Using SSP-TOPSIS in Sustainable Resource Selection for Mobile Crowd Computing

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Abstract

The widespread adoption of smart mobile devices (SMDs) with advanced computing capabilities presents a valuable resource for mobile crowd computing (MCC). Efficient task scheduling in MCC relies on selecting the right SMDs, which poses a complex multi-criteria decision-making challenge due to the diverse hardware specifications of the devices and the presence of non-compensatory parameters. Traditional multi-criteria decision analysis (MCDA) methods, such as the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS), typically assume full compensability between criteria. However, this assumption may conflict with strong sustainability principles. To tackle this issue, the authors introduce the Strong Sustainability Paradigm based Technique for Order Preference by Similarity to Ideal Solution (SSP-TOPSIS) method, an extended version of TOPSIS that incorporates linear compensation reduction. This enhancement allows for a more accurate reflection of sustainability requirements in the decision-making process. The SSP-TOPSIS method demonstrates improved analytical capabilities compared to classical TOPSIS and provides a framework that supports sustainability-driven decisions.

Keywords: SSP-TOPSIS, Strong sustainability paradigm, Mobile crowd computing, Mobile cloud computing, Smart mobile devices multi-criteria selection.

1. Introduction

The advancement of electronics and the increasing trend towards miniaturization have led to a rise in the popularity of smart mobile devices (SMDs), which offer significant computing capabilities [1]. As a result, SMDs - particularly smartphones and tablets - are preferred by users, often serving as their primary computing devices over laptops and desktops [9]. These devices possess substantial computing resources that can be utilized by applications requiring additional processing power for compute-intensive tasks when they are not in use by their owners [8]. By connecting these unused computing resources, we can foster an economical and sustainable environment. Public SMDs, whose owners have agreed to make their computing resources available can be employed as computing resources in mobile crowd computing (MCC), effectively creating a mobile cloud computing [2].

The efficiency and reliability of MCC heavily depend on the selection of suitable resources for scheduling tasks. Given the diverse specifications that encompass various criteria and the wide range of available SMDs, choosing the right SMD or combination of SMDs for MCC services presents a multi-criteria problem. In this context, multi-criteria decision analysis (MCDA) methods can be effectively applied [6].

SMD computing resources are specified by the criteria used for selection. Choosing SMDs based on their parameters, which often conflict with one another, can be complex. Additionally, these parameters are not interchangeable, as each one serves a specific function. For instance, computational capability influences response time, throughput, and task execution time. SMDs are also highly diverse in terms of hardware characteristics, including CPU and GPU clock frequency, the number of cores, sizes of primary and secondary memory, battery capacity, and varying computing capabilities [7].

The multi-criteria problem of selecting smart mobile devices (SMD) for mobile crowd computing (MCC) necessitates a preference for sustainable alternatives while adhering to the principles of the strong sustainability paradigm [4]. This approach emphasizes the need to limit the linear compensation of criteria. Linear compensation implies that excellent values achieved for several criteria can compensate for poor values in other criteria. It is undesirable when searching for balanced alternatives, which should achieve good values for as many criteria as possible [10]. Although some multi-criteria decision analysis (MCDA) methods, such as those in the PROMETHEE (Preference Ranking Organization METHod for Enrichment of Evaluation) or ELECTRE (ELimination and Choice Expressing the Reality) families, respect these limits on criteria compensation, the most popular MCDA methods - such as TOPSIS, AHP (Analytical Hierarchy Process), and VIKOR (VlseKriterijumska Optimizacija I Kompromisno Resenje) - tend to be compensatory in nature [5]. To address this gap, the authors propose a multi-criteria approach called the Strong Sustainability Paradigm based Technique for Order Preference by Similarity to Ideal Solution (SSP-TOPSIS) method, that enhances the well-established TOPSIS method. This enhancement allows for modeling the degree of linear compensation reduction among criteria, thereby adapting compensatory MCDA methods for evaluating multi-criteria problems within the context of the strong sustainability paradigm.

