Management Science Advances, Volume 2, Issue 1 (2025) 282-287

Management Science Advances

Journal homepage: www.msa-journal.org
eISSN: 3042-2205

Variance Measure in Decision-Making Process: An Interpretation

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ARTICLE INFO

Article history:
Received 19 June 2025
Received in revised form 26 July 2025
Accepted 7 August 2025
Available online 20 August 2025

Keywords:
Decision-making, Variance measure, Uncertainty modelling, Attitudinal traits.

ABSTRACT

This paper considers variance measure that is popularly used in multi-attribute decision-making (MADM) either as a holistic approach or as a snippet of a holistic approach for determining values of key decision entities such as attributes and/or alternatives. Specifically, we attempt to understand the results that emanate from the variance measure through a detailed interpretive construct, which will serve as a guide to decision-making scholars for rational usage of the popular approach in their respective MADM problems. We present illustrative examples to clarify the interpretations. Furthermore, we explore how the interpretive construct can be extended to analyze consistency in attribute weighting, thereby strengthening the reliability of MADM results. We also demonstrate how the variance measure can complement rank-based and aggregation-based methods, offering a unified perspective that integrates statistical interpretation with decision-making logic.

1. Introduction

As the advancement in artificial intelligence (AI) is growing tremendously, data-driven decision-making is gaining much attention. Multi-attribute decision-making (MADM) is at the heart of decision science, where different competing/conflicting attributes are considered for an option and based on the choices/rating from agents, a suitable decision is made, which is typically backed by mathematical formulation – thus allowing corrections/rectifications in the future along with learning from mistakes, which otherwise would not be possible.

Specifically, in the MADM context, a set of options serves as a candidate set from which a suitable option must be selected by considering a set of attributes of varying types (benefit or cost) and trade-offs. Manual assessment of candidates based on a diverse attribute set might lead to subjectivity and bias hindering the rational decision process, and to overcome this challenge, method-based decision-making is presented under the roof of MADM.

Statistical variance (SV) is a simple yet popular method used by researchers in MADM to determine the values of key decision entities such as attributes or alternatives. In general, SV is a

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https://doi.org/10.31181/msa21202519

standalone decision method, or it is used as a step of an entire procedure – for example, the CRITIC method [1], LOPCOW method [2], and alike. The intent of using SV is to understand the hesitation of experts during rating, as argued by [3]. It is noticed that a higher variance value indicates high hesitation. As a result, in the process of uncertainty handling in MADM, it is essential to consider this information, which is done by assigning higher importance to that entity. Another train of thought emphasizes reducing the importance of such an entity that invites hesitation/doubt. A balanced way out would be to consider a linear combination of both forms to strike a balance between risk appetite and risk-averse nature.

This idea is mapped to cognitive fatigue and response bias in psychology or behavioral science. Simply put, if variance is low, there is a tendency towards cognitive fatigue and response bias. As a result, the thoughts contradict, and it becomes essential for a decision analyst to consider both thoughts equally. The key research question considered in this paper is:

RQ: What is the viable interpretation of results from the SV method in the context of MADM?

To address this question, we present the following contributions

- Apply the SV method to different example cases to understand the interpretation of the results.
- Ameliorate the decision entity value determination process via the SV method to handle common or same rating – which typically yields zero as a result of the traditional SV procedure.

The rest of the paper is organized as follows. The SV procedure for decision entity value determination via MADM is presented in the next section. Following this, we present the ameliorated procedure for SV, which mitigates the abovementioned challenge. Later, examples are presented with interpretations to aid the decision analyst with appropriate usage of the method. Finally, concluding remarks and future directions are provided.

2. Review of the SV method and proposed amelioration

2.1 Literature review

Liu *et al.,* [4] presented an integrated framework for cloud vendor selection by considering the SV method for weight determination. Tayak and Timor [5] presented variance-based AHP for ranking in a decision-making problem. Zhao *et al.,* [6] presented a deviation method under a hesitant fuzzy context for the rating decision process. Further, maximizing deviation determines the criteria weights in a decision problem. Selvachandran *et al.,* [7] presented deviation-based TOPSIS for the decision-making process under a neutrosophic context. Wang and Zhou [8] combined maximizing deviation with PROMETHEE under a neutrosophic context along with social media mining for large-scale decisions. While in the earlier works, researchers focused on maximizing deviation, some researchers have also considered minimizing deviation, which is yet another thought process for determining values of decision entities (Xu *et al.,* [9]; Xu [10]).

