2020 International Conference on Informatics, Multimedia, Cyber and Information System (ICIMCIS)

The Criteria That Have A Significant Effect on Forecasting the Number of Sales Using the Best-Worst Method

1st Rendra Gustriansyah
Universitas Indo Global Mandiri
Doctoral Student of Universitas Sriwijaya
Palembang, Indonesia
rendra@uigm.ac.id

2rd Ermatita*
Faculty of Computer Science
Universitas Sriwijaya
Palembang, Indonesia
ermatita@unsri.ac.id

3th Dian Palupi Rini
Faculty of Computer Science
Universitas Sriwijaya
Palembang, Indonesia
dprini@unsri.ac.id

4th Reza Firsandaya Malik
Faculty of Computer Science
Universitas Sriwijaya
Palembang, Indonesia
rezafm@unsri.ac.id

2020 International Conference on Informatics, Multimedia, Cyber and Information System (ICIMCIS) | 978-1-7281-9167-6/20/$31.00 ©2020 IEEE | DOI: 10.1109/ICIMCIS51567.2020.9354276

***Abstract*— Forecasting the number of sales is an effort for forecasting the number of product sales for a certain period in the future. The company's failure to supply products will have negative effects on the quality of service to customers, thereby reducing the company's competitiveness. One of the critical success factors on forecasting the number of sales is determining the criteria required by the decision support system. The problem is what criteria are needed or influential in forecasting the number of sales. Furthermore, most of the problems in decision making are uncertainties associated with input criteria. Therefore, this study will investigate the criteria that a significant effect in forecasting the number of sales by using the recent decision support method, namely the Best-Worst Method by considering uncertainty so that the optimum forecasting of the number of sales can be achieved. The results achieved in this study indicate that the three most significant criteria for forecasting the number of sales are frequency, quantity, and monetary. Preliminary experimental results have shown that perturbations in the case study had no significant effect on the final ranking of the decision support system criteria.**

Keywords—best-worst method, decision support system, decision-making, sales forecasting, uncertainty.

I. Introduction

A company engaged in the sale or distribution of products always wants success in its activities in the future. One of the most important ways to achieve this is by estimating or forecasting the number of sales or customer demand for goods or services produced [1].

One of the critical success factors in forecasting the number of sales is determining the criteria required by the decision support system [2]. The problem is what criteria are needed or have an influence on forecasting the number of sales.

Furthermore, most of the problems in decision making associated with input criteria are uncertainty. Uncertainty arises because it is difficult to determine a precise value indicating the priority of the two qualitative criteria to each other, causing some final decisions to be complicated and unrealistic [3].

The respondent may have made some mistakes when assigning values for pairwise comparisons so that we need to consider uncertainties to obtain a rational final decision. Therefore, this study will investigate the criteria that have have a major impact on forecasting the number of sales by using the recent decision support method, namely the Best-Worst Method (BWM) [3], [4] by considering uncertainty so that the optimum forecasting of the number of sales can be achieved.

The BWM approach has been implemented in various decision-making cases such as selection [3], [5]–[7], assessment [8], [9], evaluation and classification [10]–[12], strategy-making and innovation [13], investment development [14], key success factors [15], and group decision-making problems [16], [17]. Meanwhile, in this study, the BMW approach will be implemented to determine the criteria that have a significant effect on forecasting the number of sales.

This study is expected to contribute that there are other important criteria (not just quantity [1], [18]–[20]) that have a major impact on forecasting the number of sales.

II. Research Method

A. Research Approach

The research phases proposed in this study include six phases as illustrated in Fig. 1 as follows:

978-1-7281-9167-6/20/$31.00 ©2020 IEEE

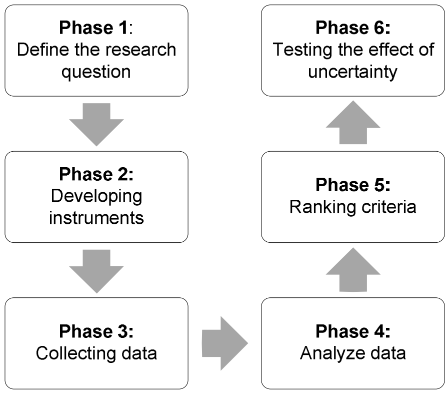

Fig. 1. The six phases of research in this study.

