Strojniški vestnik - Journal of Mechanical Engineering 67(2021)11, 611-621

DOI:10.5545/sv-jme.2021.7356

Original Scientific Paper

Received for review: 2021-08-03
Received revised form: 2021-10-07
Accepted for publication: 2021-11-08

Applicability of MCDM Algorithms for the Selection of Phase Change Materials for Thermal Energy Storage Heat Exchangers

Paul Gregory Felix* - Velavan Rajagopal - Kannan Kumaresan
PSG College of Technology, Department of Mechanical Engineering, India

Latent heat thermal energy storage heat exchangers store heat energy by virtue of the phase transition that occurs in the thermal storage media. Since phase change materials (PCMs) are utilized as the media, there is a critical necessity for the appropriate selection of the PCM utilized. Since multiple thermo-physical properties and multiple PCMs are required to be evaluated for the selection, there arises a need for multiple criteria decision making (MCDM) algorithms to be adopted for the selection. But owing to the different weight estimation techniques employed and the voluminous quantity of selection algorithms available, there arises a need for a comparative methodology to be adopted. This study was intended to select an optimal PCM for a sustainable steam cooking application coupled with a thermal energy storage system. In this research study, six PCMs were chosen as the alternatives and five thermo-physical properties were chosen as the criteria for the evaluation. 11 different algorithms were augmented with 3 different weight estimation techniques and therefore a total of 33 algorithms were employed in this study. All of the algorithms have chosen Erythritol as the optimal PCM for the application. The outcomes of the MCDM algorithms have been validated through an intricate Pearson's correlation coefficient study.

Keywords: latent heat, multiple criteria decision making, phase change material, thermal energy storage

Highlights

- *A comparative methodology has been proposed to select the optimal PCM for thermal energy storage heat exchangers.*
- *An optimal PCM for a sustainable steam cooking application has been selected by adopting multiple MCDM algorithms.*
- *A clear demarcation has been presented between the functionality of all of the algorithm combinations adopted.*
- *A three case Pearson's correlation coefficient study has validated the reliability of the ranking outcomes.*

0 INTRODUCTION

Phase change materials (PCMs) play an important role in latent heat thermal energy storage (TES) systems. PCMs act as heat sinks to absorb and store excess heat energy from then heat source and then release the stored heat energy as and when required. To facilitate this process of heat energy storage and release, TES heat exchangers are employed at the application site. Several types of heat exchangers can be adopted for such latent heat systems [1]. On the other hand, the research outcomes based on renewable sources of energy, more specifically, based on solar thermal energy has improved over the recent years, that even steam cooking can be done directly using steam generated from solar parabolic trough collectors (PTCs) [2]. But the non-availability of solar energy throughout the day and night demands the necessity for a TES system that would store the excess thermal energy during sunshine hours, and the stored thermal energy could be retrieved during the off-sunshine hours. At the application site, steam generated from the TES heat exchanger can be utilized for cooking during the off-sunshine hours, whereas the steam generated directly from the solar source (PTCs) can be utilized for cooking during the sunshine hours. Taking into consideration the fact that latent heat TES systems based on PCMs store much more higher heat than sensible heat systems, it can be asserted that such TES systems are suitable for this sustainable steam cooking application. For designing TES heat exchangers for this application, the first important step has to be the appropriate selection of the PCM [3]. This is because, each PCM has different thermo-physical properties and the choice of the PCM explicitly affects the design. For instance, PCMs having lower latent heat will increase the size of the heat exchanger. Hence, the selection of the appropriate PCM suitable for the application is required to be performed on scientific evaluation grounds with multiple criteria and alternatives (PCMs) considered.

Multiple criteria decision making (MCDM) has evolved as a mathematical tool to aid designers to perform subjective evaluations in operation research [4]. The applications of MCDM algorithms in the domain of mechanical engineering are multiple. Few examples include determination of the threshold for extreme load extrapolation [5], choosing systems for drying paltry-seeds [6], assessment of energy crops for producing bio-gas [7], ranking renewable energy resources [8] and optimal material selection [9]. Concerning PCMs, it has also been observed that

*Corr. Author's Address: PSG College of Technology, Department of Mechanical Engineering, Avinashi road, Coimbatore, India, 1807rm01@psgtech.ac.in

researchers have applied MCDM algorithms to select the appropriate PCM for low-temperature applications [10], ground source heat pump application [11] and even for domestic water heating [12]. While selecting a suitable material, it is necessary to estimate strategic weights for each evaluative criterion such that the decision becomes subjective. But the choice of the algorithms applied for a particular case depends on the decision of the heat exchanger designer. It has been observed from peer literature that many research studies have limited their study designs to a very few algorithms with a limited choice of weight estimation techniques. Concerning the weight estimation techniques, it has been learned that using either only subjective or only objective weighting scheme in the study can be considered as a deficiency [11]. Hence, heat exchanger designers are required to refer to multiple literature sources to understand the functional mechanism of several algorithms and will need to perform an intricate study on various weight estimation and MCDM techniques to arrive at a conclusion to select which MCDM algorithm would be appropriate. But, in this study, a methodology incorporating a comparative study design has been proposed.

This current study presents a novel comparative approach than several previous works such that an intricate comparative selection can be made. This research study, through its proposed methodology, asserts that, for a PCM selection involving multiple alternatives, a comparative study involving multiple MCDM algorithms can provide a reliable solution to the selection process. This is asserted because, the methodology does not rely only on one algorithm, but instead has adopted multiple combination of algorithms for the selection. Hence, the PCM selected through this methodology will be a reliable choice for the heat exchanger.

1 METHODS

1.1 Study Design

This current study was performed in three parts. The first part of this study was to select the alternative PCMs and criteria through a pre-screening and then estimating the desired weights through entropy weight method (EWM), criteria importance through inter-criteria correlation (CRITIC) method and analytic hierarchy process (AHP) method. The second part was to apply the derived weights to select the suitable PCM through 11 selected algorithms. The third part of the research was to perform a Pearson's correlation coefficient study to correlate the outcomes of various algorithms and validate the concurrence of the outcomes. The study design adopted is presented in Fig. 1.