2. Methodology

The Strong Sustainability Paradigm based Technique for Order Preference by Similarity to Ideal Solution (SSP-TOPSIS) method is based on the well-known Multi-Criteria Decision Analysis (MCDA) technique called TOPSIS, which evaluates variants by measuring their distances from two vectors representing two reference solutions, which are ideal and anti-ideal. The presented approach introduces a novel phase that addresses the limitation of many multi-criteria methods related to criteria compensation reduction, which involves a calculation known as the reduction of linear compensation. It is achieved by performing subtraction of the Mean Deviation (MD) from the efficiency value from the decision matrix. The MD is calculated by subtracting the mean performance for particular criteria calculated for all variants from the alternative's efficiency. Then, multiplying the obtained outcome by the sustainability coefficient s used to model the reduction of linear compensation is performed. s may be set to real values from 0 to 1. In its simplest form, it may be adjusted to the standard deviation of numbers contained in the decision matrix after normalization. The sustainability coefficient parameter can be compared to the s coefficient introduced in the PROSA-C method (PROMETHEE for Sustainability Assessment - Criteria) [10], which also considers compensation reduction. PROSA-C can be used as the reference method for comparing SSP-TOPSIS results. The commonly used value for the s parameter based on literature [10] is 0.3, which can also be used in the case of SSP-TOPSIS.

To assign weights to the criteria that reflect their importance, the authors used Criteria Importance Through Inter-criteria Correlation (CRITIC) which is an objective weighting method. This method determines the weights of the criteria based on the numbers provided in the decision matrix, taking into account the variability of each criterion among the alternatives. The CRITIC method was chosen because it provides an objective strategy for estimating criterion weights based on the intensity of contrast and conflict between criteria, avoiding the ambiguity resulting from expert opinion [3]. The detailed steps of the SSP-TOPSIS method are provided below.

2.1. The SSP-TOPSIS method

Step 1. Create the two-dimensional decision matrix $X = [x_{ij}]_{m \times n}$ with efficiency values x_{ij} collected for m alternatives regarding n criteria. Subtract the mean value $\overline{x}_j$ from x_{ij} for particular criteria C_j, obtaining the Mean Deviation MD_{ij}. After that, multiply the outcome of the previous operation by the sustainability coefficient (s_j) reflecting the rate of compensation reduction for each criterion. Considered criteria representing parameters are enumerated by $j = 1, 2, \ldots, n$. The sustainability coefficient takes real numbers from 0 to 1. The higher the coefficient value, the higher the compensation reduction. The Mean Deviation is calculated by Equation (1).

$$MD_{ij} = (x_{ij} - \overline{x}_j)s_j \tag{1}$$

Step 2. Match zeros to MD_{+ij} less than zero. If MD_{+ij} is less than zero it implies that x_{+ij} is less than $\overline{x}_{+j}$. Associate zeros to MD_{-ij} bigger than zero. It means that x_{-ij} are bigger than $\overline{x}_{-j}$. This action is performed according to Equation (2),

$$MD_{ij} = 0 \,\forall\, MD_{+ij} < 0 \;\vee\; MD_{-ij} > 0 \tag{2}$$

where MD_{+ij} represents the mean deviation computed for criteria with the goal of maximizing, and MD_{-ij} defines the mean deviation determined for criteria with the aim of minimizing. The discussed phase is important since it allows to avoid unintended improvements of efficiency values outlying from the mean towards deterioration.
Step 3. In this step MD_{ij} values have to be subtracted from x_{ij} following Equation (3).

$$t_{ij} = x_{ij} - MD_{ij} \tag{3}$$

The remaining stages are performed analogously to the primary TOPSIS method.
Step 4. Perform the normalization of the decision matrix $T = [t_{ij}]_{m \times n}$ with the preferred technique, for example, the Minimum-Maximum or Vector, which is used in the TOPSIS method by default. Using the Minimum-Maximum method, r^+_{ij} representing normalized numbers for criteria with the goal of maximizing (stimulants) and r^-_{ij} denoting criteria with the goal of minimizing (destimulants) are derived with Equation (4). The Minimum-Maximum technique is more widely applicable because it can also be used for negative values.

$$r^+_{ij} = \frac{t_{ij} - min_j(t_{ij})}{max_j(t_{ij}) - min_j(t_{ij})},\; r^-_{ij} = \frac{max_j(t_{ij}) - t_{ij}}{max_j(t_{ij}) - min_j(t_{ij})} \tag{4}$$