This study took three opinions of experts who have more than 12 years of experience in the field of sales and inventory at retail companies.

The first data collection in the form of gathering all the criteria that affect the number of sales. Then the criteria are chosen by experts. Only the criteria selected at least two experts will be further processed for the second data collection using the Best-Worst Method.

B. Best-Worst Method

Multi-criteria decision-making (MCDM) is an important subset of the theory of decision-making. A recent MCDM method named Best-Worst Method (BWM) will be implemented in this study to analyze the criteria affecting sales volume and its weights.

BWM is the MCDM method that Rezaei introduced in 2015, which is capable of obtaining the weights of criteria and alternatives by comparing the best criterion against the other criteria (alternatives) and all the other criteria against the worst criterion for various criteria based on pairwise comparisons with the use of fewer comparative results [4].

The BWM is consists of five steps which will be used to derive the criteria weights [3], [4].

Step 1: Sets a list of decision criteria.

Suppose that there are n decision criteria, which are very important for the fair performance of the alternative evaluation.

Step 2: Selecting the best and worst criteria.

Through this step, the experts will select the best (most influential) criterion and the worst (least influential) criterion among all the criteria identified in Step 1 from their perspective. Only the criteria and not the criteria values are selected here. The best criterion is defined as c_B, the worst criterion being c_W.

Step 3: Establish the best criterion for the priority rating over all other criteria.

A number from 1 to 9 (1: equally important, 9: extremely more important) is used to denote the priority. The resulting a "Best-to-Others" vector as follows: $\mathbf{a}_B = (a_{B1}, a_{B2}, \ldots, a_{Bn})$, where a_{Bj} represents the rating of the best criterion B over any other criteria j (j=1,2,…,n), and $a_{BB} = 1$. The consensus of the various experts on finalization of priority ratings shall be adopted.

Step 4: Establish the priority rating for all other criteria over the worst criterion.

In this case, the number from 1 to 9 is used. The resulting an "Others-to-Worst" vector as follows: $\mathbf{a}_W = (a_{1W}, a_{2W}, \ldots, a_{nW})^T$, where a_{jW} represents the rating of any criteria j over the worst criterion w, and $a_{ww} = 1$. Similarly, the final value can be arrived by consensus of all the experts involved in decision making.

Step 5: Calculates the optimum weights of all the criteria $(w_1^*, w_2^*, \ldots, w_n^*)$.

The objective is to calculate the weights of criteria so that the maximum absolute differences for all j are minimized of the following set $\{|w_B - a_{Bj}w_j|, |w_j - a_{Bjw}w_w|\}$, that can be formulated to the min-max model as in (1).

$$\min \max_j \left\{ \left| \frac{w_B}{w_j} - a_{Bj} \right|, \left| \frac{w_j}{w_w} - a_{jw} \right| \right\} \tag{1}$$

Equation (1) could be transferred to the following linear programming model:

$$\begin{aligned} &\min \xi \\ &\text{s.t.} \\ &\left| \frac{w_B}{w_j} - a_{Bj} \right| \le \xi^*, \text{ for all j} \\ &\left| \frac{w_j}{w_w} - a_{jw} \right| \le \xi^*, \text{ for all j} \\ &\sum_j w_j = 1 \\ &w_j \ge 0, \text{ for all j} \\ &j = 1,2,\ldots,n \end{aligned} \tag{2}$$

Multiplying the first set of the constraints of (2) for any value of ξ by w_j and the second set of constraints by w_w, it can be seen that the solution (2) is an intersection of 4n-5 linear constraints (obtained from 2(2n-3) of comparison constraint and 1 constraint for the number of weights) thus, provided that the solution is not empty enough. Compute (2) then the optimum weights of the criteria $(w_1^*, w_2^*, \ldots, w_n^*)$ and ξ^* will be generated.