Since steam is required to be generated (from the heat exchanger) at the application site at a minimum temperature of 100 °C, PCMs were desired to have a melting temperature around 120 °C. Hence from an initial screening, six PCMs were selected. The selected PCMs along with their thermo-physical properties (criteria) are presented in Table 1. In Table 1, it can be observed that a mix of both laboratory grade PCMs and commercial PCMs have been considered. But however, all of the PCMs were selected such that they share a close melting temperature to 120 °C. But, out of the alternatives, one PCM is required to be selected based on the other thermo-physical properties. There has been no specific preference among the mix of laboratory grade and commercial grade PCMs in this analysis. The research methodology has been oriented such that there exists no bias between selecting laboratory and commercial grade materials and hence this methodology can be envisaged to select any kind of PCM that would be technically appropriate for the particular application in study. Among the listed criteria, specific heat alone was categorized as a non-beneficial criterion. This is because, for the steam cooking application, higher magnitudes of melting temperature, heat of fusion, density, thermal conductivity was preferred. Hence, the aforementioned four parameters were considered as beneficial criteria. Whereas, for the application, lower specific heat magnitude is preferred, as a higher specific heat will increase the melting time of the PCM. Since this steam cooking application is intended to be integrated with solar energy, faster melting and charging of the PCM was preferred as the entire charging process will have to be completed within the sunshine hours. Hence specific heat alone was considered as a non-benefit criterion.

1.2 Estimation of the criteria weights

1.2.1 EWM

In this method, the decision matrix X was normalized using the sum method (Eq. (1)), and the weights w_j were estimated through calculating the entropy value E_j [12], as presented in Eq. (2). The decision matrix X is an array of the considered m alternatives and n criteria. In the equation, p_{ij} indicates the normalized value of the decision matrix X.

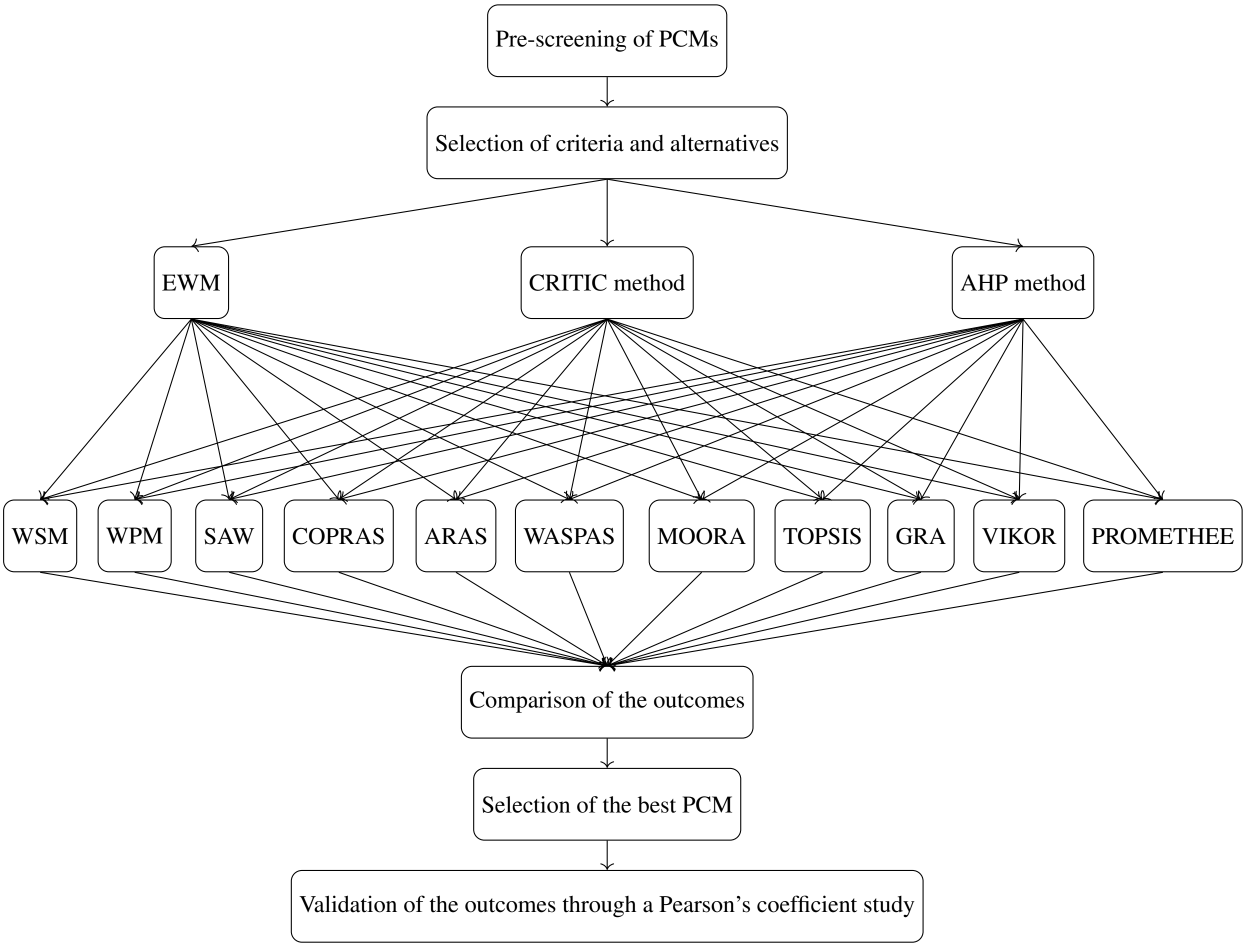


Fig. 1. *Study design adopted*

Table 1. *Considered alternatives and criteria*

PCM no.	Name	Melting temperature	Heat of fusion	Density	Thermal conductivity	Specific heat	Reference
		[°C]	$[\mathrm{kJ\,kg^{-1}}]$	$[\mathrm{kg\,m^{-3}}]$	$[\mathrm{W\,m^{-1}\,K^{-1}}]$	$[\mathrm{kJ\,kg^{-1}\,K^{-1}}]$	
1	Erythritol	120	331	1480	0.733	1.35	[14]
2	$MgCl_2.6H_2O$	117.5	200	1569	0.704	2.25	[15]
3	PlusICE A118	118	195	900	0.22	2.2	[16]
4	PlusICE H120	120	120	2220	0.506	1.51	[17]
5	PlusICE S117	117	125	1450	0.7	2.61	[16]
6	PlusICE X120	120	180	1245	0.36	1.5	[17]

$$p_{ij} = \frac{x_{ij}}{\sum_{j=1}^{n} x_{ij}}, \tag{1}$$

$$E_j = -\frac{\sum_{i=1}^{m} p_{ij}.\ln\, p_{ij}}{\ln n} \quad \text{and} \quad w_j = \frac{1-E_j}{\sum_{i=1}^{m}(1-E_j)}. \tag{2}$$