Step 5. Obtain the weighted normalized decision matrix by multiplying numbers included in the normalized decision matrix by appropriate criteria weights w_j as Equation (5) presents.

$$v_{ij} = r_{ij}w_j \tag{5}$$

The weights of the criteria assessment were computed by applying the CRITIC method.
Step 6. Establish the Positive Ideal Solution (PIS) with Equation (6) and Negative Ideal Solution (NIS). PIS consists of the maximal numbers of the weighted normalized decision matrix. On the other hand, NIS incorporates its minimums. Converting destimulants into stimulants is not needed because of the normalization performed previously.

$$v^+_j = \{v^+_1, v^+_2, \ldots, v^+_n\} = \{max_j(v_{ij})\},\; v^-_j = \{v^-_1, v^-_2, \ldots, v^-_n\} = \{min_j(v_{ij})\} \tag{6}$$

Step 7. Compute Euclidean distance from PIS D_i^+ and NIS D_i^- for particular variants as Equation (7) demonstrates.

$$D_i^+ = \sqrt{\sum_{j=1}^{n} (v_{ij} - v_j^+)^2}, \; D_i^- = \sqrt{\sum_{j=1}^{n} (v_{ij} - v_j^-)^2} \tag{7}$$

Step 8. To determine the final result for evaluated variants, use Equation (8). The C_i is between 0 and 1. The variant with the biggest C_i is indicated as the ranking leader. Finally, variants are ranked by sorting their scores by decreasing value.

$$C_i = \frac{D_i^-}{D_i^- + D_i^+} \tag{8}$$

2.2. The dataset

A dataset has been utilized to demonstrate the application of the SSP-TOPSIS method for selecting the most sustainable alternative smart mobile devices (SMDs) for mobile crowd computing (MCC). This dataset, along with the evaluation criteria, is derived from the research paper by Pramanik et al. (2021) [9]. Table 1 presents the criteria used to assess SMDs as resources in MCC. Table 2 presents the performance values of selected SMDs in relation to the set of criteria for assessment.

Table 1. List of assessment criteria.

Code	Criteria	Unit	Effect direction	Code	Criteria	Unit	Effect direction
C_1	CPU frequency	GHz	↑	C_8	Wi-Fi strength	1-5	↑
C_2	CPU cores	numbers	↑	C_9	CPU load	%	↓
C_3	GPU frequency	GHz	↑	C_{10}	GPU load	%	↓
C_4	Total RAM	GB	↑	C_{11}	CPU temp	°C	↓
C_5	Available memory	MB	↑	C_{12}	Battery temp	°C	↓
C_6	Battery capacity	mAh	↑	C_{13}	GPU Architecture	nm	↓
C_7	Battery available	%	↑				

Table 2. Decision matrix including performance values for selected SMDs.

A_i	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}	C_{11}	C_{12}	C_{13}
A_1	1.3	8	650	8	1807	3000	10	4	13	8	31	38	10
A_2	2.5	2	450	6	1767	4000	24	2	53	93	45	44	10
A_3	2.2	8	650	6	1916	3000	11	1	19	77	32	39	14
A_4	1.7	2	450	6	2855	4000	22	5	62	9	32	40	10
A_5	1.5	4	624	6	2851	3500	31	4	71	2	39	42	10
A_6	1.3	4	710	6	3537	3500	37	2	4	16	37	37	28
A_7	1.3	8	710	6	2755	3000	92	4	1	48	34	39	14
A_8	1.3	8	450	8	2690	4000	56	4	22	13	33	34	28
A_9	2.5	8	650	4	2628	3500	69	4	94	11	42	40	28
A_{10}	1.3	8	450	6	1753	4000	29	3	91	64	39	45	28

These parameters are essential for evaluating the resource requirements of MCC computing tasks. The computational capabilities of SMDs are determined by various resource parameters, which include 13 SMD selection criteria. Among these parameters, eight are marked with an upward arrow (↑), indicating that higher values are preferred, while five are marked with a downward arrow (↓), signifying that lower values represent the most favorable choice.

