JOURNAL OF STATISTICAL METHODS AND DATA SCIENCE

ISSN Online 3025-1605
Journal of Statistical Methods and Data Science
Volume 01 Number 2 December 2023
https://jurnalmipa.unri.ac.id/jsmds

AUTOMATIC WEIGHT CRITERIA FOR SAW-BASED DECISION SUPPORT SYSTEM USING GRADIENT DESCENT

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Article Info:
Received: 20-03-2024
Accepted: 23-03-2024
Available Online: 05-04-2024

Keywords:
decision support system
gradient descent
linear regression
SAW

Abstract: *This research proposes an automatic weight criteria optimization, introducing a new approach by combining the SAW method with Gradient Descent to automatically determine criteria weights and taking advantage of the similarities between SAW and linear equations. The main advantage of this method is that users do not need in-depth knowledge of the cases to be created, enabling the SAW-based DSS to be performed automatically. It should be noted that SAW requires weights to function and cannot run without them being initialized at the beginning. SAW method is a prevalent approach used in DSS for evaluating alternatives based on specific criteria. However, the subjectivity inherent in determining criteria weights in SAW poses a significant challenge. The experiment results show that this method produces more accurate and unbiased criteria weights, as confirmed by the Mean Square Error (MSE) analysis. In conclusion, incorporating Gradient Descent into the Decision Support System has the potential to greatly improve its effectiveness by automating the criteria weight determination process in various decision-making scenarios, leading to more accurate and less subjective decision support in organizations.*

1. INTRODUCTION

Decision Support Systems (DSS) have become an integral part of modern organisations and businesses. SPK assists decision-makers in processing information, analysing alternatives, and selecting the best solution from several available options. One method that is often used in SPK is the Simple Additive Weighting (SAW) method, which allows the assessment of alternatives based on several criteria.

The SAW method has advantages over other decision-making methods, one of the advantages is the ability to make more accurate judgements because it is based on the value of each criterion and the weights that have been set. In addition, the total number of changes in the resulting value is greater, making it very relevant to overcome problems in decision-making (Astuti & Fu'ad, 2017). However, this method still has shortcomings, namely having to determine the correct weight on each criterion.

Determining the right weight in the SAW method is an important factor to produce accurate and objective evaluation results. Most MCDA (Multi-Criteria Decision Analysis) techniques are used with the condition that each criterion has the same weight in selecting the optimal choice or alternative. Decision-makers must be able to calculate the weight of each criterion because it is very important for decision making and the resulting relative weight is greatly influenced by the elicitation or substitution procedure used to calculate the weight (Sudipa & Sri Aryati, 2019). Currently, the determination of weights in the SAW method is often done subjectively by managers or decision-makers involved in the process of selecting the best alternative. This approach can cause uncertainty and bias in decision-making if the weights are only obtained from data alone without involving experts.

The SAW method has conceptual similarities with a system of linear equations. In SAW, alternative valuations are linearly summed with certain weights, resulting in a total value. Analogously, this is similar to a linear equation system where variables are weighted and summed to produce a total value. This similarity shows the potential to adopt optimisation techniques used in the case of linear equation systems, such as to address the weighting problem in SAW. Therefore, in this study, researchers will determine the weights in the SAW method using the Gradient Descent technique.

2. LITERATURE REVIEW

2.1. Decision Support System

A Decision Support System (DSS) is an information system that aids in business decision-making activities. It combines data, sophisticated analytical models, and user-friendly software to support decision-makers in making more informed and better decisions. These systems help in analyzing massive datasets, providing comprehensive insights, and facilitating complex decision-making processes (Sutisna & Basjaruddin, 2016).

