



Decision Support System for New Employee Admission Selection Using a Combination of LOPCOW and MARCOS

Imron¹, Eka Rini Yulia^{2*}, Andriansah³, Sefrika⁴

^{1,3,4}Information System, Universitas Bina Sarana Informatika, Indonesia

²Information System, Universitas Nusa Mandiri, Indonesia

¹imron.imr@bsi.ac.id, ^{2*}eka.erl@nusamandiri.ac.id, ³andriansah.aiy@bsi.ac.id, ⁴sefrika.sfe@bsi.ac.id

Abstract: The selection of new hires is an important process in human resource management to ensure that the organization gets the individuals who best suit the company's needs and goals. The main problem in the selection of new employee admissions is often related to the difficulty of achieving objectivity and fairness in the assessment process. Reliance on subjective assessment, lack of structured selection methods or absence of valid and reliable measurement tools can result in inaccurate decisions. The ranking results in the selection of new employee admissions show the value generated from each candidate, Candidate AE is ranked first with the highest score of 24.48, followed by Candidate DS with a score of 22.95. JE Candidate was ranked third with a score of 21.36, followed by FY Candidate with a score of 21.3. These results reflect the performance of each candidate in meeting the selection criteria that have been determined. This research contributes to improving accuracy and fairness in selection decision-making, by reducing subjectivity bias in weighting and ranking candidates. With transparent and measurable results, this research helps companies in systematically selecting the best candidates, while improving the efficiency and effectiveness of the recruitment process. The combination of the LOPCOW and MARCOS methods offers the flexibility to be applied in a variety of selection contexts, not only in employee admissions, but also in other multi-criteria decision-making.

Keywords: Combination; Decision Making; LOPCOW; MARCOS; Selection;

1. INTRODUCING

The selection of new hires is an important process in human resource management to ensure that the organization gets the individuals who best suit the company's needs and goals [1], [2]. This process involves various stages, ranging from administrative assessments, competency tests, interviews, to evaluation of the interpersonal and technical abilities of prospective employees. The selection criteria are usually adjusted to the characteristics of the position needed, such as special skills, work experience, and adaptability to the organization's work culture. Through an objective and transparent selection, companies can increase the chances of getting employees who are competent, have integrity, and are able to make maximum contributions to organizational growth. The main problem in the selection of new employee admissions is often related to the difficulty of achieving objectivity and fairness in the assessment process. Reliance on subjective assessment, lack of structured selection methods or absence of valid and reliable measurement tools can result in inaccurate decisions. Misalignment between selection criteria and position requirements is also a challenge, which can lead to hiring employees who are less suitable for the role or company culture. All of this emphasizes the importance of a systematic, data-driven, and bias-free selection approach to ensure optimal results.

A Decision Support System (DSS) is a systematic and data-driven approach to assist organizations in complex decision-making processes, including the selection of new hires. By using DSS, various

Eka Rini Yulia: *Corresponding Author



Copyright © 2025, Imron, Eka Rini Yulia, Andriansah, Sefrika.



alternative decisions can be analyzed objectively based on predetermined criteria. DSS integrates analytical methods and mathematical algorithms to evaluate each candidate transparently and consistently, this data-driven approach allows for more accurate and rapid decision-making, as it leverages historical and real-time data to support the analysis[3]–[5]. DSS is an effective tool to improve the quality of selection and ensure that decisions are made in line with the strategic needs of the organization. The measurement of alternatives and ranking according to compromise solution (MARCOS) method is one of the methods in DSS.

The MARCOS method is one of the methods in DSS that is designed to evaluate each alternative based on the proximity of the alternative to the ideal solution[6], [7], this method takes into account the relationship of each alternative to the ideal solution, thus providing a balanced and realistic result in DSS. The advantage of the MARCOS method lies in its comprehensive approach, where MARCOS considers the relationship of each alternative with the ideal solution value of all alternatives, thus providing a more balanced and realistic evaluation[8]–[10]. In addition, this method is very flexible because it can be applied to various types of decisions and criteria, both profit and cost. MARCOS is also designed to produce a compromise solution by considering all criteria simultaneously, making it suitable for contexts where there is a conflict between criteria. With a relatively simple but effective calculation process, MARCOS is an efficient choice in solving data-driven decision-making problems in various fields. The MARCOS method has a weakness in terms of criterion weighting, the criterion weighting in MARCOS is generated based on the intuition and preferences of decision-makers, so it is susceptible to personal judgment and does not reflect objective conditions. This subjectivity can affect the final result, especially if the weights do not correspond to the level of importance of each criterion in a given context. In addition, in situations where there are multiple decision-makers or parties involved, agreeing on the weight of criteria can be challenging, resulting in a longer or less consistent process. Therefore, to reduce the impact of subjectivity, the MARCOS method often needs to be combined with a data-based weighting method, namely logarithmic percentage change-driven objective weighting (LOPCOW), so that the resulting criterion weights are more objective and accountable.