3. Results

This section presents the results of selecting the most sustainable option from a chosen set of System-on-Module Devices (SMDs) using the SSP-TOPSIS method. The research utilized a linear compensation approach to reduce criteria within each group of SMD parameters that serve as evaluation criteria. The analysis was conducted for the following groups: CPU parameters (C_1, C_2, C_9, and C_{11}), GPU parameters (C_3, C_{10}, and C_{13}), Battery parameters (C_6, C_7, and C_{12}), and Memory parameters (C_4 and C_5). Criterion C_8 has not been assigned to any group but has been included in the final scenario that considers the reduction of compensation across all parameters. The results for specific groups of parameters are presented in Table 3.

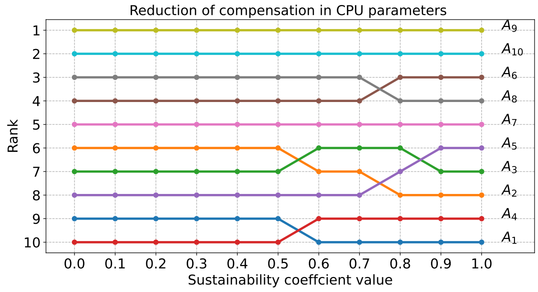
Table 3. Results of SSP-TOPSIS with sustainability coefficient set as standard deviation value in particular groups of SMDs' parameters.

A_i	None	CPU	GPU	Battery	Memory	All	None	CPU	GPU	Battery	Memory	All
A_1	0.4122	0.4132	0.4187	0.4136	0.4125	0.4231	9	9	9	9	9	9
A_2	0.4678	0.4710	0.4678	0.4692	0.4704	0.4761	6	6	7	6	6	8
A_3	0.4642	0.4696	0.4763	0.4663	0.4681	0.4875	7	7	6	7	7	6
A_4	0.3946	0.4057	0.3954	0.3979	0.4010	0.4161	10	10	10	10	10	10
A_5	0.4372	0.4513	0.4470	0.4499	0.4445	0.4819	8	8	8	8	8	7
A_6	0.4963	0.5033	0.4986	0.5069	0.4992	0.5208	4	4	5	3	5	3
A_7	0.4951	0.4967	0.5040	0.4970	0.5009	0.5150	5	5	4	5	4	5
A_8	0.5049	0.5079	0.5065	0.5064	0.5079	0.5155	3	3	3	4	3	4
A_9	0.6343	0.6352	0.6411	0.6459	0.6386	0.6598	1	1	1	1	1	1
A_{10}	0.5376	0.5396	0.5398	0.5393	0.5402	0.5484	2	2	2	2	2	2

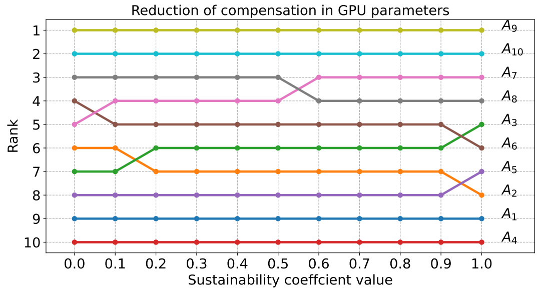
The column titled ”None” contains results for a scenario without compensation reduction for any criterion, which is analogous to the classic TOPSIS method. The column called ”All” includes results for compensation reduction in all parameters. It is evident that, regardless of the evaluated parameter group with reduced compensation levels, the highest-rated alternative is consistently A_9. This indicates that the device performs favorably across most of the considered criteria, allowing it to achieve good evaluation results even when compensation possibilities in certain parameter groups are limited.

The alternative A_8 achieved third place in all analyzed parameter groups, with the exception of the Battery parameters and the group considering all parameters. When the compensation of criteria was reduced in these two groups, A_8 dropped to fourth place. This change occurred because A_8 exhibited the most favorable values for the Battery capacity, Battery temperature, and one of the most favorable values for the Battery availability parameters. Reducing compensation in these groups limited the ability to compensate weaker values in the other criteria, resulting in a lower score for A_8 compared to scenarios where compensation was not reduced or adjusted for the other parameter groups. Similar conclusions can be drawn for the other alternatives included in the investigation.