Simple Additive Weighting (SAW), often referred to as the weighted sum method, is a widely recognized technique in the field of multi-criteria decision making (MCDM). Its primary application is to solve problems that involve various conflicting criteria. The method is appreciated for its simplicity and straightforward computational approach, which involves assigning weights to each criterion, indicative of their relative importance, and then evaluating each alternative based on these criteria. The essence of SAW lies in its ability to aggregate the performance scores of each alternative across all criteria into a single, comprehensive score.

$$Score_i = \sum_{j=1}^{n} (w_j \times x_{ij}) \tag{1}$$

Equation 1 shows the formula for determining the score of the i -th alternative, where w_j represents the weight for criterion j, and x_{ij} is the value of alternative i for criterion j.

SAW is particularly beneficial in scenarios where criteria are quantitative and can be directly compared. Its adoption spans diverse fields such as resource allocation, vendor selection, and project management. Despite its widespread use, the SAW method does have limitations, especially in dealing with qualitative or subjective criteria. Its reliability heavily depends on the proper assignment of weights to criteria, which sometimes introduces subjectivity into the decision-making process.

2.2. Gradient Descent

To obtain optimal outcomes, characterized by the minimum of the curve, Gradient Descent serves as a repetitive optimization technique employed in the field of Machine Learning. (Swasono, 2022). The primary objective of Gradient Descent is to identify parameters or weights that minimize the value of the objective function. The working mechanism of Gradient Descent can be explained in several stages as follows:

1. **Initialization of Weights**: Initially, weights or parameters are determined either randomly or based on prior knowledge, $w = [w_1, w_2, \dots w_n]$. These weights will be iteratively updated throughout the optimization process. The choice of initial weights can significantly influence the efficiency and outcome of the Gradient Descent algorithm.
2. **Choose a Learning Rate**: Select a learning rate α, which determines the size of the steps taken towards the minimum of the loss function
3. **Iterative Optimization:**
   Compute Gradient: Calculate the gradient of the loss function with respect to the weights. The gradient is a vector that points in the direction of the steepest increase of the loss function. Mathematically, it's represented in eq 2 where L is the loss function.
   $$\nabla L(w) = \left[\frac{\partial L}{\partial w_1}, \frac{\partial L}{\partial w_2}, \dots, \frac{\partial L}{\partial w_n}\right] \quad (2)$$
   Weight Update: Weights are updated by subtracting a small quantity of the gradient multiplied by the learning rate. The learning rate is a hyperparameter that determines the size of the steps taken in each iteration. By updating the weights, we aim to approximate the minimum value of the objective function.
   $$w = w - \alpha \nabla L(w) \quad (3)$$
4. **Convergence Check**: Repeat the above steps until the weights converge. Convergence is typically determined by the change in loss function value being below a small threshold, or by reaching a set number of iterations.
5. **Optimal Result**: After the iterations are complete, we obtain weights that yield the most optimal or near-minimum value of the objective function.

3. METHODOLOGY

3.1. Data and Source

The research data for this study is sourced from the exemplary employee data at BKKBN (The National Population and Family Planning Board) in Riau Province. Additionally, the researcher has compiled secondary data from other studies. This includes data extracted from the thesis on the K-Means Algorithm in Selecting Outstanding Students and the SAW (Simple Additive Weighting) Method for Predicting Scholarship Recipients as well as from the Decision Support System for Determining the Best Employees Using the SAW Method: A Case Study at PT Pertamina RU II Dumai (Maya & Sari, 2014).

3.2. Data Analysis

The research stages conducted are as follows:

i. **Data analysis**. This stage involves analyzing data to determine the presence of dependent and independent data. Gradient Descent requires labelled data to find new weights. Labeled data is obtained from the results of decision-making that have been done previously. These results can also be used to calculate the MSE value of the decision support system using the SAW method with weights generated by the system.

ii. **Design Algorithm**.
In the context of the SAW method, Gradient Descent can be utilized to determine the optimal weights for each criterion to achieve the desired outcome. In this stage, we outline the Gradient Descent algorithm tailored to fit the SAW method. The steps are as follows:

- **Linear Model for SAW**: The model we consider is $\hat{y} = w_1 x_1 + w_2 x_2 + .. + w_n x_n$ where $\hat{y}$ is predicted score for alternative, w_i is the weight for criterion x_i and n is the number of criteria
- **Loss Function**. Assuming we use Mean Squared Error (MSE) as the loss function, it's defined as $L = \frac{1}{m}\sum_{i=1}^{m}(\hat{y}_i - y_i)$, where m is the number of observation and y_i is actual score in real implementation.
- **Gradient Calculation**. The gradient of MSE with respect to weight w_j is the partial derivative of L with respect to w_j, $\frac{\partial L}{\partial w_j} = \frac{2}{m}\sum_{i=1}^{m}(x_{ij}(\hat{y}_i - y_i))$ where x_{ij} is the value of criterion j for observation i.
- **SAW Weight Update**. Each weight w_j is updayed using calculated gradient $w_j = w_j - \alpha\frac{\partial L}{\partial w_j}$, where α is the learning rate.

iii. **Implementation**.The model is developed using Visual Studio Code with the Python programming language. Model development is carried out using the Gradient Descent algorithm approach to obtain the latest weights.

iv. **Weight Evaluation**. Once the optimum weights are obtained, implementation in the SAW Method can proceed. It is expected that there will be differences in the ranking results from the initial model weights compared to the model results from Gradient Descent.

v. **Interpretation**.After implementation, the calculation results can be compared with prediction data and the error value calculated using the Mean Square Error (MSE) method.

4. RESULT AND DISCUSSION

4.1 Application to Exemplary Employee Data at BKKBN Riau Province

In the dataset for determining the exemplary employee at BKKBN in the Riau Province region, there are five criteria: Work duration (C1), Number of children(C2), Tardiness(C3), Performance appraisal (C4), and Innovation (C5). Detailed values of this data are shown in Table 1.

Table 1. Employee Data of BKKBN Riau

Candicate	C1	C2	C3	C4	C5
A1	1	1	0.75	0.9	1
A2	1	1	0.75	0.8	0.75
A3	1	1	0.5	0.9	0.75
A4	1	1	0.75	0.8	0.5
A5	1	1	1	0.9	0.75
A6	1	1	0.25	0.8	0.5
A7	1	1	0.75	0.8	0.5

The implementation of Gradient Descent in determining the weights for exemplary employees at BKKBN uses a learning rate of 0.01 with 1000 iterations. The optimum weights using Gradient Descent are shown in Table 2. In addition, Figure 1 also shows the decrease in error in the training process as the number of iterations increases. The figure illustrates where the error rate starts from around 0.7 and decreases sharply to below 0.1 within the first 200 iterations. After this initial drop, the curve flattens out, showing a gradual reduction in error as it approaches 0 over 1000 iterations. The figure also shows that the Gradient Descent algorithm quickly improves the accuracy of the model initially and then makes smaller incremental improvements as it approaches the optimal set of parameters.

