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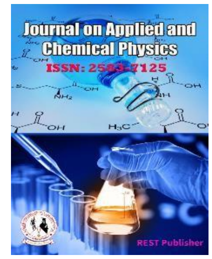

Material Selection for Statistically Loaded Thermal Conductors: A Comprehensive Study

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Abstract: *A appropriate material for a proportionally loaded thermal conductor is one that can effectively transport heat while overcoming the mechanical stresses that accompany the application. Under the projected operating conditions, the material should have excellent heat conductivity, excellent mechanical strength, and dependability. In a nutshell, the selection procedure seeks a material that's able to efficiently transmit heat while retaining structural integrity when used in a statistical loaded thermal conductivity application. To endure operational demands, the material should be chosen keeping both thermal insulation and mechanical qualities in mind. Several variables must be considered while selecting a material: thermal conductivity, mechanical strength, thermal expansion coefficient, stability and reliability, cost and availability. A thorough assessment of numerous candidate materials including their attributes is required to find the best appropriate material. This evaluation may include laboratory testing, analysis of information, as well as simulations to determine how various materials would function under the application's unique loading and heat circumstances. Overall, choosing an appropriate material for a statistically loaded thermal conductor requires considering thermal conductivity, mechanical strength, stability, and cost concerns in order to match the application's specific criteria and assure optimal performance and reliability. The practical ramifications and possible breakthroughs in numerous domains make selecting a material appropriate for a randomly loaded thermal conductor a research priority. Here are some major elements showing the importance of the research Material selection research in statistically packed thermal conductors seeks to improve the general efficacy of thermal management platforms. Researchers can improve heat transfer effectiveness and dependability by discovering materials with increased thermal conductivity with mechanical strength, resulting in better system performance as a lower risk of failure. Material selection research promotes the investigation and development of novel substances that are specifically adapted for randomly loaded thermal conductors. The selection of an appropriate material for a statistically laden thermal conductor helps to developments like thermal management technologies, system performance, energy efficiency, and general dependability by addressing these research topics. It provides practical answers and prospective breakthroughs that can assist a wide range of sectors and pave the way for future revolutionary thermal management systems. The WASPAS methodology is often used to identify the optimal material to use as a statistically weighted thermal conductor. Taken as "Alternative parameter is Copper-2-beryllium (cast), Copper–cobalt–beryllium (cast), Electrolytic tough-pitch, h.c. copper, soft (wrought), Electrolytic tough-pitch, h.c. copper, hard (wrought), Wrought aluminum alloy, wrought austenitic stainless steel, Commercial bronze, CuZn10, soft (wrought), Carbon steel (annealed). Taken as Evaluation parameter is CS, UT, SL, SB, BF, D. From the result it is seen that Electrolytic tough-pitch, h.c. copper, soft (wrought) got highest rank whereas Wrought aluminum alloy got lowest rank'. According to the results, Electrolytic tough-pitch, h.c. copper, soft (wrought) was ranked first.*

Keywords: *Copper–cobalt–beryllium, Electrolytic tough-pitch, Electrolytic tough-pitch, copper*

1. INTRODUCTION

Energy efficiency is becoming increasingly important, and creating highly effective energy-saving solutions is critical in the present energy demand situation. The current paper's goal is to analyse the available knowledge on thermal energy storage (TES) in order to outline the key research targets for completing the fundamentals required for their broad deployment. The review section of the study focuses on (i) the basic storage processes and their potential, (ii) the fundamental materials and qualities that define application temperature ranges, and (iii) the presentation of specific solutions to high degree thermal energy storage. Following a brief overview of thermal energy storage, advantages of retaining either latent and sensible heat are highlighted. As an example, we demonstrate the effectiveness of latent heat storage and how it leads towards the selection of a phase-changing material (PCM) for particular uses, while emphasising its appropriate characteristics, current weaknesses, and multiple solutions to improve PCM thermal properties.