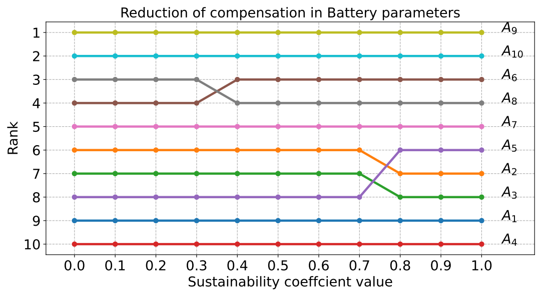
The next stage of the investigation will involve gradually increasing the sustainability coefficient for each parameter group within the range of real numbers from 0 to 1. A value of 0 indicates no reduction in compensation at all, while a value of 1 signifies a maximum reduction in compensation. Figure 1a illustrates the analysis of increasing compensation reduction within the CPU parameters. The gradual reduction of compensation within GPU parameters is depicted in Figure 1b, while Figure 1c presents the results for battery parameters, Figure 1d covers memory parameters, and Figure 1e consolidates all criteria. The graphs indicate that alternative A_9, which was the leader in the first stage of the study, maintains its leading position in the context of increasing compensation reduction across all analyzed criteria groups. This suggests that alternative A_9 is sustainable, as its performance across all parameters contributes to its top ranking. Alternative A_{10} also demonstrates sustainability, consistently securing a stable second place in the rankings, with the exception of scenarios involving high compensation reduction across all criteria.



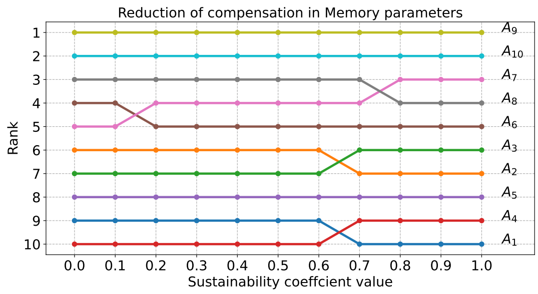
(a) SSP-TOPSIS ranks for increasing compensation reduction in CPU parameters.



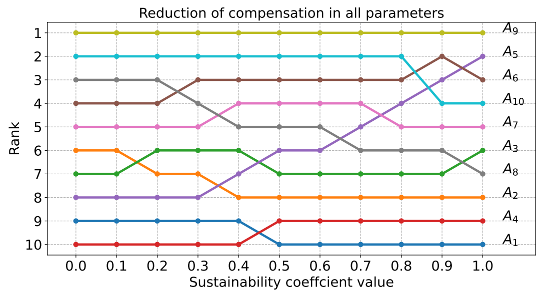
(b) SSP-TOPSIS ranks for increasing compensation reduction in GPU parameters.



(c) SSP-TOPSIS ranks for increasing compensation reduction in Battery parameters.



(d) SSP-TOPSIS ranks for increasing compensation reduction in Memory parameters.



(e) SSP-TOPSIS ranks for increasing compensation reduction in all parameters.

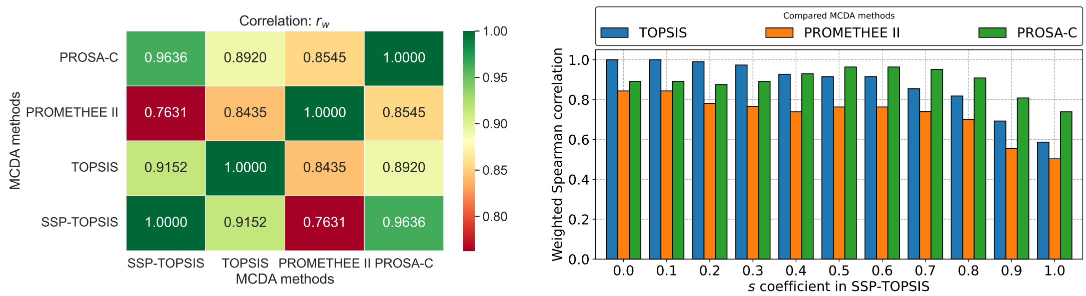
Fig. 1. SSP-TOPSIS ranks for increasing compensation reduction in particular groups of parameters.