The LOPCOW method is an approach based on data changes to logarithmic percentages for objective determination of criterion weights based on data used in decision-making[11]–[13]. This method aims to produce objective weights by considering the variation or distribution of data of each criterion in the decision matrix. LOPCOW is particularly useful in situations where the reliability of subjective weights is questionable, as its focus is on raw data analysis without the influence of decision-maker preferences. LOPCOW is based on the concept that the weight of the criteria should reflect the relative contribution of each criterion to decision-making. Criteria with greater variation or influence on alternatives will have a higher weight compared to criteria with small or uniform contributions[14], [15]. LOPCOW is perfect for cases where objective weighting is required, as in this case, i.e. employee admission selection. With this data-driven approach, decision-making becomes more accurate, transparent, and free from personal opinions.

Combining MARCOS with LOPCOW can combine the advantages of each method to produce more accurate and objective decisions in multi-criteria decision-making. MARCOS is an effective method in assessing alternatives based on solution compromises, by considering the relationship of alternatives to positive and negative ideal solutions. It provides a balanced evaluation of each alternative based on relevant criteria. LOPCOW, on the other hand, offers an objective weighting approach by using logarithmic percentage changes in the values of the criteria to calculate the weights. This method gives weight that is more in line with the relative contribution of each criterion to the decision, without being influenced by personal preference. By integrating LOPCOW weighting into the MARCOS process, it can minimize subjective preferences in determining the weight of criteria. By combining MARCOS and LOPCOW, it can create a more comprehensive approach and produce more accurate and stable rankings, better reflecting the relative influence of the criteria. Combining the LOPCOW and MARCOS methods is necessary to produce more accurate, objective, and comprehensive multi-criteria decision-making. This combination also increases the flexibility and resilience of the system to changes in data or weights, providing a more reliable and relevant solution in a variety of decision contexts.



The purpose of this study is to implement a comprehensive and objective decision support system to assist the selection process of new employee admissions which will increase the accuracy and credibility of the selection process by producing a more objective ranking for each candidate based on relevant criteria. This method allows for a more balanced and transparent evaluation, and provides a solid basis for informed decision-making in selecting candidates who best suit the needs of the organization.

2. RESEARCH METHODOLOGY

The research methodology includes a variety of systematic and planned steps to collect, analyze, and interpret data to address problems in the research[16], [17]. Figure 1 is the research methodology carried out in the selection of new employee admissions.

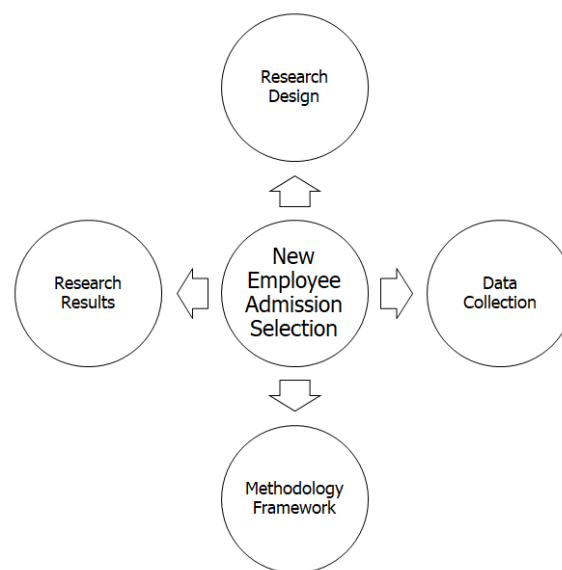


Figure 1. Research Methodology

The research methodology in the selection of new employee admissions shown in figure 1 has several questions that are carried out. The first stage, namely research design, uses a quantitative approach with a descriptive-exploratory model to develop DSS in the new employee selection process. This approach aims to combine the MARCOS and LOPCOW methods as a method of evaluation and weighting criteria. The second stage is data collection, which includes primary and secondary data. Primary data was obtained through interviews with the company's HRD team to identify relevant new employee selection criteria, to provide an assessment of the level of importance of each criterion. Secondary data includes documents or historical data related to the previous employee selection process. The results of this assessment are represented in the form of numerical scores. The third stage is the methodology framework which involves 2 main processes, namely the LOPCOW method aims to determine the objective weight of each criterion. The MARCOS method aims to assess the distance between each alternative to the ideal solution and the anti-ideal is calculated to measure the relative performance of each alternative. The last stage is the result of this study that the combination of the LOPCOW and MARCOS methods is able to produce an objective and accurate decision support system for the selection of new employees.

2.1. LOPCOW Method

The LOPCOW method is one of the techniques to objectively determine the weight of criteria, the LOPCOW method is useful for reducing the level of subjective weight and providing a more objective way to prioritize criteria in the decision-making process.[18], [19].