1.2.2 CRITIC Method

In this method, the decision matrix elements x_{ij} were normalized using Eq. (3) and the weights were estimated using C_j as presented in Eq. (4) [13]. In the equation, r_{jj^n} represents the relative correlation coefficient between the j^{th} and $j^{n\ \text{th}}$ criteria and σ_j represents the standard deviation of the normalized matrix.

$$p_{ij} = \frac{x_{ij} - \min_j(x_{ij})}{\max_j(x_{ij}) - \min_j(x_{ij})}, \quad (3)$$

$$w_j = \frac{C_j}{\sum_{j^n=1}^{n} C_j} = \frac{\left[\sigma_j \sum_{j^n=1}^{n} (1 - r_{jj^n})\right]}{\sum_{j^n=1}^{n} \left[\sigma_j \sum_{j^n=1}^{n} (1 - r_{jj^n})\right]}. \quad (4)$$

1.2.3 AHP method

In this method, a relative importance decision matrix with elements a_{jj^n} was constructed using the Saaty's scale [10] and the weights were estimated by using Eq. (5). The relative matrix is a matrix representing the importance of one criterion over another.

$$w_j = \frac{a_{jj^n}}{\left[\sum_{j^n=1}^{n} a_{jj^n}\right] n}. \quad (5)$$

1.3 Estimation of the Optimal PCM

1.3.1 Weighted Sum Method (WSM)

In this method, the decision matrix was normalized using the square root method. The alternatives were ranked based on the weighted sums S_i^{WSM} estimated using Eq. (6).

$$S_i^{WSM} = \sum_{j=1}^{n} w_j \times \frac{x_{ij}}{p_{ij}} = \sum_{j=1}^{n} w_j \times \frac{x_{ij}}{\sqrt{\sum_{j=1}^{n} x_{ij}^2}}. \quad (6)$$

1.3.2 Weighted Product Method (WPM)

In this method, the weighted product for each alternative was estimated by raising the normalized decision matrix elements to the power of the weights, as presented in Eq. (7) and the alternatives were ranked based on P_i^{WPM}.

$$P_i^{WPM} = \prod_{j=1}^{n} \left[\frac{x_{ij}}{p_{ij}}\right]^{w_j} = \prod_{j=1}^{n} \left[\frac{x_{ij}}{\sqrt{\sum_{j=1}^{n} x_{ij}^2}}\right]^{w_j}. \quad (7)$$

1.3.3 Simple Additive Weighting (SAW) method

This method is similar to WSM, except to the fact that the normalization of the decisive matrix with elements x_{ij} was performed separately for both the benefit criteria elements and the non-benefit criterion elements. The normalization was performed using Eq. (8). The preference index V_i was then estimated using Eq. (6) and the alternatives were ranked.

$$p_{ij} = \begin{cases} \frac{x_{ij}}{\max_j x_{ij}}, & \text{for benefit criteria.} \\ \frac{\min_j x_{ij}}{x_{ij}}, & \text{for non-benefit criterion.} \end{cases} \quad (8)$$

1.3.4 Complex Proportional Assessment (COPRAS) Method

In this method, the decision matrix was normalized using the sum method. Then, the maximizing index S_{+i} for the benefit criteria was estimated as a row-wise sum of the weighted normalized matrix for the benefit criteria values, and the minimizing index S_{-i} was estimated in the same way for the non-benefit criterion [18]. Utilizing the estimated values, the relative weight $Q_{c,i}$ was computed using Eq. (9). Then the performance index U_i was estimated using Eq. (10) and the alternatives were then ranked based on U_i.

$$Q_{c,i} = S_{+i} + \frac{\min_i S_{-i} \sum_{i=1}^{m} S_{-i}}{S_{-i} \sum_{i=1}^{m} \frac{\min_i S_{-i}}{S_{-i}}}, \quad (9)$$

$$U_i = \frac{Q_{c,i}}{Q_{c,max}} \times 100. \quad (10)$$

1.3.5 Additive Ratio Assessment (ARAS) Method

In this method, for each criterion, the optimal value was determined based on whether the criterion was a benefit or a non-benefit attribute and the decision matrix augmenting the optimal value was then weight normalized using the sum method. Then, the optimality function S_i and the utility degree K_i was estimated using Eq. (11) [19]. The alternatives were then ranked based on K_i.

$$K_i = \frac{S_i}{S_{opt}} = \frac{\sum_{j=1}^{n} p_{ij}^{aug} w_j}{S_{opt}}. \quad (11)$$

1.3.6 Weighted Aggregated Sum Product Assessment (WASPAS) Method

This method is a combination of WSM and WPM. In this method, the normalized decision matrix was estimated by segregating the beneficial criteria and non-beneficial criterion using the maximum-minimum method as presented in Eq. (8). Then the total relative importance Q_i was estimated through Eq. (12) [20]. The alternatives were ranked based on the total relative importance. In the equation, λ represents a transformation constant. In this case, a λ of 0.5 was adopted.

$$Q_i = \lambda \sum_{j=1}^{n} p_{ij} w_j + (1-\lambda) \prod_{j=1}^{n} p_{ij}^{w_j}. \quad (12)$$

1.3.7 Multi-Objective Optimization on the Basis of Ratio Analysis (MOORA) Method

In this method, the decision matrix was normalized using the square root method as in WSM and WPM [21]. Then the normalized assessment sum S_i for each alternative was estimated by subtracting the weighted sum of the non-benefit attributes from the weighted sum of the benefit attributes, as presented in Eq. (13). Then the alternatives were ranked based on the assessment sum.

$$S_i = \underbrace{\sum_{j=1}^{n} p_{ij} \times w_j}_{\text{Weighted sum of non-benefit attributes}} - \underbrace{\sum_{j=1}^{n} p_{ij} \times w_j}_{\text{Weighted sum of benefit attributes}}. \quad (13)$$

1.3.8 Technique for Order Preference by Similarity to Ideal Solution (TOPSIS)

In this method, the decision matrix was normalized using the square root method as in Eq. (6). Then the relative closeness to the ideal solution P_i was estimated by Eq. (14) [12]. In the equation, A_j^* represents the best criterion value of the weighted normalized matrix (positive ideal) and A_j^- represents the worst criterion value (negative ideal). The alternatives were then ranked based on the relative closeness.

