INTERNATIONAL JOURNAL OF COMPUTERS COMMUNICATIONS & CONTROL
Online ISSN 1841-9844, ISSN-L 1841-9836, Volume: 17, Issue: 6, Month: December, Year: 2022
Article Number: 5010, https://doi.org/10.15837/ijccc.2022.6.5010

CCC Publications

A New Joint Strategy for Multi-Criteria Decision-Making: A Case Study for Prioritizing Solid-State Drive

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Abstract

Solid-state data storage is becoming a widely accepted technology and is looking for new ways to provide cost-effective solutions across various information systems. Solid-state drives (SSDs), existing in different types and models, have several sustainable features: storage, dimensions, volume, etc. Due to the wide range of attributes, designing a robust method can easily select from the purchaser/retailer/wholesaler point of view. This work offers a joint multi-criteria decision-making (MCDM) to rank SSD alternatives, and a newly developed approach, namely Measurement Alternatives and Ranking according to the Compromise Solution (MARCOS) technique, is utilised, and a comparative investigation has also been achieved with other MCDM methods. Data of separate SSDs have been collected from the Indian market with twenty-six different models of eleven brands. The Bonferroni operator (BFO) allocates and compiles the objective weights using the Entropy weights technique (EWT), the Criteria Importance through Inter criteria Correlation (CRITIC) and the Method based on the Removal Effects of Criteria (MEREC). The sensitivity analysis using objective weights considering 18 scenarios was performed, and analysis with the Standard deviation shows that the joint MCDM possesses high accuracy and robustness. The results achieved have been tested with Spearman's rank and Wojciech-Salabun (WS) coefficient, and the first rank goes to SSD-7. The presented results benefit the manufacturers to understand the market requirement better and for the consumer to make a wise decision while purchasing SSD. It also offers future scope for applying the proposed methodology in similar areas, social sciences and engineering, to make complex decisions.

Keywords: Solid-State Drive, Joint multi-criteria decision-making, Objective weights, Sensitivity Analysis.

1 Introduction

Solid-state data storage is now gaining widespread acceptance. Storage based on random access memory and flash chips is getting much more attention than mechanical hard disk drive (HDD). It meets the industry's reliability, efficiency, and cost requirements more effectively than ever before. Consumer electronics sales have increased the knowledge of flash and solid-state storage (SSS) solutions. While it has been available for decades, this technology seeks new ways to provide cost-effective solutions across various commercial and government information systems. It has many enterprise applications requiring higher efficiency, reliability, and capability than consumer products such as music and video players, cell phones, PCs, and laptops [25], [24]. Since enterprise-grade SSS directly accesses data from RAM or flash chips. The data input and output levels can be much higher than traditional magnetic storage devices such as HDDs. In the past, enterprise SSS solutions were mainly focused on RAM, with batteries and backup HDDs to ensure consistency. More recently, as manufacturers have learned to make it robust and efficient enough to meet business needs, NAND flash-based SSS has been launched into the marketplace [33]. Filip [9] explained how the development of new working practices had been facilitated and spurred by computers and automation, which have also improved people's lives.

Sales of the HDD are diminishing, but solid-state drive (SSD) sales are growing and are expected to grow by 190 million units. The primary reason for sweeping out the HDD from the tech market is the sustainability of SSD in every aspect [13]. Various sustainable factors, viz. noise, damage resistance and material etc., of SSD make it a better choice than HDD. From the material point of view, SSDs have a lower impact on the environment than conventional HDDs. However, the semiconductor material used in SSDs differs significantly from HDDs [33]. The casing of HDDs is generally made up of aluminium with less corrosion resistance and often requires an extra coating for protection. The cobalt coating is usually done for protection, but it quickly develops dust, which harms the device and adds additional cost. The rotating discs in traditional drives produce heat, decreasing their performance over time and creating noise. The traditional HDDs consume 8-10% of the laptop power, but the SSDs provide power consumption sustainability and optimal speeds. These technological advances in storage drives make traditional technology stand nowhere near SSDs. The SSDs are cheaper, usually more reliable, consume less power than HDDs, and offer higher processing space, better storage price per unit, and longer product life [39]. An HDD currently dominates the data storage device market in India. Yet India's SSD market is expected to rise triple, and the SSD sector acquired the country's most extensive market revenue share [33].

SSD is more lightweight than traditional HDD, has no moving components, is resistant to magnetic fields, and can handle more shocks and vibrations than conventional platter disks. SSD is sufficient in progressively larger capacities while its cost is falling [13]. The SSDs have several attributes connected with them, e.g., SSD quality, data transmission speed, storage space, weight, and height, and thereby turn out to be an MCDM matter for a buyer, even for a supplier or programmer of intelligent systems or website maker comparing appliances/gadgets, etc. The MCDM techniques are effectively used for shortlisting. Filip [10] gave a transparent, fair, and comprehensive explanation of the fundamental ideas and significant groups of auxiliary information systems that enable decision-making processes involving several cooperating participants.

The Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) is an MCDM applied in various selection problems. The connection to the optimal solution and the proximity to the ultimate negative solution is considered by TOPSIS because of their relative vicinity to the optimal solution. Therefore, it is possible to establish alternate priority orders by contrasting the close distances [3]. A general overview of fuzzy TOPSIS was explored and presented concerning decision-making [27]. For example, TOPSIS used other methods to select a location for a charging station for electric vehicles [49]. Handmade carpets were picked with the TOPSIS technique, and the results were compared with other methods [11]. The additive manufacturing printer selection problem is also addressed by TOPSIS [32] and renewable energy source location selection [31]. A hospital site was selected using the TOPSIS method because of its mathematical simplicity and flexibility in defining the alternative set [2]. The weighted aggregated sum product assessment (WASPAS) approach is part of a novel cohort of MCDM practices reported in [48] and has been effectively employed in various fields to solve challenges of multiple types [41]. WASPAS technique was used to rank attendance software in hospitals, and weights were assigned with Criteria Importance Through Inter criteria Correlation (CRITIC) [45].