The decision matrix is the first stage in this method made with equation (1).

$$X = \begin{bmatrix} x_{11} & \cdots & x_{1n} \\ \vdots & \ddots & \vdots \\ x_{m1} & \cdots & x_{mn} \end{bmatrix} \quad (1)$$

The value of matrix normalization is the next process which is defined as follows.

$$n_{ij} = \frac{x_{ij}}{m + \sum_{i=1}^m x_{ij}^2} \quad (2)$$

Calculating the preference value is the next process that is carried out, the preference value is defined as follows.

$$PV_i = 100 * \left| \frac{\sqrt{\sum_{i=1}^m n_{ij}^2}}{\ln \frac{m}{\sigma}} \right| \quad (3)$$

Calculating the final weight of each criterion is the next process carried out, the final weight of each criterion is defined as follows.

$$w_j = \frac{PV_i}{\sum_{j=1}^n PV_i} \quad (4)$$

By utilizing logarithmic percentage changes, the LOPCOW method can overcome complexity and integrate all criteria to produce weights objectively.

2.2. MARCOS Method

The MARCOS method is designed to provide a systematic and objective evaluation of a number of alternatives taking into account relevant criteria[20], [21]. This method is designed to provide a systematic and objective evaluation of a number of alternatives by considering relevant criteria.

The decision matrix in the MARCOS method serves as a tool for compiling, organizing, and analyzing information about alternatives that are evaluated based on various criteria. The decision matrix is created using equation (1).

Solution value is the second stage used to assess the performance of alternatives based on specified criteria. The value of the ideal solution is the best set of values from each benefit criterion defined as follows.

$$AAI = \min_{x_{ij}}; AI = \max_{x_{ij}} \quad (5)$$

The value of the anti-ideal solution is the set of the worst values of each cost criterion defined as follows.

$$AAI = \max_{x_{ij}}; AI = \min_{x_{ij}} \quad (6)$$

Data normalization is the process of making all values on a uniform scale. Normalization is defined as follows.

$$n_{ij} = \frac{x_{ij}}{x_{ai}} \quad (7)$$

$$n_{ij} = \frac{x_{ai}}{x_{ij}} \quad (8)$$

Normalization has 2 types of equations, for equation (7) for the benefit criterion, and equation (8) for the cost criterion.

Weight multiplication is used to calculate the preference value of an alternative based on the criteria that have been weighted. The multiplication of weights is defined as follows.

$$v_{ij} = w_j * n_{ij} \quad (9)$$

The value of alternative utilities is a measure that describes the extent to which each alternative is close to the ideal solution. The utility value is calculated by comparing the weighted value of each alternative to the weighted value of the ideal solution calculated using the equation below.

$$S_i = \sum_{i=1}^n v_{ij} \quad (10)$$

$$K_i^- = \frac{S_i}{S_{aai}} \quad (11)$$

$$K_i^+ = \frac{S_i}{S_{ai}} \quad (12)$$



Utility value is a measure that provides a comprehensive picture of the performance of each alternative. This allows the decision maker to choose the alternative that is closest to the desired criteria in the context of multi-criteria decision-making calculated using the equation below.

$$f(k_i^-) = \frac{K_i^+}{K_i^+ + K_i^-} \quad (13)$$

$$f(k_i^+) = \frac{K_i^-}{K_i^+ + K_i^-} \quad (14)$$

$$f(k_i) = \frac{K_i^+ + K_i^-}{1 + \frac{1-f(k_i^+)}{f(k_i^+)} + \frac{1-f(k_i^-)}{f(k_i^-)}} \quad (15)$$

The final result of the value in the MARCOS method is an important stage in the decision-making process that involves several alternatives based on various criteria.

3. RESULT AND DISCUSSIONS

In an effort to improve the selection process of new employees, this study applies the use of DSS which combines the MARCOS and LOPCOW methods. The main goal is to provide an objective and transparent solution in assessing candidates based on various important criteria. The results of this method incorporation provide more accurate rankings and provide in-depth insights into which candidates are best suited for the position offered. Through this study, it is hoped that it can contribute to a better understanding of the application of multi-criteria techniques in the selection process, as well as provide guidance for organizations looking to improve efficiency and effectiveness in employee recruitment.

3.1. Data Collection

Data collection is a very important first step in the new employee selection process to ensure decisions are made based on complete, relevant, and objective information. The data collected includes a variety of information related to candidates' qualifications, competencies, and potential, which is used to evaluate them based on specific criteria. In the context of a decision support system, the data collection process is carried out systematically to ensure the quality and validity of the data.

Collecting criteria data in the new employee selection process is an important step to determine the level of candidate compatibility with the organization's needs. Selection criteria are used to evaluate candidates based on the standards that have been set, so that the decisions taken become more objective and systematic. This process includes identifying relevant criteria, gathering information from candidates, as well as processing data for further analysis. The selection criteria are determined based on the position to be filled and the needs of the organization. The criteria used are shown in table 1.