Some researchers have directly used variance for the decision process. Sarwar *et al.,* [11] used SV method for weight calculation in the rough fuzzy integrated cloud context. Likewise, Krishankumar *et al.,* [12] used the SV method under a probabilistic version of hesitant fuzzy for decision-making. Wen *et al.,* [13] prepared a risk assessment model with the SV method for objective weight calculation. Kamari *et al.,* [14] extended MEREC and variance methods under a Pythagorean neutrosophic context for the decision process.

2.2 SV method for determining decision entities

Key decision entities include attributes and alternatives, whose values are calculated by applying the SV method directly. The procedure is as follows:

Step 1: Collect vectors from the dataset upon which the SV must be applied. Determine the mean of that vector and calculate the SV.

Step 2: Normalize the variance vector to determine the values of attributes or alternatives. This step yields a value between 0 and 1, and the sum of values in the vector yields unity.

It must be noted that the values emanating from SV are non-negative and represent the two trains of thought as mentioned above.

2.3 Ameliorated SV method

The procedure for using the SV method is mentioned above, and from the steps, it is inferred that though the approach is simple and practically feasible, some challenges must be addressed, like the same value in vector(s) leading to zero variability even though the semantics of the rating are different. For example, if a criterion gets a rating from different experts and the value is 'very low', by all experts, the variability value is zero, and henceforth, the weights that emanate are also zero. Likewise, if the criterion gets a rating as 'very high' from all experts, even then the variability is zero – weight is also zero, which is not logical.

The ameliorated steps for weight assignment via SV are given below:

Step 1: Collect the rating data from experts on each attribute. d experts provide a rating on each attribute to form $1 \times c$ vector

Step 2: Apply the SV method for determining the variance value associated with each attribute, which forms a vector of $1 \times c$.

- If the input vector value is unique, apply the SV method directly.
- If the input vector value is the same, the SV becomes zero – to resolve the issue,
    - Calculate the mean; if it is greater than or equal to the mid value in the rating scale, assign maximum variance from the variance set to that criterion.
    - If the mean is less than the mid value in the rating scale, then assign the minimum variance from the variance set to that criterion.
    - If the mean is equal to the mid value in the rating scale, then assign the average of the maximum and minimum variance from the variance set to that criterion.

Step 3: Normalize the variance vector to obtain weights of attributes. Further calculate (de)variance vector and normalize the same for obtaining another weight vector. Both these vectors are of order $1 \times c$.

Step 4: Determine the linear combination of these two vectors to obtain the final weights of attributes.

3. Illustrative examples and comparison

Example 1: Let us consider the weights of four attributes as 0.20, 0.30, 0.40, and 0.10, respectively. Apply the ameliorated SV method for the decision process.

Table 1
Results for Example 1

Rank	Rank 3	Rank 2	Rank 1	Rank 4	Weights
Attributes	A1	A2	A3	A4	
Var = 0.016667	0.2	0.3	0.4	0.1	Weights from variance
Complement	0.8	0.7	0.6	0.9	
Var = 0.001852	0.266667	0.233333	0.2	0.3	Weights from complement
Var = 0.001852	0.233333	0.266667	0.3	0.2	Combined weights

Example 2: Consider four experts providing their rating on five attributes that will be used for selecting candidates to a research lab for pursuing research activities under a project pertaining to the assessment of barriers hindering women's empowerment in rural regions. Expert data is obtained, and the variance procedure is applied to determine the weights/importance of attributes.