The concept of evaluation based on distance from the average solution (EDAS), which evaluates alternatives using positive and negative distances from the mean answer, is considered [19]. The enhanced EDAS method was implemented for supplier selection and used to tackle MCDM issues in a fuzzy context. The extended fuzzy EDAS approach for resolving MCDM issues is effective and stable, according to a sensitivity analysis [18]. Fuzzy EDAS coupled with Analytic Hierarchy Process (AHP) was utilized to pick warehouse locations [8]. EDAS-M was implemented in autonomous vehicle decision-making [47].

The EDAS and WASPAS-N were used to ensure the robustness of results to select teahouse locations [4]. Stanujkic et al. [38] used the extended EDAS while using grey numbers and applied it to solve a different numerical problem and verified results with COPRAS and MOORA. An extended EDAS for type-2 fuzzy sets was implemented for the subcontractor and supplier selection [47], [17]. The Fuzzy AHP and EDAS models combine to select third-party logistics providers for success in outsourcing [7]. The WASPAS method was proposed as the best-appropriate MCDM method [41]. A comparative analysis between WASPAS, TOPSIS, COPRAS, EDAS, and VIKOR proves the validity and stability of concerned methods in varying conditions using the newly developed CODAS method, making them best suitable for hybrid decision-making [16]. A new MCDM tactic was presented for construction equipment evaluation and compared with EDAS, SWARA, and CRITIC in fuzzy environments [16]. Saren et al. [34] discussed the decision-making for machines, components, and allotted tools in transitioning and concentrated on executing decisions and tactics in a flexible production cell utilizing coloured and hierarchy methodologies.

The MARCOS method was implemented to rank the suppliers in the healthcare industry. Eight alternatives concerning twenty-one criteria were considered. Sensitivity analysis was also carried out using twenty-one scenarios, verifying the MARCOS method's validity [40]. A traffic risk assessment model was also evaluated using the MARCOS method, in which a 7.4 km section of a road network having 38 sections was studied. A comprehensive validity test was also carried out to validate the results in examining the relevance of model input parameters and the influence of dynamic elements [37]. A comprehensive model was obtained using the MARCOS method that investigates the link between five significant processing restrictions. Using the Taguchi method, twenty-seven experiments were carried out, and ten different optimization approaches were used to determine the optimality

[26]. A multi-agent CRITIC method was presented to allocate cars with rigorous delay constraints and minimum bandwidth consumption. Some simulation experiments were also conducted to validate the method's effectiveness [14]. CRITIC and WASPAS techniques were adopted to solve the model based on time and attendance software selection. The six criteria and five alternatives were weighted using the CRITIC method and ranked using WASPAS [45]. The CRITIC method was used to grade decision-making units, and the two models were formulated and integrated using data envelopment analysis [29]. The MEREC method was utilized to regulate the objective weights and verified using computational examples and illustrations. A simulation-based analysis was also carried out to compute the consistency and firmness of the method [20].

The exhaustive literature review has revealed that various applications and methods under the MCDM approach have contributed to solving numerous decision-making problems. However, the methods used in the present study have unique features for finding solutions. In most cases, the ranks' results differ by applying different approaches. Therefore, there is a gap and a clear need to integrate and explore all these features through a joint strategy for MCDM. The primary contribution made by this study, to the best of the author's information, is the creation of a collaborative multi-criteria decision-making approach and its implementation to the rank and choosing of SSD. The reported study can help the buyer of SSD select the most appropriate one with the required attributes. The idea is novel in this field, as previous researchers have made no concrete efforts from this angle.

Several SSDs technology elements, such as material, the heat produced, noise, damage resistance etc., make SSDs more environmentally friendly than traditional HDDs. Therefore, they have a vital effect on sustainable purchase intentions. Furthermore, the efficiency and reliability SSDs make them a better choice concerning eco-once logical impacts, and technological advancements in future will make them an even better option. Furthermore, SSDs are inexpensive, consistent, and more energy-efficient than HDDs, have larger processing space, lower storage price per unit, and have longer product life. So, SSD selection becomes the need of the hour with some suitable methods while considering its sustainable features.

2 Selection of the Benchmark: Solid-State Drive (SSD)

An SSD is a kind of memory device that doesn't have any moving parts and permanently saves data on solid-state flash memory. An SSD comprises of a NAND flash memory chip and a flash controller. Due to its innovative architecture, the SSD provides higher read and write capability for both sequential and random data demands. Solid-state discs and flash drives are other names for SSDs. An SSD has no movable parts that can break or spin up and down, unlike an HDD. An SSD recites and inscribes data to a substrate made of linked silicon flash memory chips. To attain diverse densities, SSD industrial companies arrange chips in a grid to create SSDs. Floating gate transistors are used in the design of SSDs to hold the electrical charge and reduce volatility. Even when attached to a power source, it enables an SSD to maintain stored data [15]. HDD has been used in businesses and computer industries in the long run because of its lower cost and sophisticated robustness, although SSDs are now commonly used in portable storage devices.

2.1 Research Gaps, targets and expected contributions

Undoubtedly, consumers are entirely shifting from HDD to SSD in their electronic devices since they are always doubtful about selecting the best SSD choice, which is more durable, cost-effective, and sustainable in usage. Many studies have been conducted in this regard, but the existing literature still lacks a suitable approach to meeting these required parameters. Hence, in a structured investigation, the lacunas have enlightened the present research and attempted to bridge the cleft with functional outcomes.