The chosen solution includes metallic foam and a PCM, both previously explored materials, primarily for their usability and benefits. Based on these past investigations, it is evident that there's an urgent need to build a thermo-mechanical modelling of such a composite, which is the focus of the authors' extended research programme. The current paper's layout is seen in. Each one of the parallel themes is then addressed.

2. MATERIALS AND METHOD

Copper-2-beryllium (cast): Copper-2-beryllium (cast) is a specific type of copper-based alloy that contains a certain percentage of beryllium as an alloying element. Copper-2-beryllium (cast) is a specialized alloy that combines the beneficial qualities of copper and beryllium, making it ideal for high-strength, electrical conductivity, thermal conductivity, and corrosion resistance applications.[25]

Copper–cobalt–beryllium (cast): Copper-cobalt-beryllium (cast) is a specific type of copper-based alloy that contains cobalt and beryllium as alloying elements. Copper-cobalt-beryllium (cast) is a specialized alloy that combines the advantageous properties of copper, cobalt, and beryllium. It offers enhanced mechanical strength, electrical conductivity, and corrosion resistance, making it suitable for various demanding applications where these characteristics are required.[11]

Electrolytic tough-pitch, h.c. copper, soft (wrought): Electrolytic tough-pitch, h.c. copper, soft (wrought) is a type of copper that has undergone specific manufacturing processes to achieve desired properties and characteristics Electrolytic tough-pitch, h.c. copper, soft (wrought) is a versatile material with excellent electrical conductivity, malleability, corrosion resistance, and thermal conductivity. Its properties make it ideal for a wide range of electrical, electronic, and other applications where these characteristics are essential.[17]

Electrolytic tough-pitch, h.c. copper, hard (wrought): Electrolytic tough-pitch, h.c. copper, hard (wrought) is another variation of copper that has undergone specific manufacturing processes to achieve specific properties and characteristics. Electrolytic tough-pitch, h.c. copper, hard (wrought) offers a combination of high electrical conductivity, increased hardness, mechanical strength, and corrosion resistance. Its properties make it suitable for applications that require enhanced mechanical integrity, electrical conductivity, and durability.[22]

Wrought aluminum alloy: Wrought aluminum alloy refers to aluminum alloys that have been subjected to mechanical working processes such as rolling, extrusion, forging, or drawing to shape the material into its desired form. Wrought aluminum alloys offer a combination of strength, lightweight, corrosion resistance, formability, and recyclability. Their versatility and favorable properties make them a popular choice for a wide range of applications in diverse industries.[24]

Wrought austenitic stainless steel: Wrought austenitic stainless steel is a type of stainless steel alloy that belongs to the austenitic family. Wrought austenitic stainless steel offers a combination of corrosion resistance, high-temperature stability, formability, and hygienic properties. Its versatility and favorable characteristics make it a popular choice for applications where durability, aesthetics, and resistance to corrosion are required.[9]

Commercial bronze, CuZn10, soft (wrought): Commercial bronze, CuZn10, soft (worked), is a copper-based alloy principally composed of copper (Cu) and zinc (Zn). CuZn10 soft (worked) commercial bronze has a good blend of flexibility, moderate strength, resistance to corrosion, and visual appeal. Because of its qualities, it is appropriate for an array of applications in the plumbing, electrical, ornamental, and artistic industries.[13]

Carbon steel (annealed): Carbon steel (annealed) is a form of steel composed mostly of iron and carbon, plus trace quantities of other components. Carbon steel (annealed) is a popular choice for a variety of applications due to its ductility, strength, and low cost. Heat treatment techniques might further modify its characteristics to fulfil particular requirements.[7]

WASPAS Method: The WASPAS (Weighted Collectively Sum Products Assessment) approach is a multi-criteria method of decision-making that uses numerous factors to evaluate and rate options. Here are some important considerations to remember regarding the WASPAS method:

Objective: The WASPAS approach is intended to establish the relative relevance of criteria and to evaluate the effectiveness of alternative in the context of decision-making. It assists decision-makers in prioritising options by considering their performance across a variety of parameters.