Table 1. Criteria Data

Criteria Code	Criteria Name	Description
NE-1	Technical Ability	Work-related competencies, such as mastery of certain tools or software.
NE-2	Work Experience	The amount and type of experience relevant to the position being applied for.
NE-3	Education	The level of education or academic expertise that the candidate has.
NE-4	Interpersonal Skills	Communication skills, teamwork, and leadership.
NE-5	Innovation and Creativity	Ability to generate relevant new ideas.
NE-6	Selection Test	Measures a candidate's technical, logical, creative, or personality abilities.
NE-7	Interview	Dig into in-depth information about the candidate's motivations, attitudes, and interpersonal skills.





Systematic collection of criteria data helps ensure that the selection process takes place in a fair, transparent, and effective manner, so that organizations can select the most suitable candidates for available positions.

The collection of alternative assessment data is an important stage in the selection process to evaluate the performance of candidates (alternatives) based on predetermined criteria. This data is the basis in the DSS to determine the best candidates through objective calculations and analysis. The alternative assessment data used in the selection of new employees is shown in table 2.

Table 2. The Alternative Assessment Data

Employee Candidate Name	NE-1	NE-2	NE-3	NE-4	NE-5	NE-6	NE-7
AE Candidate	85	5	2	4	5	90	5
RB Candidate	78	3	4	3	4	80	4
EC Candidates	92	7	3	5	5	95	5
DS Candidate	88	4	4	4	4	85	4
IE Candidates	80	6	3	4	5	88	5
FY Candidate	76	3	3	3	3	75	3
AG Candidate	90	5	4	4	5	92	4
JE Candidate	85	5	3	4	5	90	5

The grading scale used in the new employee selection process is designed to reflect the various important aspects that are assessed. Technical Ability is assessed on a scale of 1–100, based on the results of technical skills tests relevant to the job position. Work Experience is measured in the number of years a candidate has worked in a related field, with higher scores reflecting broader experience. Education uses a scale of 1–5, where the value of 1 indicates high school graduates, 2 for Diploma, 3 for Bachelor's (S1), 4 for Master's (S2), and 5 for Doctoral (S3). Interpersonal skills are measured on a scale of 1–5 based on evaluations of communication, cooperation, and relationship-building abilities within a team. Innovation and Creativity are assessed on a scale of 1–5 to reflect the candidate's ability to generate new ideas and innovative solutions. The Selection Test is the result of a written or technical test that is assessed on a scale of 1–100. Finally, the interview was assessed on a scale of 1–5 based on aspects of motivation, attitude, communication skills, and understanding of the work observed during the interview session. This scale allows the assessment process to be carried out in a structured and objective manner.

3.2. LOPCOW Method for Determining the Weight of New Employee Admission Selection Criteria

The LOPCOW method is a technique used to objectively determine the weight of criteria in the multi-criteria decision-making process, this method can help assess the weight of the importance of each criterion based on the relationship between the candidate and the ideal criterion, so that the results of weight determination are more accurate and objective.

The decision matrix is the first process carried out in this method which is made by equation (1) based on the assessment data that has been obtained.

$$X = \begin{bmatrix} 86 & 5 & 2 & 4 & 5 & 90 & 5 \\ 78 & 3 & 4 & 3 & 4 & 80 & 4 \\ 92 & 7 & 3 & 5 & 5 & 95 & 5 \\ 88 & 4 & 4 & 4 & 4 & 85 & 4 \\ 80 & 6 & 3 & 4 & 5 & 88 & 5 \\ 76 & 3 & 3 & 3 & 3 & 75 & 3 \\ 90 & 5 & 4 & 4 & 5 & 92 & 4 \\ 85 & 5 & 3 & 4 & 5 & 90 & 5 \end{bmatrix}$$

The matrix normalization value is the next process of the LOPCOW method which is calculated using equation (2).



$$n_{11} = \frac{x_{11}}{8 + \sum_{i=1}^m x_{11,18}^2} = \frac{85}{57026} = 0.0015$$

The results of the calculation of the normalization value in the overall LOPCOW method are shown in table 3.

Table 3. The Results of the Calculation of the Normalization Value

Employee Candidate Name	NE-1	NE-2	NE-3	NE-4	NE-5	NE-6	NE-7
AE Candidate	0.0015	0.0248	0.0208	0.0305	0.0287	0.0015	0.0303
RB Candidate	0.0014	0.0149	0.0417	0.0229	0.0230	0.0013	0.0242
EC Candidates	0.0016	0.0347	0.0313	0.0382	0.0287	0.0016	0.0303
DS Candidate	0.0015	0.0198	0.0417	0.0305	0.0230	0.0014	0.0242
IE Candidates	0.0014	0.0297	0.0313	0.0305	0.0287	0.0014	0.0303
FY Candidate	0.0013	0.0149	0.0313	0.0229	0.0172	0.0012	0.0182
AG Candidate	0.0016	0.0248	0.0417	0.0305	0.0287	0.0015	0.0242
JE Candidate	0.0015	0.0248	0.0313	0.0305	0.0287	0.0015	0.0303

The third stage in the LOPCOW method is to calculate the preference value using equation (3).

$$PV_1 = 100 * \left| \frac{\sqrt{\sum_{i=1}^m n_{11,18}^2}}{\ln \frac{8}{\sigma_1}} \right| = 100 * \left| \frac{0.00418729}{11.34383386} \right| = 0.0369$$

The results of the calculation of the preference value in LOPCOW method are shown in table 3.