The research gaps have identified and framed the objectives of the present investigation along with the intended contribution. The study has laid down examination objectives discussed below:

a) To determine the significant primary criteria in the selection of the best SSD;

b) To rank the SSDs under examination and to select the best alternative for a user;

Numerous studies have been described in a recent literature survey on solid-state drives and purchase decisions. But the extensive survey has outlined that none of the structured studies has been conducted with detailed solicitation of MCDM techniques with variable weights methods and evaluating the ratings with requisite ranking tools. Hence, this work aims to bridge this gap and contribute by deploying various sustainable ranked solutions with requisite techniques and MCDM methods for selecting an SSD by users. The rationale of combining all these methods is to average the rankings and select an SSD that is most appropriate in all senses comprising attributes. The outcomes of the study are also to help the SSD seller rate the requirements of SSD buyers better.

a) The study will summarize the criteria/attributes drawn from a survey of SSD dealers.

b) The study will rank these criteria so that the user or ultimate consumer may not have much hassle selecting an SSD that best matches their requirements.

c) The study will help the producers and marketers understand the gap in their expected and actual turnover and why their ranking is lower than other competitive options for consumers.

2.2 Research design methodology

The present study on selecting the best solid-state drives (SSDs) has been conducted with a comprehensive empirical research design. Portable SSDs available in India constitute the mark population in the current examination. The sampling units are generally from portable SSDs usable in laptops, smartphones, gaming appliances, music players, cameras, and other movable electronic appliances. A convenience sampling technique was adopted for the cybernetic survey of SSDs available in India, and a list of 97 suppliers was prepared. The sampling unit in the present investigation is SSDs available in the Indian market. However, these suppliers are mainly from China, Taiwan, South Korea, the United States, Russia, England, Japan, and Germany. Out of these 97 available suppliers, 26 different SSDs constituting eleven different brands associated with these suppliers have been shortlisted, fulfilling exhaustive and desirable details on attributes.

A small pilot survey of 60 respondents buying SSDs from dealers at his office has been made to enquire about their first preference while buying an SSD. The primary data has been collected by observing or attending their conversation or a brief discussion about their purchase preference. The study has come up with a list of seven primary attributes/criteria that have become the final study. These attributes have been finally discussed and shortlisted with hardware engineers, mainly responsible for replacing and fitting SSD in a device. Their final discretion has been used to finalize these significant routine attributes. The study has used these seven primary attributes to select the best possible SSD for a user. The user wants sustainability in their devices while purchasing any hardware item. SSD is also one of the major hardware components of an electronic device, ensuring consistent sustainability in terms of efficiency and performance.

In this case study, seven significant features/attributes are expected to pick the best option SSD. In decision-making, typically valuable criteria refer to an utmost value, e.g., SSD's data transfer speed. On the other hand, the non-beneficial to the smallest value, e.g., SSD cost. The methodology for selecting the attributes has been defined in the following sub-section. The attributes shortlisted are given below:

1. Cost of SSD in Indian Rupees (INR), as (S-1); non-beneficial criteria.
2. Weight of SSD in gram, as (S-2); non-beneficial criteria.
3. Dimensions of SSD are taken in terms of the SSD volume in cm^3, as (S-3); non-beneficial criteria.
4. The storage capacity of SSD in TB, as (S-4); beneficial criteria.
5. USB connectivity of SSD, e.g. 3.0, 3.1 etc., as (S-5); beneficial criteria.
6. Data transfer speed of the SSD in Mbps, as (S-6); beneficial criteria.
7. The colour variation of SSD in number, e.g., 1, 2, 3, etc., as (S-7); beneficial criteria.

The joint MCDM technique picks the best option from twenty-six available transportable SSD in the Indian market. However, some constraints were present when data collection was completed, such as the cost of SSD from INR 5000 to 35000, the capacity of SSD from 256 GB to 2 TB, form factor, and wired USB 3.0 to USB 3.2 connectivity. The detailed investigation procedure has been discussed in the forthcoming sub-section.

3 Joint Decision-Making Methodology

The anticipated joint procedure is shown in (Figure 1). MARCOS method is considered for ranking various alternatives. The ranking obtained using the MARCOS technique was contrasted with MCDM approaches such as TOPSIS, ARAS, MABAC, SAW, WASPAS, CoCoSo and EDAS have different principles to compute a composite score. These methods were applied to rank twenty-six SSD alternatives having seven attributes. The significance weights are assigned with objective preference calculated by the Entropy weights, CRITIC, and MEREC methods. Further compiled and finalised weights of importance were obtained using Bonferroni Operator.