Table 2
Results for Example 2

DM	A1	A2	A3	A4	A5
D1	5	4	7	3	8
D2	5	5	8	5	7
D3	7	6	4	6	7
D4	6	6	5	8	5
Variance	0.916666667	0.916667	3.333333	4.333333	1.583333
Var = 0.019351	0.082707016	0.082707	0.300753	0.390979	0.142858
	Rank 5	Rank 4	Rank 2	Rank 1	Rank 3
Complement	0.917292984	0.917293	0.699247	0.609021	0.857142
Var = 0.001209	0.229323418	0.229323	0.174812	0.152255	0.214286
	Rank 1	Rank 2	Rank 4	Rank 5	Rank3
Var = 0.002721	0.156015217	0.156015	0.237782	0.271617	0.178572
	Rank 4	Rank 5	Rank 2	Rank 1	Rank 3

Example 3: Consider a situation where three experts give their rating on seven attributes by considering a 9-Likert scale rating. The results from SV and ameliorated SV are given below.

Table 3
Results for Example 3

Intra_Variance	DM	A1	A2	A3	A4	A5	A6	A7
	D1	4	6	7	6	5	8	7
	D2	4	5	6	4	4	8	5
	D3	4	7	8	4	7	8	6
	Variance	0	1	1	1.333333	2.333333	0	1
0.014524	Weight	0	0.15	0.15	0.2	0.35	0	0.15
	Adj_Variance	1	1	1	1.33	2.33	2.33	1
0.003957	Adj_Weight	0.1001	0.1001	0.1001	0.133133	0.233233	0.233233	0.1001

The results from Table 1, Table 2, and Table 3 clarify the effect of considering the ameliorated variance measure. Specifically, the ameliorated measure handles two crucial issues- the zero variability condition and consideration of a neutral trait during the decision process – by considering the mean of the two extremes, risk-averse and risk-appetite nature.

From the three examples, we can infer that the ameliorated variance is rational and yields a lesser intra-variability, indicating consistency within the distribution. Though some readers may argue on the discrimination power of the model, it is essential to note that there are two train of thoughts towards variance that are used for weight determination and due consideration must be given to both the thoughts and eventually, this leads to lesser intra variability, which is further mapped to consistency/stability of the result.

4. Comparison

Tables 1 and 2 show that the intra-variability of the determined weight vector significantly varies after the amelioration process. Though some readers may argue that the variability decreases, allowing less discrimination of attributes/alternatives, it must be noted that attitudes, preferring hesitation and clarity, are crucial when determining entities' relative importance (weights). Specifically, the tendency of reduced variability after combining these two attitudes implies a neutral state of the experts, which is feasible during the decision process.

Furthermore, the changes in the relative importance value imply that these two attitudes affect the decision process, and the final decision becomes more rational based on this ameliorated process. Besides, the original SV method cannot handle vectors with the same rating data and yields zero as importance, which is not rational/logical. The ameliorated SV method offers clarity in this challenging circumstance by providing a way out based on the abovementioned rules. This not only improves the applicability of the SV method, but also provides a rational sense to the decision process, which is lacking in the literature considering the usage of the SV method.

5. Conclusion

This paper presents an amelioration to the popular SV method, which is used in MADM to determine entity weights. The two key issues, viz., the zero variability and attitudinal traits of stakeholders, are addressed in this paper by presenting an ameliorated procedure for using the SV method to determine weights. Specifically, we understand that both the thought process related to the SV method and the neutral standpoint support the rational determination of weights of entities.

Furthermore, a procedure for handling the zero-variability situation is also provided, where a higher or lower preference of the same value for an attribute/alternative yields a variance of zero, which is not rational during weight calculation and is resolved via an amelioration in the procedure. Despite these merits, some limitations exist, such as partial information on entities not being accepted by the procedure and the procedure not being able to handle missing data. Some managerial implications are: (i) the model considers a neutral standpoint after due consideration to both the traits of stakeholders, (ii) the procedure is ready for use by decision analyst for logically determining weights, (iii) the procedure follows simple yet elegant improvements to handle the issues raised during the decision process, and (iv) practical training to stakeholders facilitate the potential use of the procedure in the decision process.

The limitations can be addressed in the future with improvements to the base method. Furthermore, plans are made to embed learning strategies with such methodologies for effective reasoning, and plans are being made to extend this framework to diverse decision frameworks for rationally determining weights of entities – experts, attributes, and/or alternatives.