$$P_i = \frac{\sqrt{\sum_{j=1}^{n} (p_{ij}.w_j - A_j^-)}}{\sqrt{\sum_{j=1}^{n} (p_{ij}.w_j - A_j^*)} + \sqrt{\sum_{j=1}^{n} (p_{ij}.w_j - A_j^-)}}. \quad (14)$$

1.3.9 Grey Relational Analysis (GRA) method

In this method, the alternatives were ranked based on the grey relational degree b_i [22]. The deviation Δ_{0i} was estimated as a difference between the reference series (largest value series) and the individual alternative series [22]. By estimating Δ_{0i}, the values of b_i were calculated as presented in Eq. (15).

$$b_i = \sum_{j=1}^{n} w_j \frac{\min_i \min_j \Delta_{0i}(j) + \delta \min_i \min_j \Delta_{0i}(j)}{\Delta_{0j}(j) + \delta \min_i \min_j \Delta_{0i}(j)}. \quad (15)$$

1.3.10 VIKOR method

VIKOR is an abbreviation for its Serbian expansion ‘Vise kriterijumska optimizacija i kompromisno resenje’ which means Multi-criteria compromise ranking. In this method, the normalized decision matrix was obtained using the square root method as in Eq. (6). From the normalized matrix, the maximum criterion value p_j^* and the minimum criterion value p_j^- were estimated and were applied to Eqs. (16) to (18) to estimate the aggregate function U_i^V (also referred as VIKOR index) for each alternative. In the equations, the superscripts ‘*’ and ‘−’ represents the maximum and minimum value respectively. The alternatives were then ranked in the **increasing** order of U_i^V [23].

$$U_i^V = v \underbrace{\left[\frac{S_i - S^*}{S^- - S^*}\right]}_{I} + (1-v) \underbrace{\left[\frac{R_i - R^*}{R^- - R^*}\right]}_{II}, \quad (16)$$

$$I = \frac{\left[\sum_{j=1}^{n} w_j \left(\frac{p_j^* - p_{ij}}{p_j^* - p_j^-}\right)\right] - \left[\sum_{j=1}^{n} w_j \left(\frac{p_j^* - p_{ij}}{p_j^* - p_j^-}\right)\right]^*}{\left[\sum_{j=1}^{n} w_j \left(\frac{p_j^* - p_{ij}}{p_j^* - p_j^-}\right)\right]^- - \left[\sum_{j=1}^{n} w_j \left(\frac{p_j^* - p_{ij}}{p_j^* - p_j^-}\right)\right]^*}, \quad (17)$$

$$II = \frac{\left[\max_i w_j \left(\frac{p_j^* - p_{ij}}{p_j^* - p_j^-}\right)\right] - \left[\max_i w_j \left(\frac{p_j^* - p_{ij}}{p_j^* - p_j^-}\right)\right]^*}{\left[\max_i w_j \left(\frac{p_j^* - p_{ij}}{p_j^* - p_j^-}\right)\right]^- - \left[\max_i w_j \left(\frac{p_j^* - p_{ij}}{p_j^* - p_j^-}\right)\right]^*}. \quad (18)$$

1.3.11 Preference Ranking Organization Method for Enrichment Valuation (PROMETHEE)

In this method, the decision matrix was normalized and the overall global preference index P_j was estimated by estimating the difference in the values of one alternative criterion with another (preference matrix). Using the preference matrix, the positive preference flow $\phi^+(i)$ and negative preference flow $\phi^-(i)$ (for non-benefit criterion) was estimated. Then the net flow $\phi(i)$ was ultimately estimated using Eq. (19) [24]. Then the alternatives were ranked based on the net flow (PROMETHEE II).

$$\begin{aligned} \phi(i) = &\underbrace{\frac{1}{m-1} \sum_{x \in X} \sum_{j=1}^{n} w_j P_j(i,x)}_{\phi^+(i)} \\ &- \underbrace{\frac{1}{m-1} \sum_{x \in X} \sum_{j=1}^{n} w_j P_j(x,i)}_{\phi^-(i)}. \end{aligned} \quad (19)$$

Table 2. *Estimated evaluating parameters through the employed algorithms*

Algorithm index	Algorithm name	Evaluating parameter		Phase change material					
		Parameter	Symbol	1	2	3	4	5	6
1	WSM-EWM	Weighted sum	S_i^{WSM}	0.5064	0.4511	0.2896	0.3581	0.4097	0.3107
2	WSM-CRITIC	Weighted sum	S_i^{WSM}	0.4662	0.4413	0.3189	0.3811	0.4166	0.3320
3	WSM-AHP	Weighted sum	S_i^{WSM}	0.5350	0.4385	0.3282	0.3284	0.3780	0.3277
4	WPM-EWM	Weighted product	S_i^{WPM}	0.4868	0.4489	0.2641	0.3407	0.3910	0.3076
5	WPM-CRITIC	Weighted product	S_i^{WPM}	0.4491	0.4394	0.2944	0.3651	0.4027	0.3275
6	WPM-AHP	Weighted product	S_i^{WPM}	0.5140	0.4363	0.3037	0.3082	0.3574	0.3240
7	SAW-EWM	Preference index	V_i	0.9407	0.5017	0.8331	0.8166	0.1956	0.3776
8	SAW-CRITIC	Preference index	V_i	0.9402	0.6142	0.8684	0.8425	0.1014	0.1942
9	SAW-AHP	Preference index	V_i	0.9752	0.5584	0.7802	0.8887	0.1086	0.2075
10	COPRAS-EWM	Performance index	U_i, %	100	78.6542	49.3705	69.8570	67.6893	61.4469
11	COPRAS-CRITIC	Performance index	U_i, %	100	82.0728	58.1734	79.7784	73.2509	70.3310
12	COPRAS-AHP	Performance index	U_i, %	100	73.1212	54.0881	59.7485	59.4716	61.2537
13	ARAS-EWM	Utility degree	K_i	0.9403	0.7420	0.4625	0.6609	0.6408	0.5787
14	ARAS-CRITIC	Utility degree	K_i	0.9358	0.7710	0.5473	0.7517	0.6908	0.6621
15	ARAS-AHP	Utility degree	K_i	0.9752	0.7164	0.5273	0.5888	0.5858	0.6
16	WASPAS-EWM	Relative importance	Q_i	0.9356	0.7423	0.4453	0.6525	0.6339	0.5758
17	WASPAS-CRITIC	Relative importance	Q_i	0.9350	0.7785	0.5435	0.7523	0.6940	0.6699
18	WASPAS-AHP	Relative importance	Q_i	0.9728	0.7217	0.5144	0.5891	0.5852	0.6031
19	MOORA-EWM	Assessment sum	S_i	0.4205	0.3080	0.1497	0.2620	0.2437	0.2153
20	MOORA-CRITIC	Assessment sum	S_i	0.3750	0.2877	0.1687	0.2779	0.2383	0.2296
21	MOORA-AHP	Assessment sum	S_i	0.4555	0.3061	0.1986	0.2315	0.2243	0.2393
22	TOPSIS-EWM	Relative closeness	P_i	0.8452	0.6029	0.2191	0.4195	0.4786	0.3134
23	TOPSIS-CRITIC	Relative closeness	P_i	0.7929	0.5895	0.2070	0.4866	0.4722	0.3467
24	TOPSIS-AHP	Relative closeness	P_i	0.9369	0.4902	0.3004	0.2579	0.3232	0.3080
25	GRA-EWM	Grey Relational degree	b_j	0.1510	0.1024	0.0632	0.099	0.0929	0.0782
26	GRA-CRITIC	Grey Relational degree	b_j	0.1509	0.0917	0.0648	0.1190	0.0827	0.0989
27	GRA-AHP	Grey Relational degree	b_j	0.1601	0.0933	0.0666	0.0909	0.0818	0.0843
28	VIKOR-EWM	VIKOR index	U_i^V	0	0.1744	0.5	0.3973	0.3833	0.3116
29	VIKOR-CRITIC	VIKOR index	U_i^V	0	0.2273	0.5	0.3362	0.3394	0.2726
30	VIKOR-AHP	VIKOR index	U_i^V	0	0.2912	0.3043	0.5	0.4870	0.3434
31	PROMETHEE-EWM	Net flow	$\phi(i)$	0.4902	0.0918	-0.3992	0.0254	-0.0867	-0.1214
32	PROMETHEE-CRITIC	Net flow	$\phi(i)$	0.4635	-0.0482	-0.3844	0.1832	-0.2380	0.0238
33	PROMETHEE-AHP	Net flow	$\phi(i)$	0.5879	0.0347	-0.2866	-0.0674	-0.2162	-0.0524