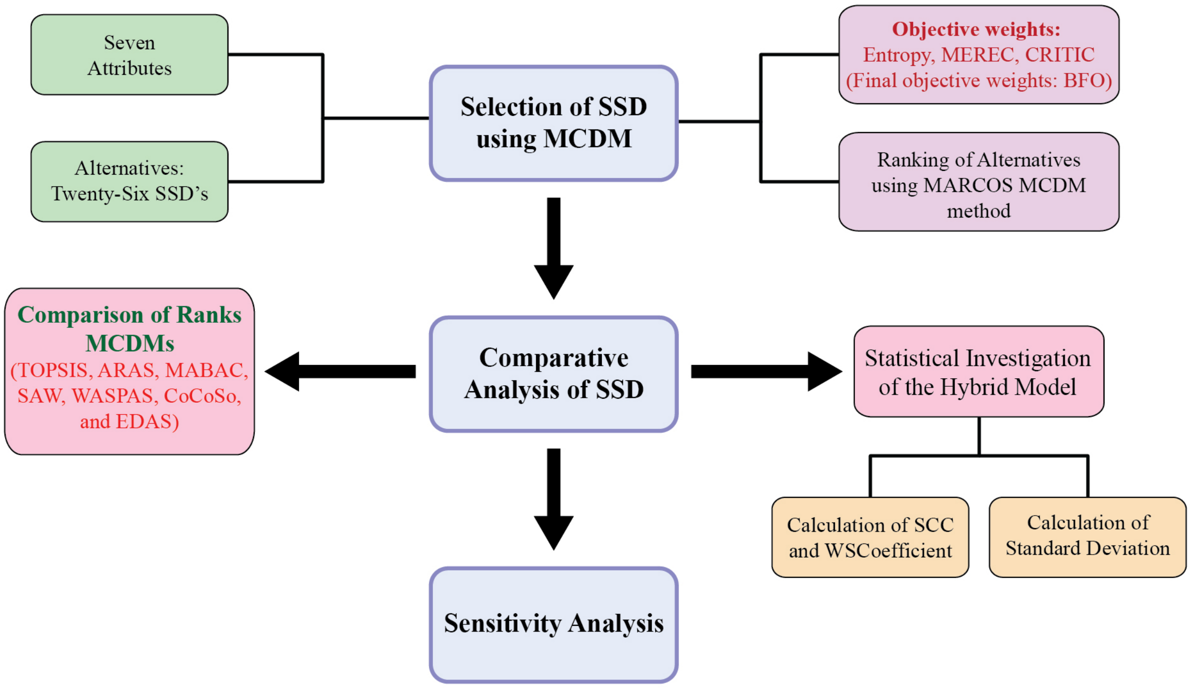

Figure 1: Proposed methodology applied to SSD selection

Therefore, the mathematical procedure for ranking the alternatives using the MARCOS technique for decision-making with 'n' criteria and 'm' options can be analysed as per the following procedure:

MARCOS method

The steps proposed and implemented by Stević et al. [40] are as:

Step 1: The decision matrix is shown in Equation (1).

Step 2: Initial decision matrix is extended by defining the ideal solution (AI) referred to in Equation (2) and anti-ideal (AAI) solutions in Equation (3). The AAI is the poorest option, while the AI is an option with the finest representative.

$$X = \begin{array}{c} AAI \\ A_1 \\ A_2 \\ \vdots \\ A_m \\ AI \end{array} \begin{array}{c} \begin{array}{cccc} C_1 & C_2 & \cdots & C_n \end{array} \\ \begin{bmatrix} x_{aa1} & x_{aa2} & \cdots & x_{aan} \\ x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \\ x_{ai1} & x_{ai2} & \cdots & x_{ain} \end{bmatrix} \end{array} \tag{1}$$

$$AI = \overset{i}{\max} x_{ij} \quad \text{if} \quad j \in P \quad \text{and} \quad \min_i x_{ij} \quad \text{if} \quad j \in Q \tag{2}$$

$$AAI = \overset{i}{\min} x_{ij} \quad \text{if} \quad j \in P \quad \text{and} \quad \max_i x_{ij} \quad \text{if} \quad j \in Q \tag{3}$$

where P is a beneficial group and Q is a cluster of cost measures.

Step 3: Normalized extended initial matrix $N = [n_{ij}]_{m \times n}$ are attained by Equation (4) and Equation (5) and where elements x_{ij} and x_{ai} belong to the matrix X.3:

$$n_{ij} = \frac{x_{ai}}{x_{ij}} \quad \text{if} \quad j \in Q \tag{4}$$

$$n_{ij} = \frac{x_{ij}}{x_{ai}} \quad \text{if} \quad j \in P \tag{5}$$

Step 4: Weighted normalized matrix $V = [v_{ij}]_{m \times n}$, is computed by Equation (6).

$$v_{ij} = n_{ij} \times w_j \tag{6}$$

Step 5: Computation of the utility degree of options U_i attained by Equation (7) and Equation (8).

$$U_i^- = \frac{R_i}{R_{aai}} \tag{7}$$

$$U_i^+ = \frac{R_i}{R_{ai}} \tag{8}$$

where $R_i(i = 1, 2, .., m)$ is represented by Equation (9), and it is the sum of the elements of the weighted matrix V.

$$R_i = \sum_{i=1}^{n} v_{ij} \tag{9}$$

Step 6: Equation (10) is utilized to compute the utility function (UF) of options $f(U_i)$.

$$f(U_i) = \frac{U_i^+ + U_i^-}{1 + \frac{1 - f(U_i^+)}{f(U_i^+)} + \frac{1 - f(U_i^-)}{f(U_i^-)}} \tag{10}$$

where $f(U_i^-)$ is the UF regarding the AAI, and $f(U_i^+)$ is the UF considering the AI. UF considering AI and AAI are computed with Equation (11) and Equation (12).

$$f(U_i^-) = \frac{U_i^+}{U_i^+ + U_i^-} \tag{11}$$

$$f(U_i^+) = \frac{U_i^-}{U_i^+ + U_i^-} \tag{12}$$

Step 7: The ranks of different options are constructed on the concluding values of utility functions—the first ranks are assigned to the highest potential value options.

Step 4 of the MARCOS method is achieved by employing objective weights, and three modes are utilized to compute weights, including the Entropy weights method [22], CRITIC [6] and MEREC method [20]. Finally, the three objective weights were combined using the Bonferroni operator [23], [46]. The essential steps of the MEREC method and computation concepts are discussed below:

Method based on the Removal Effects of Criteria (MEREC)

In order to compute the importance of each criterion in an MCDM scenario. Calculating criteria weights use the elimination influence of every factor on the combination of options. The criteria that have an enormous impact on performance are given more weight. Initially, an evaluation for other options is created, and then the performance of alternatives is calculated using a primary logarithmic measure with equal weights. Next, the absolute deviation metric determines the impact of deleting each criterion. MEREC uses the following steps to compute objective weights [20].