After finding the final result, the consistency ratio (CR) of pairwise comparisons should be calculated because the consistency ratio is a useful indicator of the consistency degree of the pairwise comparisons. The BWM consistency ratio could be determined using (3).

$$CR = \frac{\xi^*}{CI} \tag{3}$$

Where CI (consistency index) is the maximum ξ values for the various a_{BW} values as shown in Table I, ξ^* is the solution of problem (2), and CR ∈ [0,1]. CR values close to 0 showed more consistency, while CR values close to 1 showed less consistency. From (3) can be resumed that the smaller the ξ^*, the smaller the CR, and the more consistent the vector are.

TABLE I. CONSISTENCY INDEX (CI) [4]

a_{BW}	1	2	3	4	5	6	7	8	9
CI (max ξ)	0.00	0.44	1.00	1.63	2.30	3.00	3.73	4.47	5.23

C. Sadjadi and Karimi's Optimization Model for BWM

Sadjadi and Karimi's optimization model is a linear model developed by Sadjadi and Karimi [3] based on the method introduced by Soyster (1973). This model can control the level of variable uncertainty. This linear equation model can be seen in (4) [3].

$$
\begin{aligned}
&\min \xi^R \\
&\text{s.t.} \\
&w_B - a_{Bj} w_j + \hat{a}_{Bj} y_b \le \xi^R, \forall j, b \\
&a_{Bj} w_j - w_B + \hat{a}_{Bj} y_{b'} \le \xi^R, \forall j, b' \\
&w_j - a_{jw} w_w + \hat{a}_{jw} y_w \le \xi^R, \forall j, b \\
&a_{jw} w_w - w_j + \hat{a}_{jw} y_{w'} \le \xi^R, \forall j, w' \\
&\quad -y_b \le w_j \le y_b ,\ \forall\, b, j \\
&\quad -y_{b'} \le w_j \le y_{b'} ,\ \forall\, b', j \\
&\quad -y_w \le w_w \le y_w ,\ \forall\, w, j \\
&\quad -y_{w'} \le w_w \le y_{w'} ,\ \forall\, w', j \\
&\quad 0 \le w_j \le 1 , \forall j \\
&\quad \sum_{j=1}^{n} w_j = 1 \\
&\quad W, Y \ge 0
\end{aligned}
\tag{4}
$$

Where the actual value/weight (w) is within the uncertainty interval ($\pm y$).

This method is less flexible because of uncertain parameter limitations, however, this method has a good performance in this study.

III. Results and Analysis

This section presents a case study that shows how the BWM in this study is applied. The following is a detailed explanation of all BMW steps:

A. Sets a list of criteria

The set of criteria shall be justified basis on input from experts or decision-makers. The literature review was the early phase in the specification of the criteria for this research. The set of criteria was derived from research by R. Gustriansyah [21]. There were twenty criteria identified and only ten criteria were approved by experts, ie, C_1: Monetary, C_2: Lead time, C_3: Quantity, C_4: Season, C_5: Services to the customer, C_6: Check of stock, C_7: Discount, C_8: Management polish, C_9: Speculation, and C_{10}: Frequency. These criteria would be the basis for the second step of BWM.

B. Selecting the best and worst criteria

The selection of the best and worst criteria will be determined at this step. The criterion agreed upon by the expert/decision-maker as the criterion that has the most significant influence in the forecasting of the number of sales is the best criterion, while the worst criterion is the least significant criterion in forecasting the number of sales based on the perception of the expert/decision-maker. This perception was collected using a direct survey. Three experts were requested to express their priorities. The consensus of each expert shall be used to finalize the priority ratings.

C. Establish the priority rating for the best criterion over all other criteria

This step is to identify the priorities for the best criterion from among all criteria. This information is also gathered by the use of the survey form. The experts will state their priorities for the best criterion over each other criteria using values ranging from 1 to 9. The results of the questionnaire in the Best-to-Others (BO) vectors can be observed in Table II.