1.4 Validation of the Outcomes

To validate the reliability of the outcomes, a correlation of outcomes method adopted by Villacreses et al. [25] was adopted in this current study. The ranking outcomes acheived through all of the 33 algorithms were correlated with each other. Three cases of correlations were performed and Pearson's correlation coefficient was estimated for all of the cases. In the first case, the outcomes were correlated by considering all of the PCMs. In the second case, a rank-wise frequency estimation was performed and the alternatives witnessing highest first, second and third rank frequencies alone were considered for the correlation. In the third case, adopting the similar procedure, the alternatives witnessing highest first and second rank frequencies alone were considered. Based on the results of the three cases, the concurrence of the outcomes were validated. The Pearson's coefficients r_{kl} were estimated using Eq. (20). In the validation process, all 33 algorithms were correlated with each other and hence a total of 1089 Pearson's coefficients were estimated for a single case.

$$r_{kl} = \frac{\sum_{i=1}^{m}(k_i-\bar{k})(l_i-\bar{l})}{\sqrt{\sum_{i=1}^{m}(k_i-\bar{k})^2}\sqrt{\sum_{i=1}^{m}(l_i-\bar{l})^2}}. \tag{20}$$

2 RESULTS AND DISCUSSION

2.1 Selection of the Optimal PCM through MCDM Algorithms

In this study, a total of 33 solution combinations were tested. The weights were obtained, and further the obtained weights were employed to estimate the evaluating parameters. The evaluating parameter for each algorithm was estimated and the alternative PCMs were ranked based on the magnitude of the

Table 3. *Estimated weights through the employed methods*

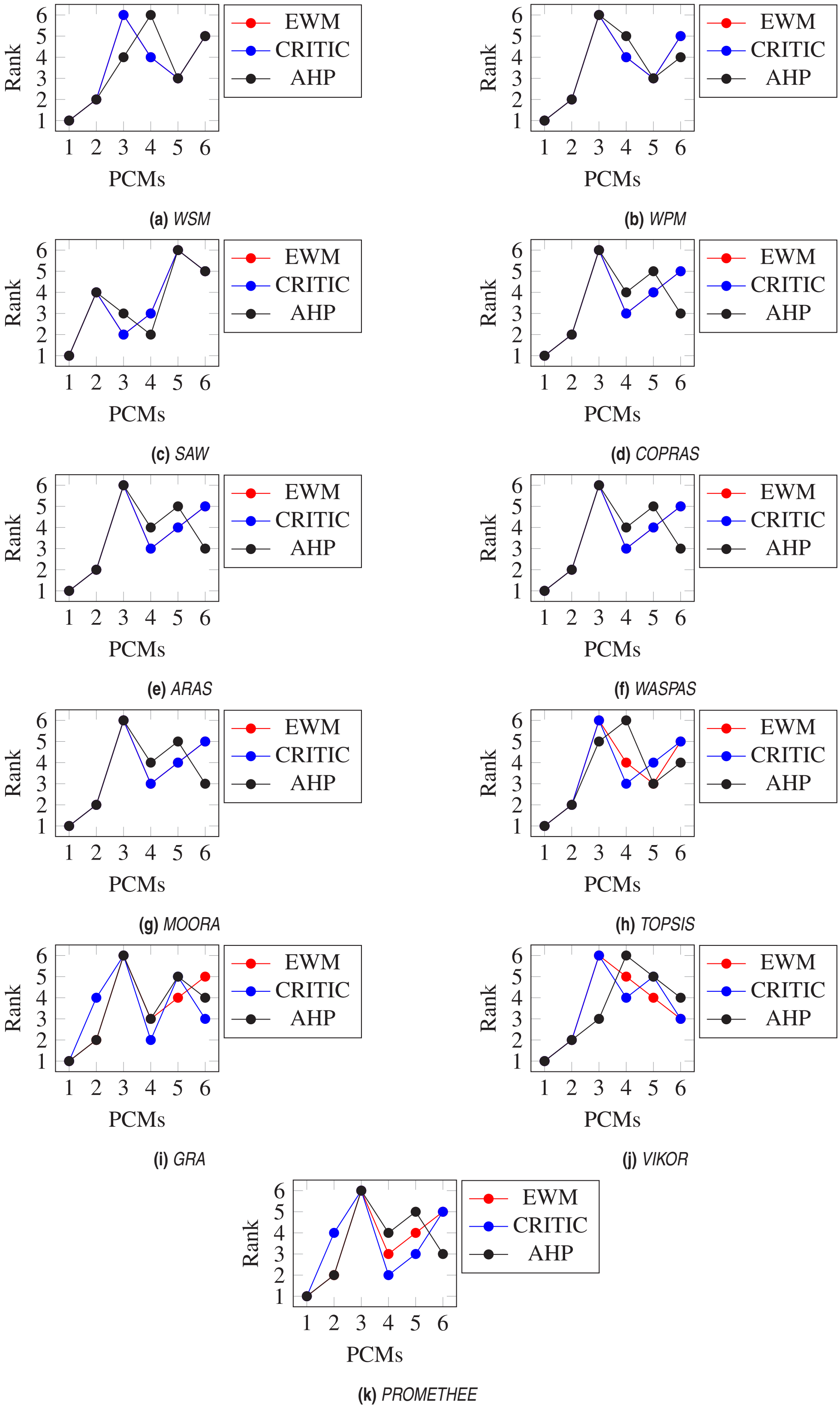
Criteria	EWM	CRITIC	AHP
Melting temperature	0.0003	0.2030	0.0676
Heat of fusion	0.3077	0.2021	0.4531
Density	0.1778	0.1794	0.0743
Thermal conductivity	0.3615	0.2515	0.2636
Specific heat	0.1528	0.1640	0.1414