- The decision matrix is shown in Equation (1).
- Normalization of the decision matrix is attained by Equation (4) and Equation (5).
- Entire performance (S_i) is attained by Equation (13) using a logarithmic measure with equal criteria weights based on a non-linear function. It confirms that inferior values of n_{ij}^x create larger values of S_i based on the preceding phase.

$$S_i = ln\left(1+\left(\frac{1}{m}\sum_j \left|ln\left(n_{ij}^x\right)\right|\right)\right) \tag{13}$$

- Calculating the effectiveness of the options requires removing every condition and using the logarithmic measure. The performance of the options is appraised by deleting each criterion one at a time. Equation (14) is utilized to compute total performance ($S_{ij}^/$).

$$S_{ij}^/ = ln\left(1+\left(\frac{1}{m}\sum_{k,k\neq j} \left|ln\left(n_{ik}^x\right)\right|\right)\right) \tag{14}$$

- Compute the total absolute deviations (E_j) as per Equation (15).

$$E_j = \sum_i \left|S_{ij}^/ - S_i\right| \tag{15}$$

- Final objectives weights (w_j) are computed by Equation (16).

$$w_j = \frac{E_j}{\Sigma_k E_k} \tag{16}$$

4 Case Study: Selection of Portable Solid-State Drive

The available portable SSD from SSD-1 to SSD-26 are shown in Table 1. In addition, the information obtained on the SSD with the seven features/attributes such as S-1, S-2, S-3, S-4, S-5, S-6 and S-7 of eleven brands with twenty-six models are presented in Table 1, also referred to as decision matrix as per Equation (1).

Objective weights were computed employing the Entropy weights method [22], CRITIC [6] and MEREC method [20]. Finally, the three objective weights were combined using the Bonferroni operator [23], [46], as shown in Table 2.

The ranks of each alternative were computed using the MARCOS method are shown in Figure 2. The objective weights were used as computed using BFO. First, the utility degree of SSD alternatives were calculated for both ideal and anti-ideal solutions (U_i^+ and U_i^-), respectively. Further, a combined utility degree of alternatives (U_i) was computed using ideal and anti-ideal utility degrees, and all SSD options were ranked accordingly.

Table 1: Decision Matrix for 26 Solid-State Drives

Alternative	S-1	S-2	S-3	S-4	S-5	S-6	S-7
SSD-1	5172	33	39.125	0.256	3.2	500	2
SSD-2	9848	60	96	0.96	3.1	440	4
SSD-3	5172	33	30.53	0.256	3.1	500	2
SSD-4	10930	73	88.253	0.512	3.1	440	1
SSD-5	18526	108	124.38	1	3.1	560	1
SSD-6	12000	58.96	21.384	1	3	372	1
SSD-7	12617	24	18.95	0.96	3.1	430	1
SSD-8	14999	45.35	39.63	1	3.1	890	1
SSD-9	13999	51	44.52	1	3.1	540	4
SSD-10	30999	51	44.52	2	3.1	540	4
SSD-11	8299	51	44.52	0.5	3.1	540	4
SSD-12	12999	58	38.76	0.5	3.2	1050	2
SSD-13	19999	58	38.76	1	3.2	1050	4
SSD-14	15379	38.9	42.185	1	3.1	550	1
SSD-15	6377	38.9	41.938	0.25	3.1	550	1
SSD-16	29999	38.9	42.185	1	3.1	550	1
SSD-17	13581	140	67.181	1	3.1	540	1
SSD-18	26708	140	67.181	1	3.1	540	1
SSD-19	12349	65	41.625	1	3	400	1
SSD-20	6099	65	41.625	0.5	3	400	7
SSD-21	22329	50	41.36	0.48	3.1	540	1
SSD-22	20450	90	78.375	0.96	3.1	540	1
SSD-23	7169	33	20.512	0.48	3.1	520	1
SSD-24	6239	35	41.17	0.48	3.1	520	1
SSD-25	29899	40	45.9	2	3.1	540	1
SSD-26	13529	55	63.101	1	3	400	2

Table 2: Weights of significance

Methods	S-1	S-2	S-3	S-4	S-5	S-6	S-7
Entropy	0.084	0.107	0.179	0.052	0.067	0.107	0.143
CRITIC	0.137	0.087	0.137	0.068	0.137	0.051	0.137
MEREC	0.192	0.240	0.072	0.154	0.092	0.045	0.058
Final BFO	**0.187**	**0.158**	**0.154**	**0.198**	**0.018**	**0.053**	**0.167**

4.1 Comparative Analysis of SSD Ranks

Comparative analysis was performed by different MCDM approaches to authenticate the results attained by the MARCOS method. It include ARAS [44], MABAC [30], SAW [21], WASPAS [21], TOPSIS [5], [36], CoCoSo [43], and EDAS [28]. As a result, SSD ranks computed by the different MCDMs are offered in Table 3.

The correlation coefficient measures how effectively a monotonous expression can reflect the connectivity between various variables. It assesses the magnitude and direction of the relationship between two ranking variables. However, the rank obtained has been tested with the Spearman correlation coefficient (SCC) and WS correlation coefficient, shown in Figure 3. Thus, the SCC and WS value of 1 for the SAW method shows a high correlation. The SCC and WS have average values of 0.914 and 0.943, respectively.

A more considerable deviation exists within the data set if the data sets are farther from the average. As a result, the bigger the standard deviation, the more scattered the data is. On the other hand, a lower standard deviation isn't always advantageous. The standard deviation of ranks accomplished by the diverse MCDM approaches is shown in Figure 4. The deviation for SSD-18 is the lowest, i.e., 0.354, which means that its rank varies the least according to different MCDM methods. The standard deviation of SSD-12 is the highest, i.e., 4.406, which indicates that its rank according to different MCDM methods varies the most. No SSD alternative has shown zero deviation, which means that the ranks obtained by different MCDM methods are not constant but vary depending on the comparative analysis. Therefore, the lesser value of the standard deviation of this SSD will indicate the closeness of the different MCDM ranks, and a higher value of standard deviation will