TABLE II. BO Vectors from Experts

Expert	Best Criterion	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}
1	Quantity	3	3	1	4	6	5	2	7	8	9
2	Monetary	1	5	2	3	5	7	2	8	6	9
3	Frequency	2	4	3	2	5	6	1	7	3	9

D. Establish the priority rating for all other criteria over the worst criterion

In this step, the experts are requested to give their priority for all other criteria over the worst. Values ranging from 1 to 9 will be used again. The results of the questionnaire in the Others-to-Worst (OW) vectors are observed in Table III.

TABLE III. OW-Vectors from Experts

Expert	**1**	**2**	**3**
Criteria	***Worst Criterion***		
	Speculation	***Speculation***	***Speculation***
C_1	8	9	8
C_2	7	3	3
C_3	9	6	7
C_4	6	7	6
C_5	4	4	3
C_6	5	2	5
C_7	8	8	9
C_8	3	3	2
C_9	2	5	4
C_{10}	1	1	1

After the finalization of the criteria, the next step is to calculate the weights of these criteria.

E. Calculation of the weights

The weights were calculated using the linear BWM model (2), where the average weight of each criterion obtained from the three experts results in a single weighted vector which can be observed in Table IV.

TABLE IV. Overall Weights from The Three Experts

Criteria		**Weights from Expert**			**Average**
		1	*2*	*3*	
C_1^*	Monetary	**0.114239**	**0.262750**	**0.154645**	**0.177211**
C_2^*	Lead time	**0.114239**	0.066013	0.077323	0.085858
C_3^*	Quantity	**0.274174**	**0.165033**	**0.103097**	**0.180768**
C_4^*	Season	0.085679	**0.110022**	**0.154645**	0.116782
C_5^*	Services	0.057120	0.066013	0.061858	0.061664
C_6^*	Check of stock	0.068543	0.047152	0.051548	0.055748
C_7^*	Frequency	**0.171359**	**0.165033**	**0.252316**	**0.196236**

Criteria		Weights from Expert			Average
		1	*2*	*3*	
C_8^*	Discount	0.048960	0.041258	0.044184	0.044801
C_9^*	Management	0.042840	0.055011	0.078679	0.058843
C_{10}^*	Speculation	0.022848	0.021715	0.021705	0.022089
	ξ^*	0.068543	0.067316	0.056975	0.064278

ξ^* is the consistency indicator for the comparisons. Table IV shows that the results were very high consistency since the value was near zero.

By solving (1) and (2) for pairwise comparison of all criteria, the weights of each criterion are generated, these weights are used for rank as well as for obtaining the priority value of each criterion.

As can be observed from Table IV and Fig. 2 that for the case company, the most significant criteria, namely 'Frequency', 'Quantity', and 'Monetary' are the three criteria of the decision support system that most influences in forecasting the number of sales, with the weight of each criterion are 0.196236, 0.180768, and 0.177211 after normalization.

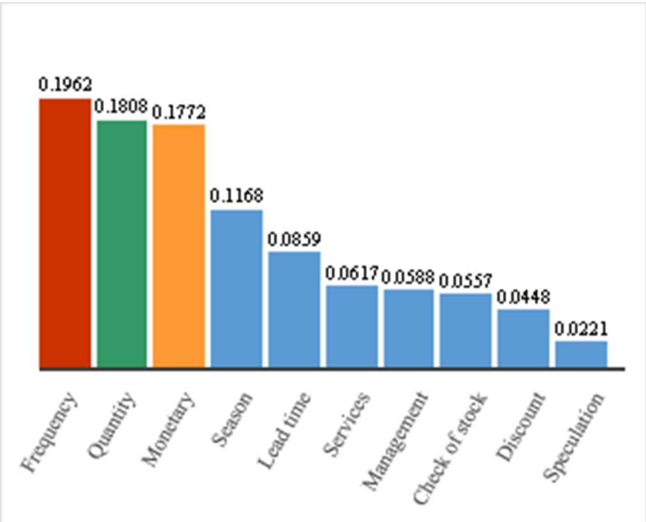

Fig. 2. Ranking of decision support system criteria that influence in forecasting the number of sales.