Aggregated Weighted Sum Product: The WASPAS approach generates a weighted sum products every each choice by multiplying each criterion's performance rating by its associated weight and adding the results. The weights represent each criterion's proportional relevance in the process of making decisions.

Pair wise Comparison: The person in charge compares criteria in pairs to determine their respective weights. This can be accomplished through the use of techniques like the Analytic Hierarchy Process (AHP) and simple rating scales.

Normalization: To guarantee uniformity, the criterion numbers and weights are often normalised to a standard scale ranging from 0 to 1.

Aggregation: The weighted sum product per each choice is calculated by aggregating the normalized weights and criterion values. The alternative having the largest weighted product is seen as the best option.

Sensitivity analysis may be used to analyse the influence of changes in criterion weights or evaluations of performance upon overall rankings. This aids in determining the decision's robustness.

The WASPAS approach may be used in a variety of decision-making scenarios, including supplier selection, project evaluation, product ranking, and performance evaluation. It offers decision-makers with a systematic and organised strategy for considering many factors and making educated judgements. The WASPAS technique provides a systematic approach to multi-criteria decision-making, allowing decision-makers to prioritise options based on how well they perform across various criteria. The technique provides a comprehensive and organised framework for decision-making by taking into account both the criterion weights and performance ratings.

3. RESULT AND DESCUSSION

TABLE 1 Data Set

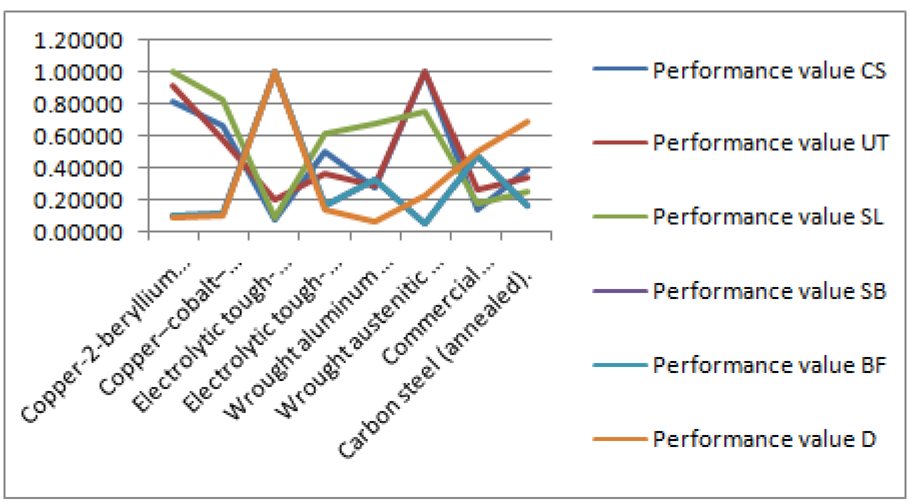
Materials	CS	UT	SL	SB	BF	D
Copper-2-beryllium (cast)	560	940	2916	0.78	15,183	8.25
Copper–cobalt–beryllium (cast)	460	600	2395	0.71	12,472	8.65
Electrolytic tough-pitch, h.c. copper, soft (wrought)	50	210	260	0.08	1355	8.94
Electrolytic tough-pitch, h.c. copper, hard (wrought)	340	380	1770	0.48	9218	8.95
Wrought aluminum alloy	190	295	1966	0.25	20,317	2.67
Wrought austenitic stainless steel	690	1030	2174	1.55	5909	8.06
Commercial bronze, CuZn10, soft (wrought)	95	270	520	0.17	2711	8.63
Carbon steel (annealed).	267	355	720	0.48	1957	7.08