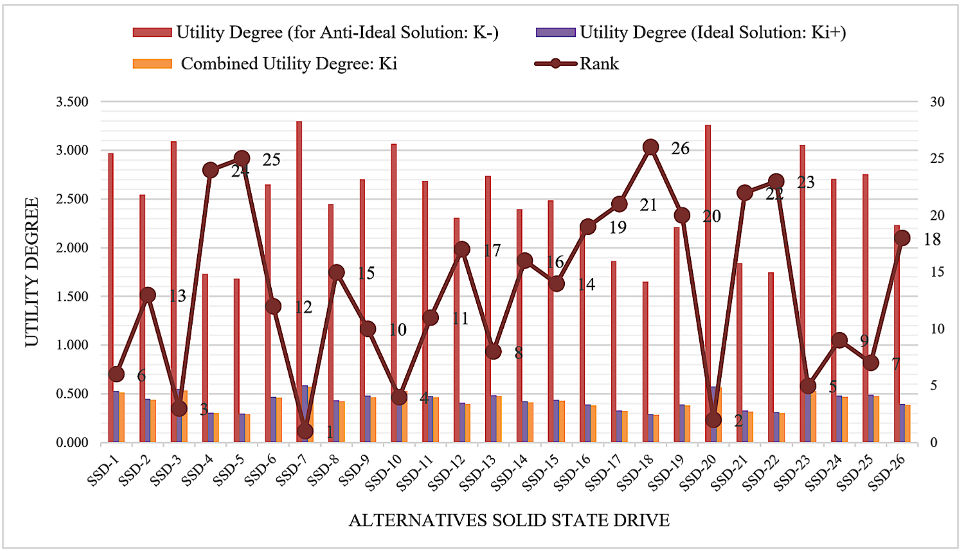

Figure 2: Ranking of SSD alternatives using the MARCOS method

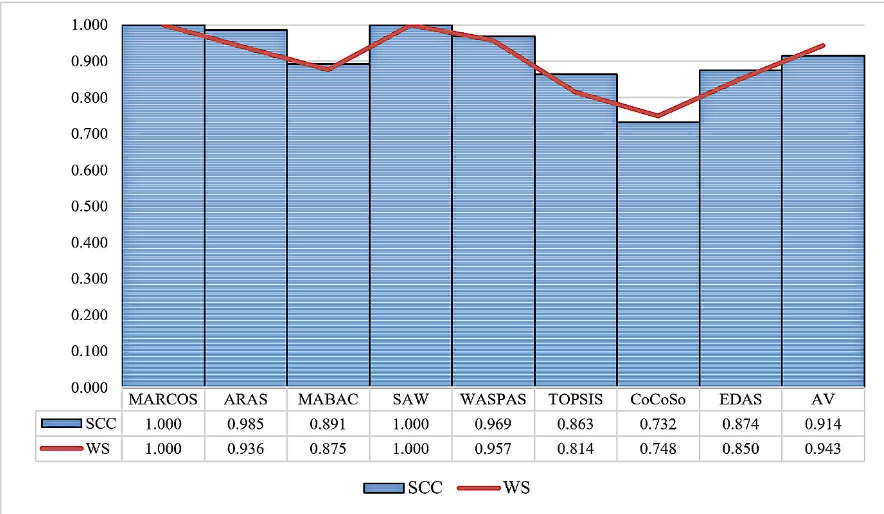

Figure 3: Spearman's coefficient of correlation and WS coefficient

indicate that ranks are spread out variedly.

4.2 Sensitivity Analysis

The instability in a quantitative judgement model's output to different threats and input changes is examined by sensitivity theory. Modifying results under different hypotheses can be helpful for various reasons, including figuring out how a variable would affect sensitivity analysis. In the beginning, it improves comprehension of the connections between the input and output variables in a system or model. Second, sensitivity analysis is crucial to model construction and quality assessment in decision-making. Third, a sensitivity approach is specifically employed to evaluate the robustness and accuracy of the solution [12], [35]. Finally, a weight adjustment method is used to crisscross the sensitivity outcomes to variations in rankings.

So, the sensitivity scrutiny was completed by altering the three most vital criteria, S-4, S-1 and S-7, on the rank results of SSDs using Equation (17) [1], [42], and a total of 18 scenarios were formed.

$$W_{n\beta} = (1 - W_{n\alpha})\frac{W_\beta}{(1 - W_n)} \tag{17}$$

Three groups, each with nine sets, were established to create three different scenarios. The most

Table 3: SSD ranks by different MCDM method

	MARCOS	ARAS	MABAC	SAW	WASPAS	TOPSIS	CoCoSo	EDAS
SSD-1	6	6	9	6	7	11	9	9
SSD-2	13	11	14	13	12	6	6	8
SSD-3	3	4	7	3	4	9	7	7
SSD-4	24	24	22	24	24	22	21	22
SSD-5	25	25	25	25	25	26	25	25
SSD-6	12	13	13	12	10	10	23	11
SSD-7	1	3	5	1	2	7	10	6
SSD-8	15	15	10	15	14	13	12	12
SSD-9	10	8	3	10	6	3	2	2
SSD-10	4	2	4	4	3	2	8	3
SSD-11	11	9	6	11	9	5	3	5
SSD-12	17	17	11	17	16	18	5	14
SSD-13	8	7	2	8	8	4	1	4
SSD-14	16	16	16	16	15	14	14	15
SSD-15	14	14	17	14	18	19	17	19
SSD-16	19	20	20	19	20	20	18	20
SSD-17	21	21	23	21	21	23	24	24
SSD-18	26	26	26	26	26	25	26	26
SSD-19	20	19	19	20	19	17	19	18
SSD-20	2	1	1	2	1	1	4	1
SSD-21	22	22	21	22	22	21	20	21
SSD-22	23	23	24	23	23	24	22	23
SSD-23	5	5	8	5	5	12	11	10
SSD-24	9	12	12	9	11	15	13	16
SSD-25	7	10	15	7	13	8	15	13
SSD-26	18	18	18	18	17	16	16	17

important criterion, S-4 was changed in the first group of situations, while criteria S-1 in the second group of scenarios and S-7 in the second group of strategies changed through various sets.