F. *Effect of uncertainty on the ranking of each criterion*

This step will investigate whether the application of uncertainty to the opinion of experts can affect the ranking of decision support system criteria. This finding can generate robust decisions against errors.

If random error (e) is inserted in each pairwise comparison for all criteria, assuming that the opinion of the decision-makers has errors it will produce an example of the Best-to-Others (BO) and Others-to-Worst (OW) vectors as can be observed in Table V and Table VI. Where the determination of the error value could be larger than 1, however, a larger error value indicates a smaller level of confidence in the opinion of the decision-maker. Then, the error value for each pairwise comparison may differ from one criterion to another, depending on the characteristics of each criterion.

TABLE V. PAIRWISE COMPARISON OF BO VECTORS WITH RANDOM ERRORS AS AN EXAMPLE

Expert		1	2	3
Criteria		***Best Criterion***		
		Quantity	*Monetary*	*Frequency*
C_1^*	Monetary	3 ± 0.25	1	2 ± 0.15
C_2^*	Lead time	3 ± 0.25	5 ± 0.45	4 ± 0.35
C_3^*	Quantity	1	2 ± 0.15	3 ± 0.25
C_4^*	Season	4 ± 0.35	3 ± 0.25	2 ± 0.15
C_5^*	Services	6 ± 0.55	5 ± 0.45	5 ± 0.45
C_6^*	Check of stock	5 ± 0.45	7 ± 0.65	6 ± 0.55
C_7^*	Frequency	2 ± 0.15	2 ± 0.15	1
C_8^*	Discount	7 ± 0.65	8 ± 0.75	7 ± 0.65
C_9^*	Management	8 ± 0.75	6 ± 0.55	3 ± 0.25
C_{10}^*	Speculation	9 ± 0.85	9 ± 0.85	9 ± 0.85

TABLE VI. PAIRWISE COMPARISON OF OW VECTORS WITH RANDOM ERRORS AS AN EXAMPLE

Expert		1	2	3
Criteria		***Worst Criterion:*** *Speculation*		
C_1^*	Monetary	8 ± 0.75	9 ± 0.85	8 ± 0.75
C_2^*	Lead time	7 ± 0.65	3 ± 0.25	3 ± 0.25
C_3^*	Quantity	9 ± 0.85	6 ± 0.55	7 ± 0.65
C_4^*	Season	6 ± 0.55	7 ± 0.65	6 ± 0.55
C_5^*	Services	4 ± 0.35	4 ± 0.35	3 ± 0.25
C_6^*	Check of stock	5 ± 0.45	2 ± 0.15	5 ± 0.45
C_7^*	Frequency	8 ± 0.75	8 ± 0.75	9 ± 0.85
C_8^*	Discount	3 ± 0.25	3 ± 0.25	2 ± 0.15
C_9^*	Management	2 ± 0.15	5 ± 0.45	4 ± 0.35
C_{10}^*	Speculation	1	1	1

The application of uncertainty to this example using (4) has resulted in the average weighting of each criterion and a ranking of the criteria as shown in Table VII and Fig. 3.

TABLE VII. NUMERICAL RESULTS AND THE RANKING OF EACH CRITERION

Criteria		Average Weights		The Ranking	
		e = 0	*e ≠ 0*	*Nominal*	*Uncertain*
C_1^*	Monetary	**0.177211**	**0.178155**	3	3
C_2^*	Lead time	0.085858	0.084390	5	5
C_3^*	Quantity	**0.180768**	**0.181203**	2	2
C_4^*	Season	0.116782	0.114980	4	4
C_5^*	Services	0.061664	0.060295	6	7
C_6^*	Check of stock	0.055748	0.054524	8	8
C_7^*	Frequency	**0.196236**	**0.196531**	1	1
C_8^*	Discount	0.044801	0.043719	9	9
C_9^*	Management	0.058843	0.063428	7	6
C_{10}^*	Speculation	0.022089	0.022775	10	10
	ξ^{R*}	0.064278	0.081818		

