V., Son, N.H., Ašonja, A., 2024, *Comparison of MCDM methods effectiveness in the selection of plastic injection molding machines*, Teknomekanik, 7(1), pp. 1-19.
17. Keshavarz Ghorabaee, M., Amiri, M., Zavadskas, E.K., Antucheviciene, J., 2018, *A new hybrid fuzzy MCDM approach for evaluation of construction equipment with sustainability considerations*, Archives of Civil and Mechanical Engineering, 18(1), pp. 32-49.
18. Keršulienė, V., Zavadskas, E.K., Turskis, Z., 2010, *Selection of rational dispute resolution method by applying new step-wise weight assessment ratio analysis (SWARA)*, Journal of Business Economics and Management, 11(2), pp. 243-258.
19. Keshavarz Ghorabaee, M., Zavadskas, E.K., Olfat, L., Turskis, Z., 2015, *Multi-criteria inventory classification using a new method of evaluation based on distance from average solution (EDAS)*, Informatica, 26(3), pp. 435-451.

20. Yılmaz Kaya, B., Dağdeviren, M., 2016, *Selecting occupational safety equipment by MCDM approach considering universal design principles*, Human Factors and Ergonomics in Manufacturing & Service Industries, 26(2), pp. 224-242.
21. Brans, J.P., Vincke, Ph., Mareschal, B., 1986, *How to select and how to rank projects: the Promethee method*, European Journal of Operational Research, 24(2), pp. 228-238.
22. Hodgett, R.E., 2016, *Comparison of multi-criteria decision-making methods for equipment selection*, The International Journal of Advanced Manufacturing Technology, 85, pp. 1145-1157.
23. Hodgett, R.E., Martin, E.B., Montague, G., Talford, M., 2014, *Handling uncertain decisions in whole process design*, Production Planning & Control, 25(12), pp. 1028-1038.
24. Taherdoost, H., Madanchian, M., 2023, *A comprehensive overview of the ELECTRE method in multi criteria decision-making*, Journal of Management Science & Engineering Research, 6(2), pp. 5-16.
25. Štirbanović, Z., Stanujkić, D., Miljanović, I., Milanović, D., 2019, *Application of MCDM methods for flotation machine selection*, Minerals Engineering, 137, pp. 140-146.
26. Opricovic, S., Tzeng, G.H., 2004, *Compromise solution by MCDM methods: a comparative analysis of VIKOR and TOPSIS*, European Journal of Operational Research, 156(2), pp. 445-455.
27. Zavadskas, E.K., Chakraborty, S., Bhattacharyya, O., Antucheviciene, J., 2015, *Application of WASPAS method as an optimization tool in non-traditional machining processes*, Information Technology and Control, 44(1), pp. 77-88.
28. Sotoudeh-Anvari, A., 2023, *Root assessment method (RAM): a novel multi-criteria decision making method and its applications in sustainability challenges*, Journal of Cleaner Production, 423, 138695.
29. Runic Ristic, M., Savic Tot, T., Ristic, I., Tot, V., Radosevic, T., Marinkovic, D., 2025, *Evaluation of leadership styles in multinational corporations using the fuzzy TOPSIS method*, Systems, 13(8), 636.
30. Tadić, D., Lukić, J., Komatina, N., Marinković, D., Pamučar, D., 2025, *A fuzzy decision-making approach to electric vehicle evaluation and ranking*, Tehnicki Vjesnik, 32(3), pp. 1066-1075.
31. Gül, A.Y., Cakmak, E., Karakas, A.E., 2025, *Drone selection for forest surveillance and fire detection using interval valued neutrosophic EDAS method*, Facta Universitatis-Series Mechanical Engineering, 23(3), pp. 433-458.
32. Žižović, M., Pamučar, D., 2019, *New model for determining criteria weights: level based weight assessment (LBWA) model*, Decision Making: Applications in Management and Engineering, 2(2), pp. 126-137.
33. Komatina, N., Marinković, D., 2026, *An Objective Multi-Attribute Decision-Making Framework for Identifying Critical Phases in Automotive Component Manufacturing*, Journal of Engineering Management and Systems Engineering, 5(1), pp. 1-9.
34. Kizielewicz, B., Sałabun, W., 2024, *SITW method: a new approach to re-identifying multi-criteria weights in complex decision analysis*, Spectrum of Mechanical Engineering and Operational Research, 1(1), pp. 215-226.
35. Stevic, Z., Ulutas, A., Topal, A., Marinkovic, D., Cavoski, S., 2025, *A new objective method for determining criteria weights in MCDM models – LOGSTA*, International Journal of Simulation Modelling, 24(4), pp. 589-600.
36. Bošković, S., Jovčić, S., Simić, V., Švadlenka, L., Dobrodolac, M., Bacanin, N., 2025, *A New Criteria Importance Assessment (CIMAS) Method in Multi-Criteria Group Decision-Making: Criteria Evaluation for Supplier Selection*, Facta Universitatis-Series Mechanical Engineering, 23(2), pp. 335-349.