$W_{n\beta}$ signifies the corrected value of criteria S-1, S-2, S-3, S-5, S-6, and S-7 denotes the $W_{n\alpha}$ impaired value of the S-4 criterion,

W_{β} signifies the unique value of the measured norm and W_n signifies the unique value of the S-4 for the first group of scenarios.

$W_{n\beta}$ signifies the corrected value of criteria S-2, S-3, S-4, S-5, S-6, S-7 signifies the $W_{n\alpha}$ impaired value of the S-1 criterion,

W_{β} signifies the unique value of the measured criterion and W_n signifies the unique value of the S-1 criterion for the second group of scenarios.

$W_{n\beta}$ signifies the corrected value of criteria S-1, S-2, S-3, S-4, S-5, and S-6 signifies the $W_{n\alpha}$ impaired value of the S-7 criterion,

W_{β} signifies the unique value of the measured criterion and W_n signifies the unique value of the S-7 criterion for the third group of scenarios.

During first case, the S-4 criterion's value was decreased by 15% while the values of the other criteria were modified accordingly using Equation (17). By maintaining the weight value equal to one, the new values of criteria weights are shown in Table 4.

Eighteen different sets of weights are used to perform sensitivity analysis. Spearman's coefficient of correlation and WS coefficient for new ranks obtained while changing criteria weights are shown in Table 5. The high Spearman's coefficient and WS coefficient of one for set 0 of weight criteria. The changing weight criteria by ranks by MCDM are shown in Figure 5. SSD-7 achieved rank one by a maximum of 12 times out of 18 sets of different weight criteria, followed by SSD-20 by six times.

4.3 Discussion and Managerial Implications of the study

With the opening of the Indian Market in 1991 with new industrial policy, regulations of world trade organizations in 1995, the introduction of computer and the internet, the emergence of the Fourth Industrial revolution in 2011 in Germany, rising usage of technology-enabled devices, robotics,

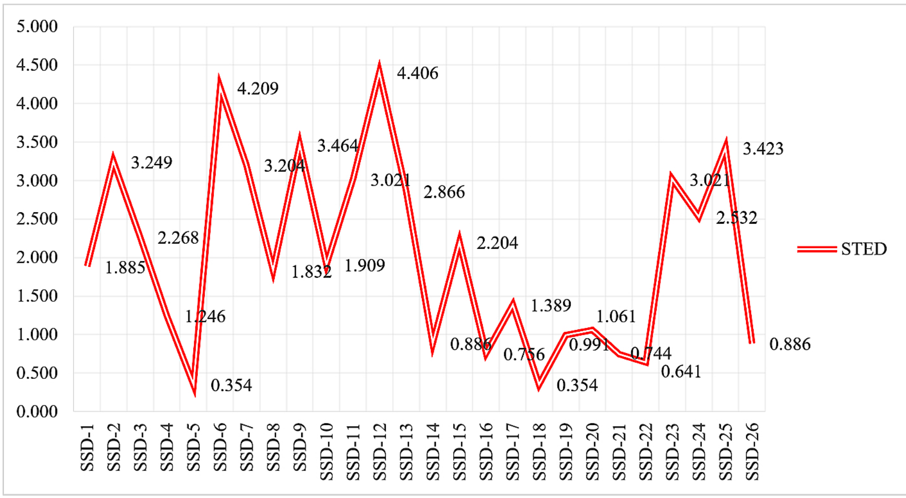

Figure 4: Standard deviation of SSD alternative ranks for different MCDM methods

Table 4: New criteria weights; 18 different scenarios (Sc-1 to Sc-18)

	W1	**W2**	**W3**	**W4**	**W5**	**W6**	**W7**
Sc-1	0.194	0.164	0.160	0.168	0.019	0.054	0.173
Sc-2	0.201	0.170	0.165	0.138	0.019	0.056	0.180
Sc-3	0.208	0.176	0.171	0.109	0.020	0.058	0.186
Sc-4	0.214	0.182	0.177	0.079	0.021	0.060	0.192
Sc-5	0.221	0.188	0.182	0.049	0.021	0.062	0.198
Sc-6	0.228	0.194	0.188	0.020	0.022	0.064	0.204
Sc-7	0.159	0.164	0.159	0.204	0.019	0.054	0.173
Sc-8	0.131	0.169	0.165	0.211	0.019	0.056	0.179
Sc-9	0.103	0.175	0.170	0.218	0.020	0.058	0.184
Sc-10	0.075	0.180	0.175	0.225	0.020	0.060	0.190
Sc-11	0.047	0.186	0.180	0.232	0.021	0.062	0.196
Sc-12	0.019	0.191	0.186	0.238	0.022	0.063	0.202
Sc-13	0.192	0.163	0.159	0.204	0.018	0.054	0.142
Sc-14	0.198	0.168	0.163	0.210	0.019	0.056	0.117
Sc-15	0.204	0.173	0.168	0.215	0.020	0.057	0.092
Sc-16	0.209	0.178	0.172	0.221	0.020	0.059	0.067
Sc-17	0.215	0.182	0.177	0.227	0.021	0.060	0.042
Sc-18	0.221	0.187	0.182	0.233	0.021	0.062	0.017

digitalization, and growing competition has compelled systems to be more advanced, spacious and sustainable. The rapidly increasing and unswerving use of SSDs in most electronic devices has compelled users to look for a sustainable option. The market is flooded with numerous options and the end-user, primarily ignorant of selective criteria, is always in a hiccup in accepting and rejecting alternatives. The consumer always looks for ready-made expert advice and available web material to assist in purchasing. Hence, this paper has integral managerial implications in advising the end-users and helping the marketers offer customized and most demanded substances to such consumers.