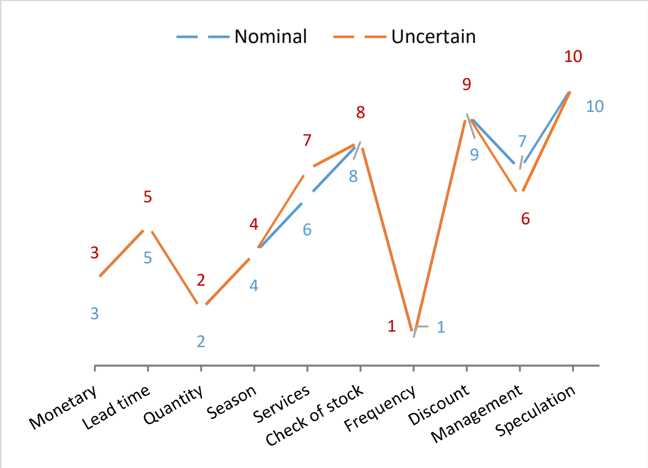

Fig. 3. Comparison of rankings in nominal and uncertain problems.

In line with Table VII, it can be seen that applying uncertainty can reduce the consistency of pairwise comparisons. Where for $e = 0$ in this case, all criterion has the same weight and rank as the nominal situation. The resulting inconsistency level is low (0.0643) or has a high-reliability level ($\cong$ 94%).

As for $e \neq 0$, the resulting inconsistency level is still low (0.0818). This means that the level of reliability and consistency is high ($\cong$ 92%). This indicates that the application of uncertainty to the criteria in this case study will not lead to inconsistencies and thus will not reduce the rationality of the results.

The experimental results show that applying uncertainty to a decision support system can change the ranking criteria and can influence the final decision as shown in Fig. 3. However, in this case, the change in ranking did not have a significant effect on the results of this study.

IV. Conclusion

According to the findings in the empirical case study on the results of this study that the BWM can determine the most significant criteria affect in forecasting the number of sales. The three most significant criteria are Frequency, Quantity, and Monetary.

This shows that several criteria have a significant effect that must be considered in developing a decision support system for forecasting the number of sales.

Furthermore, the experimental results in this case study show that the application of uncertainty can alter the ranking of criteria, however, it did not have a significant effect so that the results of decision making (determining criteria) in this case study are rational.

As a future work in this field is to build a sales forecasting model that integrates the results of this study with the results of the study [22] to improve the performance of the research model [21].

Acknowledgment

The author would like to thank the DRPM Kemenristek/BRIN Republic of Indonesia for supporting research through the PDUPT Grant.

References

[1] R. Gustriansyah, N. Suhandi, F. Antony, and A. Sanmorino, “Single Exponential Smoothing Method to Predict Sales Multiple Products,” *J. Phys. Conf. Ser.*, vol. 1175, no. 1, pp. 1–7, 2019.

[2] R. Gustriansyah, N. Suhandi, and F. Antony, “The Design of UML-Based Sales Forecasting Application,” *Int. J. Recent Technol. Eng.*, vol. 7, no. 6, pp. 1507–1511, 2019.

[3] S. J. Sadjadi and M. Karimi, “Best-worst multi-criteria decision-making method: A robust approach,” *Decis. Sci. Lett.*, vol. 7, no. 4, pp. 323–340, 2018.

[4] J. Rezaei, “Best-Worst Multi-Criteria Decision-Making Method,” *Omega - Int. J. Manag. Sci.*, vol. 53, pp. 49–57, 2015.

[5] J. Rezaei, T. Nispeling, J. Sarkis, and L. Tavasszy, “A supplier selection life cycle approach integrating traditional and environmental criteria using the best worst method,” *J. Clean. Prod.*, vol. 135, pp. 577–588, 2016.

[6] N. Suhandi, Terttiaavini, and R. Gustriansyah, “Decision support system for subsidized housing selection based on best-worst method and simple additive weighting,” *Int. J. Adv. Trends Comput. Sci. Eng.*, vol. 9, no. 3, pp. 3384–3389, 2020.