Table 2. Optimum weight for exemplary employees at BKKBN

w_1	w_2	w_3	w_4	w_5
0.341885	0.341885	0.0522206	0.2373155	0.0266938

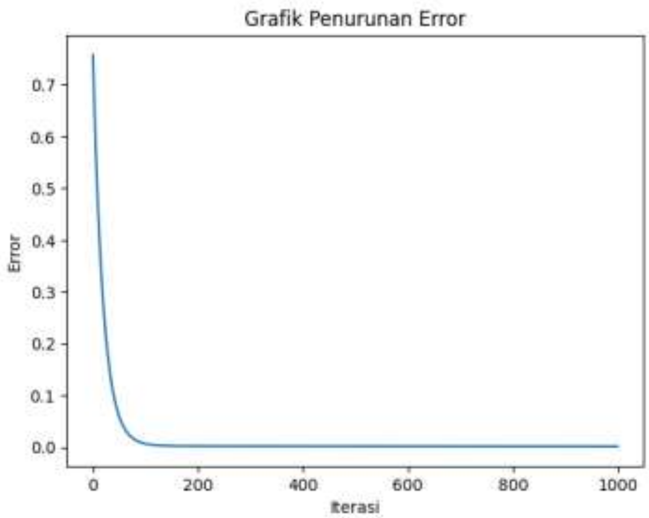

Figure 1. Gradient Descent error reduction graph of exemplary employees

Based on the weights from Table 2, the ranking process involves calculating the total score for each alternative by multiplying the normalized values of the criteria by their respective weights. The results, presented in Table 3 determine the best candidate for the exemplary employee at BKKBN in Riau Province. The table lists alternatives ranked by their scores, with alternative A3 leading at 0.967216, followed by A1 with a score of 0.965186, and down to A7 and A4, which are tied at a score of 0.925471.

Table 3. Ranking Order based on Automatic Weight

Alternative	Score
A3	0.967216
A1	0.965186
A6	0.960285
A5	0.954161
A2	0.932144
A4	0.925471
A7	0.925471

Furthermore, Table 4 compares the error rate with the error using the weights from the previous manager. On average, the error given by the manager is greater, so it can be interpreted that the weights using gradient descent are better.

Table 4. Comparison of Error between weights from Gradient Descent and weights from Manager/Researcher

Alternative	Error using Gradient Descent weight	Error using Manager weight
A1	0.002041798	0.007511
A2	0.002719039	0.017263
A3	0.004518022	0.007656
A4	0.00023935	0.050126
A5	0.002933422	0.0225
A6	0.012162713	7.72E-06
A7	0.001258188	0.041571
Average	0.003696076	0.020948

4.2 Application for the Indonesia Smart Card (KIP) Recipients

The data of the Indonesia Smart Card (KIP) recipients have 5 criteria, which are Family Income, Family Dependents, House Condition, Parents' Occupation, and Asset Ownership. The data used are already in normalized form. Table 5 shows the normalized data of the KIP recipients.

Table 5. Indonesia Smart Card (KIP) Recipients

Alternative	Criteria				
	C1	C2	C3	C4	C5
A1	0.6	0.8	0.6	0.5	0.6
A2	0.6	0.6	0.4	0.5	0.6
A3	0.6	0.8	0.4	1	0.6
A4	0.6	0.4	0.4	0.5	0.6
A5	0.6	0.8	0.6	0.5	0.8
A6	0.6	0.8	0.6	1	1
A7	0.6	0.4	0.4	0.5	0.8
A8	0.6	1	0.8	0.5	1
A9	0.6	0.8	0.6	0.5	0.6
A10	0.8	1	0.4	0.5	0.6

Similar to the previous evaluation, the automatic weights for the Indonesia Smart Card (KIP) recipients uses a learning rate of 0.01 with 1000 iterations. The weights generated are displayed in Table 6.