Hence this paper has developed necessary and appropriate managerial implications for end-users, customers, marketers, industrial experts, producers, academicians, and scholars by ranking various SSD alternatives based on the most warranted criteria. The present investigation on SSDs has theoretically explained the required prerequisite of thoughtful selection criterion with selected MCDM

Table 5: Spearman's coefficient of correlation and WS coefficient for new ranks obtained changing criteria weights

	Sc-0	**Sc-1**	**Sc-2**	**Sc-3**	**Sc-4**	**Sc-5**	**Sc-6**	**Sc-7**	**Sc-8**	**Sc-9**	**Sc-10**	**Sc-11**	**Sc-12**	**Sc-13**	**Sc-14**	**Sc-15**	**Sc-16**	**Sc-17**	**Sc-18**
SCC	1.000	0.982	0.972	0.948	0.918	0.909	0.864	0.990	0.984	0.954	0.936	0.894	0.852	0.994	0.984	0.976	0.955	0.921	0.902
WS	1.000	0.959	0.958	0.926	0.918	0.894	0.866	0.984	0.969	0.957	0.949	0.920	0.888	0.995	0.968	0.949	0.927	0.913	0.899

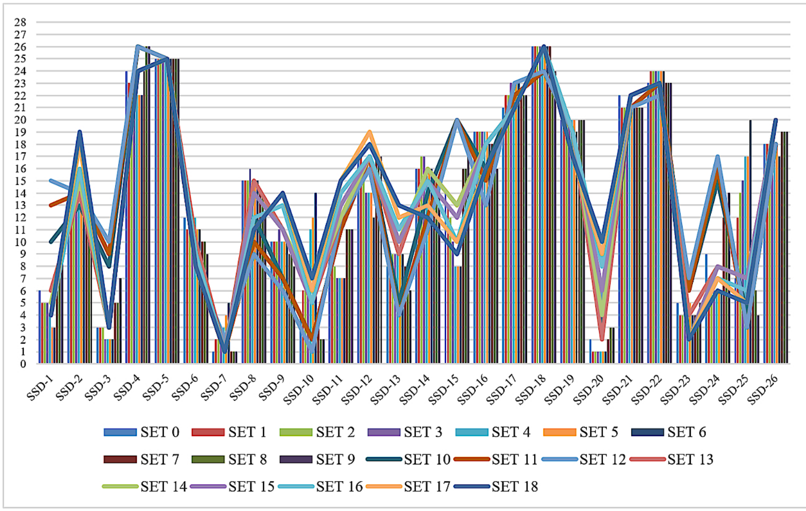

Figure 5: Ranks of SSDs by MCDM changing criteria weights

applications. The present research work has revealed that out of the twenty-six alternative SSDs under investigation, SSD-7 is preferable. For this, the analytical work has ranked distinct alternatives, assisting the end-users in selecting a sustainable option based on various criteria. Thus, this study has made a requisite attempt and a significant contribution to the already dearth of literature regarding decision-making techniques for selecting SSDs without any hassles.

Integrating AI, robotics, and SSD can change computer-operated robots' efficiency and storage capacity. Every robot system has a control program and a task program operated by a computer system. When a programming language is utilized, a language processor is included in the robot computer, which interprets the task programs and gives the data necessary by the control program to command the Robot's motions. Due to increased demand and production, robots are now used to doing various activities since they can work continuously without breaking down. SSDs are embedded within computer systems to make computer systems work more efficiently with huge data sets. The manufacturer provides the control program and the controls for each joint of the robot manipulator. The user provides the task program specifying the manipulating motions required to execute a specific task. Computer-operated Robots are widely regarded as independent learning machines that process and store information using algorithms.

5 Conclusions and Further Studies

This case study aims to identify the utmost suitable portable solid-state drive from the Indian market with fair and unbiased preferences. Data of twenty-six options of eleven different SSD brands have been composed, having various constraints, and the seven most essential attributes have been taken into account. The ranks were calculated using the MARCOS method, which reveals that the alternative SSD-7 comes out to be the first choice with 0.96 TB of storage capacity, a cost of INR 12617, a weight of 24 g, a volume of 18.95 cm^3, USB Connectivity of 3.1 and a data transfer rate of 430 Mbps with weights assigned using BFO, followed by SSD-20. The alternative SSD-20 has 0.5 TB of capacity, a cost of INR 6099, a weight of 65 g, a volume of 41.625 cm^3 with a connectivity of USB 3.0, a data transfer rate of 400 Mbps, and is available in seven different colours. Furthermore, the standard deviation results applied to comparative analysis of different joint multi-criteria decision-making methods indicate that the ranks of SSD-12 vary mostly with the highest standard deviation. In contrast, the ranks of SSD-8 go the least, with the lowest standard deviation.

Applying joint multi-criteria decision-making techniques in SSDs selection problems pursues to efficiently outline decision events to augment the final product's quality. The joint multi-criteria decision-making technique aids designers and engineers boost the fit between user requirements and design specifications. The presented technique can be used in other engineering and marketing areas where decision-making becomes complex because it satisfactorily treats uncertainties and makes more accurate and valid decisions. The joint methodology has mathematical ease and can deliver more precise outcomes than other methods. This technique has been compared with seven other strategies to authenticate the rationality of the projected scheme. The results also pave the way for applying the proposed joint multi-criteria decision-making methodology in similar areas, social sciences, and engineering to make complex decisions.

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Cite this paper as:
Kumar, R.; Goel, P.; Zavadskas, E. K.; Stević, Ž.; Vujović, V. (2022). A New Joint Strategy for Multi-Criteria Decision-Making: A Case Study for Prioritizing Solid-State Drive, *International Journal of Computers Communications & Control*, 17(6), 5010, 2022.
https://doi.org/10.15837/ijccc.2022.6.5010