evaluating parameters. The estimated evaluating parameters are presented in Table 2 and the graphical form of the ranking outcomes is presented in Fig. 2. The weights obtained for each case is presented in Table 3. From the table, it can be observed that the weights obtained through the objective and subjective methods differ from each other. Since the weights differ, the functional priority for each criterion is changed. This will have implications on the outcomes as well. The objective method EWM has prioritized thermal conductivity over the others, and has estimated melting temperature to be the least prioritized criteria. But in the case of the CRITIC method, though thermal conductivity has been prioritized over the others, all other criteria have been estimated to have similar weights. Further, observing the weights obtained through the subjective AHP method, heat of fusion has been estimated to have the highest priority and melting temperature has been estimated to have the least priority. This was expected because EWM and CRITIC are objective methods, wherein the outcomes were purely based on mathematical outcomes and AHP is a subjective approach wherein the outcomes were based on the preferences from the designer. Since in the EWM and CRITIC methods, thermal conductivity has been estimated to have the highest priority, the outcomes employing those weight will prefer materials with higher thermal conductivity. On the contrary, AHP has estimated the highest priority for latent heat of fusion. Hence the method will prefer corresponding outcomes. The results are reliable as there is a clear demarcation between the subjective and objective weighting scheme outcomes. But since this current study is intended to select a PCM through a comparative approach, this variation will be helpful to select the optimal PCM from a holistic approach. The necessity for such a holistic approach arises as this research study addresses the research gap due to the deficiency of utilizing limited weight estimation schemes.

From the figure, it can observed that the first alternative PCM Erythritol has been ranked as the best alternative in all of the algorithms. Also, it can be observed that the PCM $MgCl_2.6H_2O$ (MCHH) has been ranked as the second best PCM in most algorithms. On a comparative note, it can be further observed that the solutions derived through applying EWM weights and CRITIC weights are similar in most cases. But comparing the efforts required for each method, it was observed that COPRAS, GRA, PROMETHEE methods required more level of mathematical computations than the other methods.

2.2 Pearson's Coefficient Study

To validate the reliability of the outcomes, a three case Pearson's coefficient study was performed. The results of the study are presented in Fig. 3. In the first case of the Pearson's study, it was observed that most of the correlation coefficients were above 0.5, but yet there was a significant quantity of coefficients below 0.5. This indicates that all six ranks of the 33 algorithms did not concur each other. But, the objective of this study was to select the optimal PCM for the TES heat exchanger. If one would accentuate the objective, it is necessary that the first ranked PCM and the second ranked PCM is similar in most cases. This approach to study the concurrence of the first ranked and the second ranked PCM was employed to validate the reliability of this comparative study and as it could be noted from Table 3, PCMs were ranked purely based on their evaluating parameters. Even when there is a very small difference between the evaluating parameters, the PCMs will still be ranked based on the differences. Further, the approach does not rely upon a single combinational algorithm, but depends on the comparative conclusion derived through employing 33 combinational algorithms. In this study, all of the algorithms had ranked Erythritol as the suitable PCM, irrespective of the type of algorithm and the weight estimation scheme employed. Further, most of the algorithms have ranked MCHH as the second best suited PCM. Hence, the ranking scheme is reliable. To verify the reliability of the outcomes, two more cases were performed. A frequency study was performed to proceed further. A rank wise frequency was recorded. The rank wise data is presented in Fig. 3. It has been observed that Erythritol was the best ranked PCM (Rank 1) in all of the algorithms. Further, MCHH has been estimated as the second best PCM in 28 of 33 algorithms. Similarly for all other ranks, the frequencies were recorded. From the frequency study, it was observed that Erythritol, MCHH, and PlusICE H120 were the first three prioritized PCMs from majority of the algorithms. Hence, for the second case of Pearson's study, only the three were considered



(a) *WSM* (b) *WPM* (c) *SAW* (d) *COPRAS* (e) *ARAS* (f) *WASPAS* (g) *MOORA* (h) *TOPSIS* (i) *GRA* (j) *VIKOR* (k) *PROMETHEE*