Conflicts of Interest
The author declares no conflicts of interest.

Acknowledgment
This study did not receive any external financial support.

References

[1] Diakoulaki, D., Mavrotas, G., & Papayannakis, L. (1995). Determining objective weights in multiple criteria problems: The CRITIC method. *Computers & Operations Research, 22*(7), 763–770. https://doi.org/10.1016/0305-0548(94)00059-H

[2] Ecer, F., & Pamucar, D. (2022). A novel LOPCOW-DOBI multi-criteria sustainability performance assessment methodology: An application in developing country banking sector. *Omega, 112*, 102690. https://doi.org/10.1016/j.omega.2022.102690

[3] Kao, C. (2010). Weight determination for consistently ranking alternatives in multiple criteria decision analysis. *Applied Mathematical Modelling, 34*(7), 1779–1787. https://doi.org/10.1016/j.apm.2009.09.022

[4] Liu, S., Chan, F. T., & Ran, W. (2016). Decision making for the selection of cloud vendor: An improved approach under group decision-making with integrated weights and objective/subjective attributes. *Expert Systems with Applications, 55*, 37–47. https://doi.org/10.1016/j.eswa.2016.01.059

[5] Tayalı, H. A., & Timor, M. (2017). Ranking with statistical variance procedure based analytic hierarchy process. *Acta Infologica, 1*(1), 31–38.

[6] Zhao, H., Xu, Z., Wang, H., & Liu, S. (2017). Hesitant fuzzy multi-attribute decision-making based on the minimum deviation method. *Soft Computing, 21*, 3439–3459. https://doi.org/10.1007/s00500-015-2020-y

[7] Selvachandran, G., Quek, S. G., Smarandache, F., & Broumi, S. (2018). An extended technique for order preference by similarity to an ideal solution (TOPSIS) with maximizing deviation method based on integrated weight measure for single-valued neutrosophic sets. *Symmetry, 10*(7), 236. https://doi.org/10.3390/sym10070236

[8] Wang, J., Li, S., & Zhou, X. (2023). A novel GDMD-PROMETHEE algorithm based on the maximizing deviation method and social media data mining for large group decision making. *Symmetry, 15*(2), 387. https://doi.org/10.3390/sym15020387

[9] Xu, D. S., Wei, C., & Wei, G. W. (2018). Minimum deviation method for single-valued neutrosophic multiple attribute decision making with preference information on alternatives. *Journal of Intelligent Computing, 9*, 54–75. https://doi.org/10.6025/jic/2018/9/1/54-75

[10] Xu, Z. (2006). Minimizing deviations models for solving MADM problems with preference information on alternatives in uncertain linguistic settings. *International Journal of Operations Research, 3*(1), 30–35.

[11] Sarwar, M., Ali, G., & Chaudhry, N. R. (2023). Decision-making model for failure modes and effect analysis based on rough fuzzy integrated clouds. *Applied Soft Computing, 136*, 110148. https://doi.org/10.1016/j.asoc.2023.110148

[12] Krishankumar, R., Ravichandran, K. S., Liu, P., Kar, S., & Gandomi, A. H. (2021). A decision framework under probabilistic hesitant fuzzy environment with probability estimation for multi-criteria decision making. *Neural Computing and Applications, 33*, 8417–8433. https://doi.org/10.1007/s00521-020-05595-y

[13] Wen, T. C., Chung, H. Y., Chang, K. H., & Li, Z. S. (2021). A flexible risk assessment approach integrating subjective and objective weights under uncertainty. *Engineering Applications of Artificial Intelligence, 103*, 104310. https://doi.org/10.1016/j.engappai.2021.104310

[14] Kamari, M. S. M., Rodzi, Z. M., & Kamis, N. H. (2025). Pythagorean Neutrosophic Method Based on the Removal Effects of Criteria (PNMEREC): An innovative approach for establishing objective weights in multi-criteria decision-making challenges. *Malaysian Journal of Fundamental and Applied Sciences, 21*(1), 1678–1696. https://doi.org/10.11113/mjfas.v21n1.3600