Table 6. Optimized weight for Indonesia Smart Card (KIP) Recipients

w_1	w_2	w_3	w_4	w_5
0.001657	0.457793	0.184409	0.162691	0.19345

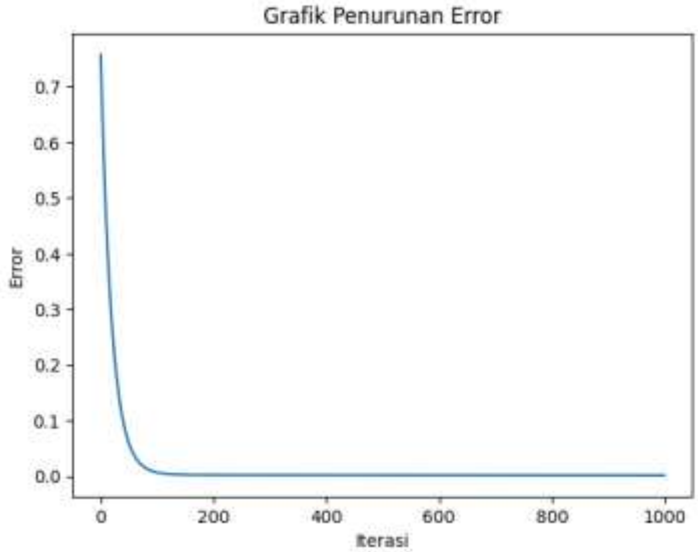

Figure 2. Gradient Descent error of KIP recipient

Figure 2 depicts the Gradient Descent error reduction graph for the KIP recipient analysis. The graph illustrates a rapid decline in error from an initial value of approximately 0.7 to below 0.1 within the first 200 iterations. This steep reduction suggests that the Gradient Descent algorithm quickly finds a more optimal set of weights for the decision-making criteria. As iterations continue beyond 200, the error rate stabilizes, indicating convergence towards an optimal solution.

Based on the weights from Table 6, the ranking process involves calculating the total score for each alternative by multiplying the normalized values of the criteria by their respective weights. The results, presented in Table 7 determine the recipent of KIP ranking. Alternative A7 tops the ranking with a score of 0.787345704, indicating the highest suitability as a recipient of the Indonesia Smart Card (KIP) based on the evaluated criteria. This is followed by alternatives A4 and A6 with scores of 0.748656 and 0.724587, respectively. The list continues, descending to alternative A10, which has the lowest score of 0.474394.

Table 7. The recipent of KIP ranking

Alternative	Score
A7	0.787345704
A4	0.748656
A6	0.724587
A8	0.643564
A5	0.604551
A3	0.601105
A2	0.596058
A1	0.565861
A9	0.565861
A10	0.474394

Next, Table 8 compares the error level with the error using weights from the previous manager. On average, the error given by the manager is larger, but there is not a significant difference, so it can be said that both sets of weights are already optimal.

Table 8. Comparison of Error between weights from Gradient Descent and weights from Manager/Researcher

Alternative	Error using Gradient Descent weight	Error using Manager weight
A1	0.110797	0.161604
A2	0.263229	0.295573
A3	0.080716	0.117649
A4	0.560485	0.5041
A5	0.049085	0.073984
A6	0.058364	0.071289
A7	0.543679	0.4624
A8	0.025781	0.047089
A9	0.110797	0.161604
A10	0.005534	0.055225
Average	0.180847	0.195052

4.3 Application to the Best Employee Data at PT Pertamina RU II Dumai

In the dataset for the best employee at PT Pertamina RU II Dumai, obtained from the research by Maya & Sari (2014), there are 4 criteria: GPA, parents' income, father's occupation, and number of dependents. This dataset has a dependent variable using the SAW method and can be used to test the model's effectiveness in improving outcomes in the SPK using the SAW method.

Table 9. The best employee Data at PT Pertamina RU II Dumai

Alternative	Criteria			
	C1	**C2**	**C3**	**C4**
A1	0.3666	0.305	0.695	0.238
A2	0.2633	0.25	0.7	0.2523
A3	0.31	0.2666	0.51	0.2785
A4	0.33	0.2904	0.45	0.238
A5	0.293	0.309	0.49	0.2549
A6	0.36	0.2549	0.44	0.309
A7	0.4366	0.238	0.44	0.2904
A8	0.28	0.2785	0.43	0.2666
A9	0.29	0.2523	0.44	0.25
A10	0.4533	0.238	0.5	0.305

Similar to the previous evaluation, the automatic weights for this dataset use a learning rate of 0.01 with 1000 iterations. The weights generated are displayed in Table 10.