Fig. 2. *Comparison of the various ranking outcomes*

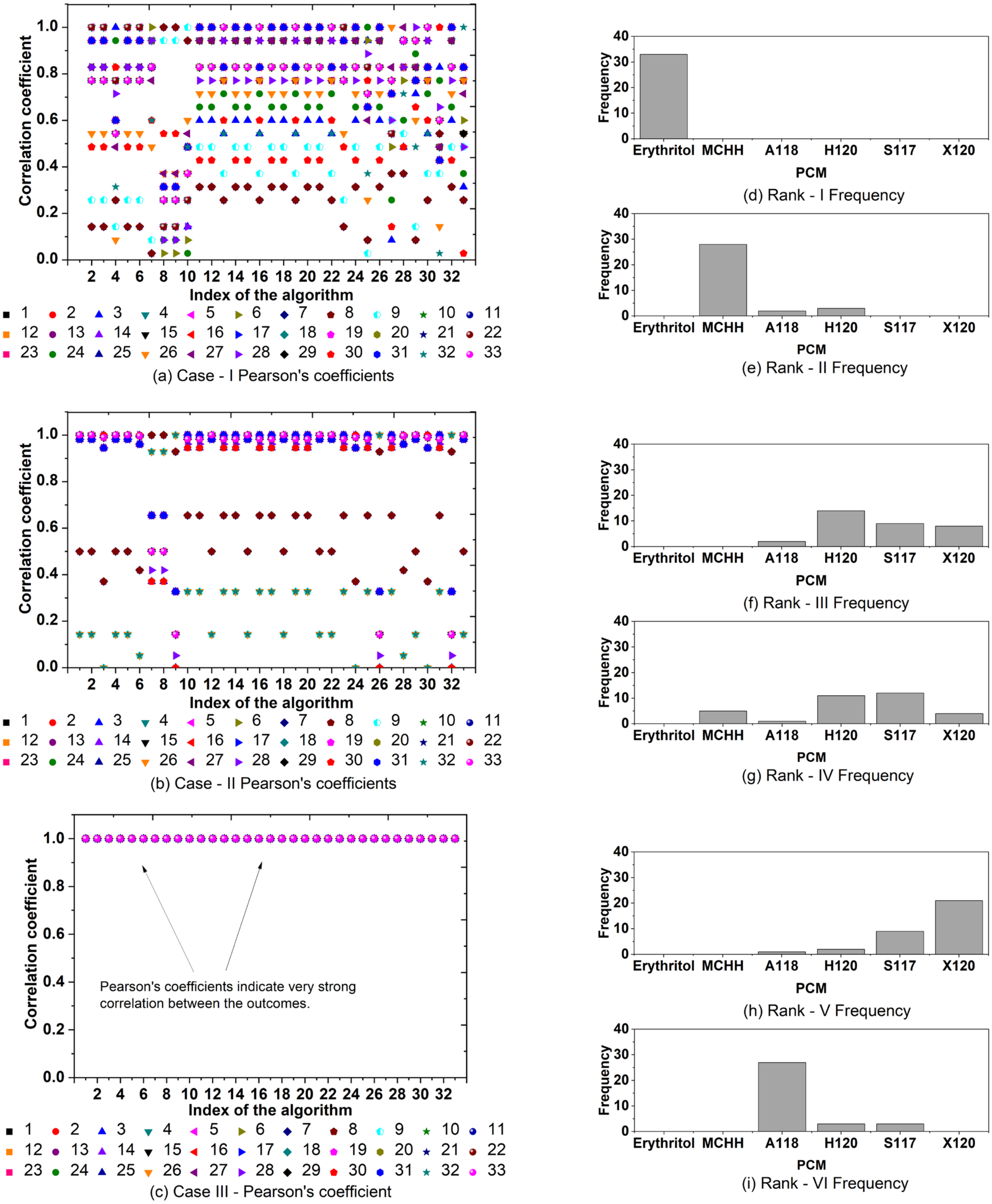


Fig. 3. *Panels (a)-(c) present the variation of the Pearson's correlation coefficients for different cases and panels (d)-(i) presents the ranking outcome frequencies of the PCM alternatives*

for correlation and for the third case of the Pearson's study, only Erythritol and MCHH were considered. The second case correlations indicates that there is comparatively stronger correlation than the first case. Further, the third case indicates that there is very strong correlation compared to other cases. All of the third case correlations have rendered a coefficient of 1. Hence from this three case analysis, the reliability of the results have been validated.

2.3 Discussion from Heat Exchanger Perspective

By applying the aforementioned algorithms, Erythritol has been selected as the optimal PCM for the steam cooking application. If one would intricately observe the functionality of the various weight estimation techniques, it can be observed that the objective techniques EWM and CRITIC have prioritized thermal conductivity whereas subjective AHP has prioritized latent heat of fusion. This can be ascribed to the Saaty's scale weights provided by the the authors. But despite this observation, all algorithms have selected Erythritol. Erythritol has the highest latent heat of fusion (331 $\mathrm{kJ\,kg^{-1}}$) among the alternatives, and hence less quantity of the PCM is required. Since, less quantity of PCM is required, the heat exchanger size will be comparatively smaller than when other PCMs are used. Further, Erythritol chosen has the highest thermal conductivity and and hence the melting time of the PCM will also be comparatively lower. The lower specific heat of Erythritol also is an added benefit. Further, if one would consider the highest density, PlusICE H120 has the highest density, but since latent heat and thermal conductivity were prioritized over density, the algorithms have preferred Erythritol over PlusICE H120 PCM. Hence, from a heat exchanger design perspective, it can be inferred that the chosen PCM can be strongly envisaged to be suitable for the sustainable steam cooking application.

From this study, a clear demarcation has been asserted between the functionality of all of the considered algorithms. From the study, by combining the weights and the main algorithms, it was observed that TOPSIS, GRA, VIKOR and PROMETHEE algorithms have significantly distinguished the outcomes based on each weight estimation scheme. Further instead of relying on one single algorithm, this method has made a reliable selection out of the various combinational algorithms proposed. Hence, this novel method integrating MCDM and Pearson's coefficient study is highly recommended for industrial practice.

3 CONCLUSIONS

Renewable energy based steam cooking paves the way for a sustainable steam cooking process when integrated with PCM based TES heat exchangers. However the optimal selection of the PCM plays a crucial role in the heat exchanger design. Hence, this research work has performed a comparative study for the selection of the appropriate PCM for the application. This study has tested 11 MCDM algorithms with 3 weight estimation techniques and through all of the algorithms, Erythritol has been chosen as the appropriate PCM. Erythritol has satisfactory thermo-physical properties to be used in the TES heat exchanger for the application. The ranking outcomes from various algorithms were validated through a three case Pearson's correlation coefficient study. The Pearson's correlation coefficient study has validated that all of the algorithms have very strong correlation in selecting the first and the second best PCMs.

4 ACKNOWLEDGEMENTS

The authors would like to thank the Department of Science and Technology (DST), Government of India and PSG College of Technology, Coimbatore, India for their financial support.

5 REFERENCES

[1] Sharma, S.D., Sagara, K. (2005). Latent heat storage materials and systems - A Review. *International Journal of Green Energy*, vol. 2, p. 1-56, **DOI:10.1081/GE-200051299**.

[2] Motwani, K., Patel, J. (2019). Cost analysis of solar parabolic trough collector for cooking in Indian hostel – a case study. *International Journal of Ambient Energy*,**DOI:10.1080/01430750.2019.1653968**.