Table 4. The Results of the Calculation of the Preference Value

	NE-1	NE-2	NE-3	NE-4	NE-5	NE-6	NE-7
PV_i	0.0369	0.9676	1.3847	1.1339	0.9762	0.0360	1.0061

The calculation of the final weight of the criteria is the final process of the LOPCOW method which is calculated using equation (4).

$$w_1 = \frac{PV_1}{\sum_{j=1}^n PV_{1,7}} = \frac{0.0369}{5.5414} = 0.0067$$

$$w_2 = \frac{PV_2}{\sum_{j=1}^n PV_{1,7}} = \frac{0.9676}{5.5414} = 0.1746$$

$$w_3 = \frac{PV_3}{\sum_{j=1}^n PV_{1,7}} = \frac{1.3847}{5.5414} = 0.2499$$

$$w_4 = \frac{PV_4}{\sum_{j=1}^n PV_{1,7}} = \frac{1.1339}{5.5414} = 0.2046$$

$$w_5 = \frac{PV_5}{\sum_{j=1}^n PV_{1,7}} = \frac{0.9762}{5.5414} = 0.1762$$

$$w_6 = \frac{PV_6}{\sum_{j=1}^n PV_{1,7}} = \frac{0.0360}{5.5414} = 0.0065$$

$$w_7 = \frac{PV_7}{\sum_{j=1}^n PV_{1,7}} = \frac{1.0061}{5.5414} = 0.1816$$

The LOPCOW method ensures that the weight of the criteria reflects the relevance of each aspect of the selection with high objectivity, so that the final result of the weight of the criteria becomes fairer and more transparent.



3.3. MARCOS Method in New Employee Selection

MARCOS is a multi-criteria decision-making method that aims to assess and rank alternatives based on their distance to ideal and anti-ideal solutions, the MARCOS method allows for the systematic evaluation of candidates by considering the contribution of each criterion to the final decision.

The decision matrix in the MARCOS method serves as a tool for compiling, organizing, and analyzing information about alternatives that are evaluated based on various criteria. The decision matrix is created using (1).

Solution value is the second stage used to assess the performance of alternatives based on specified criteria. The value of the ideal solution is the best set of values from each criterion using (3), and the value of the anti-ideal solution is the set of the worst values from each criterion using (5). The results are shown in table 5.

Table 5. The Value of the Ideal Solution and the Anti-Ideal Solution

	NE-1	NE-2	NE-3	NE-4	NE-5	NE-6	NE-7
<i>AAI</i>	92	7	4	5	5	95	5
<i>AI</i>	76	3	2	3	3	75	3

Data normalization is the third stage in the MARCOS method of all the initial normalized data so that all values are on a uniform scale. Normalization is calculated using (7).

$$n_{11} = \frac{x_{11}}{x_{ai}} = \frac{85}{92} = 0.9239$$

The results of the calculation of the normalization value in the overall LOPCOW method are shown in table 6.

Table 6. The Results of the Calculation of the Normalization Value

Employee Candidate Name	NE-1	NE-2	NE-3	NE-4	NE-5	NE-6	NE-7
AE Candidate	0.9239	0.7143	0.5000	0.8000	1.0000	0.9474	1.0000
RB Candidate	0.8478	0.4286	1.0000	0.6000	0.8000	0.8421	0.8000
EC Candidates	1.0000	1.0000	0.7500	1.0000	1.0000	1.0000	1.0000
DS Candidate	0.9565	0.5714	1.0000	0.8000	0.8000	0.8947	0.8000
IE Candidates	0.8696	0.8571	0.7500	0.8000	1.0000	0.9263	1.0000
FY Candidate	0.8261	0.4286	0.7500	0.6000	0.6000	0.7895	0.6000
AG Candidate	0.9783	0.7143	1.0000	0.8000	1.0000	0.9684	0.8000
JE Candidate	0.9239	0.7143	0.5000	0.8000	1.0000	0.9474	1.0000

Weight multiplication is used to calculate the preference value of the alternative based on the criteria that have been weighted. The multiplication of weights is calculated using (8).

$$v_{11} = w_1 * n_{11} = 0.0067 * 0.9239 = 0.0062$$

The results of the calculation of the weight multiplication in the overall LOPCOW method are shown in table 7.