[7] R. Gustriansyah, “Integration of Decision-Making Method and Data-Mining Method as A Preliminary Study of Novel Sales Forecasting Method,” *Int. J. Adv. Trends Comput. Sci. Eng.*, vol. 9, no. 4, pp. 5730–5735, Aug. 2020.

[8] N. Salimi, “Quality assessment of scientific outputs using the BWM,” *Scientometrics*, vol. 112, no. 1, pp. 195–213, 2017.

[9] J. Ren, H. Liang, and F. T. S. Chan, “Urban sewage sludge, sustainability, and transition for Eco-City: Multi-criteria sustainability assessment of technologies based on best-worst method,” *Technol. Forecast. Soc. Change*, vol. 116, pp. 29–39, 2017.

[10] N. Salimi and J. Rezaei, “Evaluating firms’ R&D performance using best worst method,” *Eval. Program Plann.*, vol. 66, pp. 147–155, 2018.

[11] Q. Yang, Z. Zhang, X. You, and T. Chen, “Evaluation and Classification of Overseas Talents in China Based on the BWM for Intuitionistic Relations,” *Symmetry (Basel).*, vol. 8, no. 11, p. 137, 2016.

[12] F. Abouhashem Abadi, I. Ghasemian Sahebi, A. Arab, A. Alavi, and H. Karachi, “Application of best-worst method in evaluation of medical tourism development strategy,” *Decis. Sci. Lett.*, vol. 7, no. 1, pp. 77–86, 2018.

[13] E. Khanmohammadi, M. Zandieh, and T. Tayebi, “Drawing a Strategy Canvas Using the Fuzzy Best–Worst Method,” *Glob. J. Flex. Syst. Manag.*, vol. 20, no. 1, pp. 57–75, 2019.

[14] K. Askarifar, Z. Motaffef, and S. Aazaami, “An investment development framework in Iran’s seashores using TOPSIS and best-worst multi-criteria decision making methods,” *Decis. Sci. Lett.*, vol. 7, no. 1, pp. 55–64, 2018.

[15] S. Ghaffari, A. Arab, J. Nafari, and M. Manteghi, “Investigation and evaluation of key success factors in technological innovation development based on BWM,” *Decis. Sci. Lett.*, vol. 6, no. 3, pp. 295–306, 2017.

[16] Q. Mou, Z. Xu, and H. Liao, “An intuitionistic fuzzy multiplicative best-worst method for multi-criteria group decision making,” *Inf. Sci. (Ny).*, vol. 374, pp. 224–239, 2016.

[17] X. You, T. Chen, and Q. Yang, “Approach to multi-criteria group decision-making problems based on the best-worst-method and electre method,” *Symmetry (Basel).*, vol. 8, no. 9, 2016.

[18] S. Kohli, G. T. Godwin, and S. Urolagin, “Sales Prediction Using Linear and KNN Regression,” in *Advances in Machine Learning and Computational Intelligence.*, 1st ed., Singapore: Springer, 2021, pp. 321–329.

[19] S. Makkar, A. Sethi, and S. Jain, “Predictive Analytics for Retail Store Chain,” in *Advances in Intelligent Systems and Computing*, Singapore: Springer, 2021, pp. 631–641.

[20] J. Feizabadi, “Machine learning demand forecasting and supply chain performance,” *Int. J. Logist. Res. Appl.*, pp. 1–24, Aug. 2020.

[21] R. Gustriansyah, D. I. Sensuse, and A. Ramadhan, “A sales prediction model adopted the recency-frequency-monetary concept,” *Indones. J. Electr. Eng. Comput. Sci.*, vol. 6, no. 3, pp. 711–720, 2017.

[22] R. Gustriansyah, N. Suhandi, and F. Antony, “Clustering optimization in RFM analysis based on k-means,” *Indones. J. Electr. Eng. Comput. Sci.*, vol. 18, no. 1, pp. 470–477, 2020.