[3] Xu, H., Sze, J.Y., Romagnoli, A., Py, X. (2017). Selection of Phase Change Material for Thermal Energy Storage in Solar Air Conditioning Systems. *Energy Procedia*, vol. 105, p. 4281-4288, **DOI:10.1016/j.egypro.2017.03.898**.

[4] Mardani, A., Jusoh, A., Nor, K.M.D., Khalifah, Z., Zakwan, N., Valipour, A. (2015). Multiple criteria decision-making techniques and their applications – a review of the literature from 2000 to 2014. *Economic Research-Ekonomska Istraživanja*, vol. 28, no. 1, p. 516-571, **DOI:10.1080/1331677X.2015.1075139**.

[5] Wang, J., Zhai, X., Liu, C., Zhang, Y. (2017). Determination of the Threshold for Extreme Load Extrapolation Based on Multi-Criteria Decision-Making Technology. *Strojniški vestnik-Journal of Mechanical Engineering*, vol. 63, no. 3, p. 201-211, **DOI:10.5545/sv-jme.2016.3557**.

[6] Prvulovic, S., Tolmac, D., Radovanovic, L. (2011). Application of Promethee-Gaia Methodology in the Choice of Systems for Drying Paltry-Seeds and Powder Materials. *Strojniški vestnik-Journal of Mechanical Engineering*, vol. 57, no. 10, p. 778-784, **DOI:10.5545/sv-jme.2008.068**.
[7] Vindiš, P., Muršec, B., Rozman, Č., Čus, F. (2010). A Multi-Criteria Assessment of Energy Crops for Biogas Production. *Strojniški vestnik-Journal of Mechanical Engineering*, vol. 56, no. 1, p. 63-70.
[8] Lee, H.C., Chang, C.T. (2018). Comparative analysis of MCDM methods for ranking renewable energy sources in Taiwan. *Renewable and Sustainable Energy Reviews*, vol. 2, p. 883-896, **DOI:10.1016/j.rser.2018.05.007**.
[9] Emovon, I., Ogheneyerovwho, S. (2020). Application of MCDM method in material selection for optimal design: A review. *Results in Materials*, vol. 7, p. 100115, **DOI:10.1016/j.rinma.2020.100115**.
[10] Wang, Y., Zhang, Y., Yang, W., Ji, H. (2015). Selection of Low-Temperature Phase-Change Materials for Thermal Energy Storage Based on the VIKOR Method. *Energy Technology*, vol. 3, p. 84-89, **DOI:10.1002/ente.201402098**.
[11] Yang, K., Zhu, N., Chang, C., Wang, D., Yang, S., Ma, S. (2018). A methodological concept for phase change material selection based on multi-criteria decision making (MCDM): A case study. *Energy*, vol. 165, p. 1085-1096, **DOI:10.1016/j.energy.2018.10.022**.
[12] Gadhave, P., Prabhune, C., Pathan, F. (2020). Selection of phase change material for domestic water heating using multi criteria approach. *Australian Journal of Mechanical Engineering*, **DOI:10.1080/14484846.2020.1842297**.
[13] Adali, E.A., Işık, A.T. (2017). Critic and Maut Methods for the Contract Manufacturer Selection Problem. *European Journal of Multidisciplinary Studies*, vol. 2, no. 5, p. 93-101, **DOI:10.26417/ejms.v5i1.p93-101**.
[14] Mayilvelnathan, V., Arasu, A.V. (2019). Characterisation and thermophysical properties of graphene nanoparticles dispersed erythritol PCM for medium temperature thermal energy storage applications. *Thermochimica Acta*, vol. 676, p. 94-103, **DOI:10.1016/j.tca.2019.03.037**.
[15] Höhlein, S.H., König-Haagen, A., Brüggemann, D. (2017). Thermophysical Characterization of $MgCl_2.6H_2O$, Xylitol and Erythritol as Phase Change Materials (PCM) for Latent Heat Thermal Energy Storage(LHTES). *Materials*, vol. 10, p. 444, **DOI:10.3390/ma10040444**.
[16] PlusICE Product Catalogue. Arena, from *https://www.pcmproducts.net/files/PlusICE%20Range%202021-1.pdf*, accessed on 2021-06-10.
[17] Xu, H., Sze, J.Y., Romagnoli, A., Py, X. (2017). Selection of Phase Change Material for Thermal Energy Storage in Solar Air Conditioning Systems. *Energy Procedia*, vol. 105, p. 4281-4288, **DOI:10.1016/j.egypro.2017.03.898**.
[18] Organ, A., Yalçin, E. (2016). Performance Evaluation Of Research Assistants By Copras Method. *European Scientific Journal*, p. 102-109.
[19] Zavadskas, E.K., Turskis, Z. (2010). A new additive ratio assessment (ARAS) method in multicriteria decision making. *Ukio Technologinis ir Ekonominis Vystymas*, vol. 16, no. 2, p. 159-172, **DOI:10.3846/tede.2010.10**.
[20] Chakraborty, S., Zavadskas, E.K. (2014). Applications of WASPAS Method in Manufacturing Decision Making. *Informatica*, vol. 25, no. 1, p. 1-20, **DOI:10.15388/Informatica.2014.01**.
[21] Brauers, W.K.M., Zavadskas, E.K. (2006). The MOORA method and its application to privatization in a transition economy. *Control and Cybernetics*, vol. 35, no. 2, p. 445-469.
[22] Wu, W. (2017). Grey Relational Analysis Method for Group Decision Making in Credit Risk Analysis. *Eurasia Journal of Mathematics, Science and Technology Education*, vol. 13, no. 12, p. 7913-7920, **DOI:10.12973/ejmste/77913**.
[23] San Cristóbal, J.R. (2011). Multi-criteria decision-making in the selection of a renewable energy projectin spain: The Vikor method. *Renewable Energy*, vol. 36, p. 498-502, **DOI:10.1016/j.renene.2010.07.031**.
[24] Bogdanovic, D., Nikolic, D., Ilić, I. (2012). Mining method selection by integrated AHP and PROMETHEE method. *Anais da Academia Brasileira de Ciências*, vol. 84, no. 1, p. 219-233, **DOI:10.1590/S0001-37652012000100023**.
[25] Villacreses, G., Gaona, G., Martínez-Gómez, J., Jijón, D.J. (2017). Wind farms suitability location using geographical information system (GIS), based on multi-criteria decision making (MCDM) methods: The case of continental Ecuador. *Renewable Energy*, vol. 109, p. 275-286, **DOI:10.1016/j.renene.2017.03.041**.