Table 7. The Results of the Calculation of the Weight Multiplication

Employee Candidate Name	NE-1	NE-2	NE-3	NE-4	NE-5	NE-6	NE-7
AE Candidate	0.0062	0.1247	0.1249	0.1637	0.1762	0.0062	0.1816
RB Candidate	0.0056	0.0748	0.2499	0.1228	0.1409	0.0055	0.1452
EC Candidates	0.0067	0.1746	0.1874	0.2046	0.1762	0.0065	0.1816
DS Candidate	0.0064	0.0998	0.2499	0.1637	0.1409	0.0058	0.1452
IE Candidates	0.0058	0.1497	0.1874	0.1637	0.1762	0.0060	0.1816
FY Candidate	0.0055	0.0748	0.1874	0.1228	0.1057	0.0051	0.1089





Employee Candidate Name	NE-1	NE-2	NE-3	NE-4	NE-5	NE-6	NE-7
AG Candidate	0.0065	0.1247	0.2499	0.1637	0.1762	0.0063	0.1452
JE Candidate	0.0062	0.1247	0.1249	0.1637	0.1762	0.0062	0.1816

The value of alternative utilities is the fifth stage in the MARCOS method which is a measure that describes the extent to which each alternative is close to the ideal solution. The utility value is calculated by comparing the weighted value of each alternative to the weighted value of the ideal solution calculated using the equations (9), (10), and (11). The results of the calculation of the value of alternative utilities are shown in table 8.

Table 8. The Results of the Calculation of the Value Alternative Utilities

Employee Candidate Name	S_i	K_i^-	K_i^+
AE Candidate	0.7834	4.3148	7.1913
RB Candidate	0.7448	4.1021	6.8369
EC Candidates	0.9375	5.1637	8.6062
DS Candidate	0.8117	4.4708	7.4513
IE Candidates	0.8703	4.7935	7.9892
FY Candidate	0.6103	3.3613	5.6022
AG Candidate	0.8725	4.8057	8.0094
JE Candidate	0.7834	4.3148	7.1913

The final utility value are the final stages in the MARCOS method which are measures that provide a thorough overview of the performance of each alternative and are calculated using the equations (12), (13), and (14). The results of the calculation of the final utility value are shown in table 9.

Table 9. The Results of the Final Utility Value

Employee Candidate Name	$f(k_i^-)$	$f(k_i^+)$	$f(k_i)$
AE Candidate	0.625	0.375	24.48
RB Candidate	0.625	0.375	19.18
EC Candidates	0.625	0.375	18.23
DS Candidate	0.625	0.375	22.95
IE Candidates	0.625	0.375	19.87
FY Candidate	0.625	0.375	21.30
AG Candidate	0.625	0.375	14.94
JE Candidate	0.625	0.375	21.36

The MARCOS method provides comprehensive results to support decision-making by identifying the most optimal alternatives based on predetermined criteria. This approach ensures that the best alternative is the one that has the best balance between proximity to the ideal solution and distance from the anti-ideal solution.

3.4. New Employee Admission Selection Ranking Using DSS

DSS is a tool used to assist decision-makers in solving problems that involve many criteria, in the selection process for new employee admissions, DSS ranks candidates based on predetermined criteria. By using DSS, the ranking in the selection of new employee admissions becomes more structured, fair, and transparent. This helps organizations select candidates who best suit their needs and criteria. Figure 2 is the result of the ranking of new employee selection using the DSS approach using a combination of LOPCOW and MARCOS.



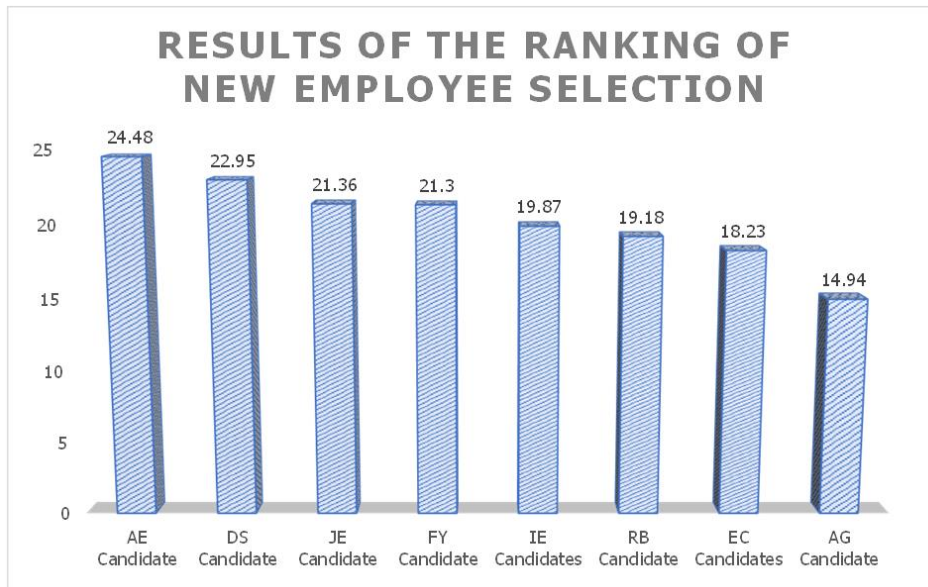


Figure 2. Results of the Ranking of New Employee Selection

The ranking results in the selection of new employee admissions in figure 2 show the score generated from each candidate, Candidate AE is ranked first with the highest score of 24.48, followed by Candidate DS with a score of 22.95. JE Candidate was ranked third with a score of 21.36, followed by FY Candidate with a score of 21.3. These results reflect the performance of each candidate in meeting the selection criteria that have been determined. Candidates with the highest scores are considered more suitable to be accepted as new employees, while candidates with lower scores indicate that they are less likely to meet expectations based on the selection criteria used.