Table 10. Automatic weight for Pertamina best employee dataset

w_1	w_2	w_3	w_4
0.24382075	0.192499	0.371515	0.192165

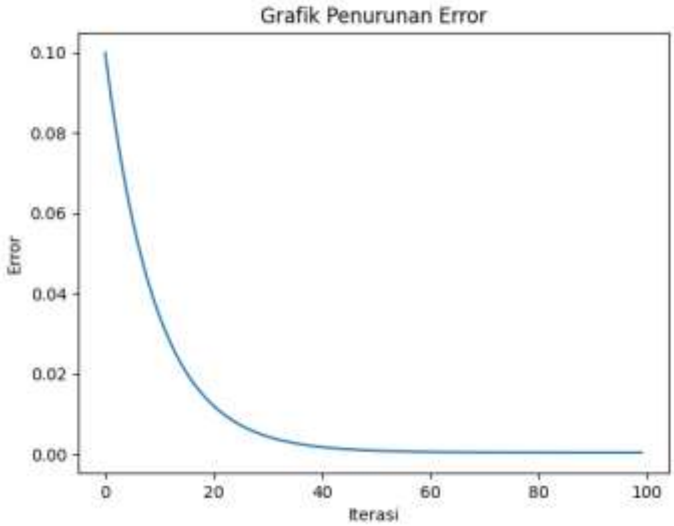

Figure 3. Gradient Descent error of Pertamina best employee dataset

Figure 3 presents the error reduction graph from the application of Gradient Descent over 100 iterations. Initially, the error starts at just above 0.1 and exhibits a sharp decline within the first 20 iterations, indicating a rapid improvement in the model's accuracy. As the iterations progress, the error continues to decrease, albeit at a slower rate, and approaches closer to 0, suggesting that the model is converging towards an optimal set of weights. The curve flattens out towards the end of the graph, which typically indicates that further iterations may result in only marginal improvements. This graph is indicative of the efficiency of Gradient Descent in optimizing the decision-making criteria in a relatively small number of iterations.

Table 11. The Pertamina best employee ranking

Alternative	Score
A1	0.90129
A10	0.851185
A2	0.820644
A7	0.802032
A6	0.781598
A3	0.777178
A5	0.76907
A4	0.747011
A8	0.719586
A9	0.703285

In Table 11, alternative A1 is ranked highest with a score of 0.90129, indicating it as the top candidate within the context of the evaluation criteria. This is followed by alternative A10 with a score of 0.851185, and the list continues with alternative A2 scoring 0.820644. As the scores decrease, alternative A7 and A6 are close with scores of 0.802032 and 0.781598, respectively. Alternatives A3, A5, and A4 follow in descending order, leading to A8 and A9, which have the lower scores of 0.719586 and 0.703285, respectively.

Table 12. Comparison of MSE SPK of Pertamina's Best Employees

Alternative	Error using Gradient Descent weight	Error using Manager weight
A1	0.270702	0.264108
A2	0.24765	0.179914
A3	0.207187	0.205154
A4	0.178094	0.219568
A5	0.198087	0.222822
A6	0.203941	0.221538
A7	0.201629	0.240207
A8	0.174378	0.192678
A9	0.166697	0.177974
A10	0.231539	0.255457
Average	0.20799	0.217942

Table 12 show the error comparison between automatic weight and manager weight. Overall, the system's weights tend to be more conservative, as indicated by a lower average weight of 0.20799 compared to the manager's average of 0.217942. Some alternatives, such as A2 and A10, show substantial discrepancies, with the manager's weights being notably higher. This variation suggests that the system's algorithm might distribute weights more evenly or that the manager's approach may incorporate additional qualitative insights, leading to a larger spread in the weight distribution and, consequently, the error levels associated with each set of weights.

5. CONCLUSION

Based on the author's research on the application of the Gradient Descent algorithm for automatic weight determination in the SAW method, several conclusions can be drawn. Firstly, the Gradient Descent algorithm is a viable tool for identifying weights within decision support systems. This algorithm's iterative approach to optimizing weights proves to be effective for enhancing the decision-making process.

Furthermore, the automated weight determination system developed using Gradient Descent can be universally applied across various decision support systems that utilize the SAW method. According to the Mean Square Error (MSE) calculations conducted in the study, the decision support system outcomes employing weights obtained from Gradient Descent are comparable, if not superior, to those from weights predetermined by other methods. This indicates that the weights determined through Gradient Descent are not only relevant but also potentially more accurate for decision support systems based on the SAW methodology.

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