One example of an alternative that demonstrates a declining trend in rankings due to an increasing reduction in criteria compensation is A_8. When we consider the parameters of CPU, GPU, Battery, and Memory within each group of criteria, A_8 falls from third to fourth place as compensation reduction increases. Conversely, when looking at all parameters collectively, A_8 drops by four positions, falling from third to seventh place. This indicates that there is a lack of sufficiently favorable performance values across a wide range of parameters, which would normally help this option secure a stable and high ranking, even with decreasing compensation for the criteria. Poor performance of A_8 is evident when compared to other alternatives that have better outcomes, especially for parameters such as C_1, C_3, and C_{13}. Furthermore, there are several criteria - specifically C_5, C_7, C_9, and C_{10} - where other alternatives achieve significantly better performance values than A_8.

The alternative that demonstrates significant potential for improvement, particularly with a decreasing criteria compensation, is A_5. For instance, this option advanced by as much as six positions, moving from eighth place to second place when the reduction in compensation was applied across all parameters. This suggests that the performance values of this alternative are sustainable, especially in contexts where decision-makers prioritize sustainability over exceptionally favorable values in specific parameter groups. In summary, the analysis clearly indicates that the most preferred and sustainable SMD option among those considered is A_9.

The next step of the research was an empirical comparison of the SSP-TOPSIS method with two other methods constraining compensation, namely PROMETHEE II and PROSA-C. Figure 2a shows the convergence of the SSP-TOPSIS ranking generated using a sustainability coefficient s set as 0.6 for all considered parameters with the rankings of the TOPSIS compensation method and the two compensation-limiting methods PROMETHEE II and PROSA-C, for which the value of the coefficient s was set to 0.3. The Weighted Spearman correlation coefficient (r_w) was used as a measure of ranking convergence. It can be noted that the SSP-TOPSIS and TOPSIS rankings differ because, although their correlation is high (0.9152), it is lower than 1, which indicates the existence of differences resulting from the reduction of compensation by SSP-TOPSIS. On the other hand, although the PROMETHEE II ranking is less consistent with SSP-TOPSIS compared to TOPSIS, which results from differences in algorithms, the correlation value between SSP-TOPSIS and PROMETHEE II is still high. Particularly noteworthy is the correlation between the SSP-TOPSIS and PROSA-C rankings (0.9636), which is higher than that between TOPSIS and PROSA-C (0.8920) and between SSP-TOPSIS and TOPSIS. This means that the SSP-TOPSIS method reduces compensation to a greater extent, giving results similar to other methods with limited compensation like PROSA-C.

Then, a study was conducted on the correlation between the SSP-TOPSIS ranking and TOPSIS, PROMETHEE II, and PROSA-C for increasing values of the sustainability coefficient in SSP-TOPSIS. Results are shown in Figure 2b.



(a) Correlation of SSP-TOPSIS with reference methods for the constant s coefficient.

(b) Correlation of SSP-TOPSIS with reference methods for the increasing s coefficient.

Fig. 2. Correlation of SSP-TOPSIS with reference MCDA methods.

It can be observed that as compensation in SSP-TOPSIS decreases, the correlation with the compensatory TOPSIS method decreases. In contrast, in the case of PROSA-C, the correlation with SSP-TOPSIS increases, especially for $s \in \{0.4, 0.5, 0.6, 0.7\}$. For larger values of s, the correlation between SSP-TOPSIS and PROSA-C decreases. However, it is higher than for TOPSIS, which confirms the ability of the SSP-TOPSIS method to reduce compensation.

4. Conclusions

This paper introduces a multi-criteria SSP-TOPSIS method that incorporates linear compensation reduction modeling for evaluating criteria. It demonstrates the method's effectiveness in addressing multi-criteria selection problems for SMDs within the context of MCC. The integration of compensation reduction modeling enhances the analytical capabilities of the traditional TOPSIS method, allowing for the identification of more sustainable solutions. Future work should focus on enhancing the model by including additional evaluation criteria, utilizing a broader dataset with more alternatives, and expanding other multi-criteria methods to support compensation reduction modeling capabilities.

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