The combination of the LOPCOW and MARCOS methods shows superior performance in multi-criteria decision-making. The LOPCOW method plays an important role in generating the weight of the criteria objectively based on information from the data, thereby minimizing the potential for subjective bias. Its logarithmic approach ensures that the resulting weight is proportional to the influence of each criterion in the decision. Meanwhile, the MARCOS method offers accurate ranking capabilities by evaluating alternatives based on their relationship to reference alternatives, both ideal and anti-ideal, thus providing comprehensive results. This combination is also very flexible to apply to various cases, such as supplier selection, employee performance appraisal, or evaluation of the best product, as it can handle different data scales and calculate weights adaptively. In addition, the combination of LOPCOW and MARCOS has proven robust, resulting in consistent ratings even when there are small changes in input data or weights. With these advantages, this approach is the optimal solution to improve accuracy, fairness, and reliability in multi-criteria decision support systems.

4. CONCLUSION

The purpose of this study is to implement a comprehensive and objective decision support system to assist the selection process of new employee admissions which will increase the accuracy and credibility of the selection process by producing a more objective ranking for each candidate based on relevant criteria. This method allows for a more balanced and transparent evaluation, and provides a solid basis for informed decision-making in selecting candidates who best suit the needs of the organization. The ranking results in the selection of new employee admissions show the value generated from each candidate, Candidate AE is ranked first with the highest score of 24.48, followed by Candidate DS with a score of 22.95. JE Candidate was ranked third with a score of 21.36, followed by FY Candidate with a score of 21.3. These results reflect the performance of each candidate in meeting the selection criteria that have been determined. Candidates with the highest scores are considered more suitable to



be accepted as new employees, while candidates with lower scores indicate that they are less likely to meet expectations based on the selection criteria used. The main contribution of this study is to improve accuracy and fairness in selection decision-making, by reducing subjectivity bias in weighting and ranking candidates. In addition, this approach offers the flexibility to be applied in a variety of selection contexts, not only in employee admissions, but also in other multi-criteria decision-making. With transparent and measurable results, this research has the potential to help companies in systematically selecting the best candidates, while improving the efficiency and effectiveness of the recruitment process. Further research is suggested to explore the application of a combination of LOPCOW and MARCOS methods in a broader and complex context, such as employee selection for specific positions that require diverse technical and non-technical criteria. Research can also focus on sensitivity testing to evaluate the durability of ranking results to changes in data or criterion weights.

5. REFERENCES

- [1] S. Korucuk, A. Aytekin, F. Ecer, Ç. Karamaşa, and E. K. Zavadskas, "Assessing Green Approaches and Digital Marketing Strategies for Twin Transition via Fermatean Fuzzy SWARA-COPRAS," *Axioms*, vol. 11, no. 12, p. 709, Dec. 2022, doi: 10.3390/axioms11120709.
- [2] A. Lia Hananto, B. Priyatna, A. Fauzi, A. Yuniar Rahman, Y. Pangestika, and Tukino, "Analysis of the Best Employee Selection Decision Support System Using Analytical Hierarchy Process (AHP)," *J. Phys. Conf. Ser.*, vol. 1908, no. 1, p. 012023, Jun. 2021, doi: 10.1088/1742-6596/1908/1/012023.
- [3] M. Gheibi *et al.*, "A Sustainable Decision Support System for Drinking Water Systems: Resiliency Improvement against Cyanide Contamination," *Infrastructures*, vol. 7, no. 7, p. 88, Jun. 2022, doi: 10.3390/infrastructures7070088.
- [4] O. Kabadurmus, Y. Kayikci, S. Demir, and B. Koc, "A data-driven decision support system with smart packaging in grocery store supply chains during outbreaks," *Socioecon. Plann. Sci.*, vol. 85, p. 101417, Feb. 2023, doi: 10.1016/j.seps.2022.101417.
- [5] J.-S. Lin and K.-H. Chen, "A novel decision support system based on computational intelligence and machine learning: Towards zero-defect manufacturing in injection molding," *J. Ind. Inf. Integr.*, vol. 40, p. 100621, Jul. 2024, doi: 10.1016/j.jii.2024.100621.
- [6] S. S. Hosseini Dehshiri and B. Firoozabadi, "A new application of measurement of alternatives and ranking according to compromise solution (MARCOS) in solar site location for electricity and hydrogen production: A case study in the southern climate of Iran," *Energy*, vol. 261, p. 125376, Dec. 2022, doi: 10.1016/j.energy.2022.125376.
- [7] M. Bitarafan, K. A. Hosseini, and S. H. Zolfani, "Identification and assessment of man-made threats to cities using integrated Grey BWM- Grey MARCOS method," *Decis. Mak. Appl. Manag. Eng.*, vol. 6, no. 2, pp. 581–599, Oct. 2023, doi: 10.31181/dmame622023747.
- [8] S. H. Hadad, A. R. Metha, S. Setiawansyah, and H. Sulistiani, "Evaluation of Salesperson Performance in the Sales Allowance Decision Support System Using the MARCOS and PIPRECIA Methods," *J. Comput. Syst. Informatics*, vol. 5, no. 2, pp. 477–486, Feb. 2024, doi: 10.47065/josyc.v5i2.4863.
- [9] S. Chakraborty, P. Chatterjee, and P. P. Das, "Measurement Alternatives and Ranking according to Compromise Solution (MARCOS) Method," in *Multi-Criteria Decision-Making Methods in Manufacturing Environments*, Apple Academic Press, 2024, pp. 297–307.
- [10] A. Abdulla, G. Baryannis, and I. Badi, "An integrated machine learning and MARCOS method for supplier evaluation and selection," *Decis. Anal. J.*, vol. 9, p. 100342, Dec. 2023, doi: 10.1016/j.dajour.2023.100342.
- [11] Z. Guo *et al.*, "An integrated MCDM model with enhanced decision support in transport safety using machine learning optimization," *Knowledge-Based Syst.*, vol. 301, p. 112286, 2024, doi: <https://doi.org/10.1016/j.knosys.2024.112286>.
- [12] Ö. Işık, M. Shabir, and S. Moslem, "A hybrid MCDM framework for assessing urban competitiveness: A case study of European cities," *Socioecon. Plann. Sci.*, vol. 96, p. 102109, 2024, doi: <https://doi.org/10.1016/j.seps.2024.102109>.
- [13] T. Van Dua, D. Van Duc, N. C. Bao, and D. D. Trung, "Integration of objective weighting methods for criteria and MCDM methods: application in material selection," *EUREKA Phys. Eng.*, no. 2, pp. 131–148, Mar. 2024, doi: 10.21303/2461-4262.2024.003171.
- [14] A. Ulutaş, F. Balı, and A. Topal, "Identifying the Most Efficient Natural Fibre for Common Commercial Building Insulation Materials with an Integrated PSI, MEREC, LOPCOW and MCRAT Model," *Polymers (Basel)*, vol. 15, no. 6, p. 1500, Mar. 2023, doi: 10.3390/polym15061500.
- [15] S. Dhruva, R. Krishankumar, E. K. Zavadskas, K. S. Ravichandran, and A. H. Gandomi, "Selection of Suitable





- Cloud Vendors for Health Centre: A Personalized Decision Framework with Fermatean Fuzzy Set, LOPCOW, and CoCoSo," *Informatica*, vol. 35, no. 1, pp. 65–98, Nov. 2024, doi: 10.15388/23-INFOR537.
- [16] L. K. Singh, M. Khanna, and R. Singh, "Artificial intelligence based medical decision support system for early and accurate breast cancer prediction," *Adv. Eng. Softw.*, vol. 175, p. 103338, Jan. 2023, doi: 10.1016/j.advengsoft.2022.103338.
- [17] M. Naiseh, D. Al-Thani, N. Jiang, and R. Ali, "How the different explanation classes impact trust calibration: The case of clinical decision support systems," *Int. J. Hum. Comput. Stud.*, vol. 169, p. 102941, Jan. 2023, doi: 10.1016/j.ijhcs.2022.102941.
- [18] Sumanto *et al.*, "Improved LOPCOW-SAW Method for Optimal Supplier Selection in Supply Chain Management," in *2024 12th International Conference on Cyber and IT Service Management (CITSM)*, 2024, pp. 1–5. doi: 10.1109/CITSM64103.2024.10775429.
- [19] V. Simic, S. Dabic-Miletic, E. B. Tirkolaee, Ž. Stević, A. Ala, and A. Amirteimoori, "Neutrosophic LOPCOW-ARAS model for prioritizing industry 4.0-based material handling technologies in smart and sustainable warehouse management systems," *Appl. Soft Comput.*, vol. 143, p. 110400, Aug. 2023, doi: 10.1016/j.asoc.2023.110400.
- [20] A. Mitra, "Cotton fibre selection based on quality value using measurement of alternatives and ranking according to compromise solution (MARCOS) method," *Res. J. Text. Appar.*, vol. 28, no. 2, pp. 299–316, Apr. 2024, doi: 10.1108/RJTA-03-2022-0030.
- [21] Ö. F. Görçün and G. Doğan, "Mobile crane selection in project logistics operations using Best and Worst Method (BWM) and fuzzy Measurement of Alternatives and Ranking according to Compromise Solution (MARCOS)," *Autom. Constr.*, vol. 147, p. 104729, Mar. 2023, doi: 10.1016/j.autcon.2022.104729.