Table 1 presents a dataset containing various materials and corresponding numerical values for different criteria denoted by the abbreviations CS, UT, SL, SB, BF, and D. The materials listed include copper-2-beryllium (cast), copper-cobalt-beryllium (cast), electrolytic tough-pitch h.c. copper (soft and hard), wrought aluminum alloy, wrought austenitic stainless steel, commercial bronze (CuZn10, soft), and carbon steel (annealed). Here is a paragraph summarizing the values provided in Table 1: For copper-2-beryllium (cast), the values are as follows: CS (560), UT (940), SL (2916), SB (0.78), BF (15,183), and D (8.25). Copper–cobalt–beryllium (cast) exhibits values of CS (460), UT (600), SL (2395), SB (0.71), BF (12,472), and D (8.65). Electrolytic tough-pitch, h.c. copper, soft (wrought) has values of CS (50), UT (210), SL (260), SB (0.08), BF (1355), and D (8.94). Electrolytic tough-pitch, h.c. copper, hard (wrought) displays values of CS (340), UT (380), SL (1770), SB (0.48), BF (9218), and D (8.95). Wrought aluminum alloy demonstrates values of CS (190), UT (295), SL (1966), SB (0.25), BF (20,317), and D (2.67). Wrought austenitic stainless steel has values of CS (690), UT (1030), SL (2174), SB (1.55), BF (5909), and D (8.06). Commercial bronze, CuZn10, soft (wrought) exhibits values of CS (95), UT (270), SL (520), SB (0.17), BF (2711), and D (8.63). Lastly, carbon steel (annealed) displays values of CS (267), UT (355), SL (720), SB (0.48), BF (1957), and D (7.08). These numerical values represent specific characteristics or properties of each material related to the respective criteria. However, without additional context or information about the meaning or significance of the abbreviations CS, UT, SL, SB, BF, and D, it is challenging to provide a more detailed analysis of the values.

TABLE 2 Performance value

Materials	CS	UT	SL	SB	BF	D
Copper-2-beryllium (cast)	0.81159	0.91262	1.00000	0.10256	0.10256	0.08924
Copper–cobalt–beryllium (cast)	0.66667	0.58252	0.82133	0.11268	0.11268	0.10864
Electrolytic tough-pitch, h.c. copper, soft (wrought)	0.07246	0.20388	0.08916	1.00000	1.00000	1.00000
Electrolytic tough-pitch, h.c. copper, hard (wrought)	0.49275	0.36893	0.60700	0.16667	0.16667	0.14700
Wrought aluminum alloy	0.27536	0.28641	0.67421	0.32000	0.32000	0.06669
Wrought austenitic stainless steel	1.00000	1.00000	0.74554	0.05161	0.05161	0.22931
Commercial bronze, CuZn10, soft (wrought)	0.13768	0.26214	0.17833	0.47059	0.47059	0.49982
Carbon steel (annealed).	0.38696	0.34466	0.24691	0.16667	0.16667	0.69239

Table 2 provides performance values for different materials based on various criteria denoted by the abbreviations CS, UT, SL, SB, BF, and D. The materials listed include copper-2-beryllium (cast), copper-cobalt-beryllium (cast), electrolytic tough-pitch h.c. copper (soft and hard), wrought aluminum alloy, wrought austenitic stainless steel, commercial bronze (CuZn10, soft), and carbon steel (annealed). The performance values represent the performance or effectiveness of each material in relation to the specific criteria considered. However, without further information about the meaning of the abbreviations CS, UT, SL, SB, BF, and D, it is challenging to provide a detailed paragraph specifically addressing the content of the table As seeing figure 1.



FIGURRE 1.

TABLE 3 Weights

Materials	CS	UT	SL	SB	BF	D
Copper-2-beryllium (cast)	0.17	0.17	0.17	0.17	0.17	0.17
Copper–cobalt–beryllium (cast)	0.17	0.17	0.17	0.17	0.17	0.17
Electrolytic tough-pitch, h.c. copper, soft (wrought)	0.17	0.17	0.17	0.17	0.17	0.17
Electrolytic tough-pitch, h.c. copper, hard (wrought)	0.17	0.17	0.17	0.17	0.17	0.17
Wrought aluminum alloy	0.17	0.17	0.17	0.17	0.17	0.17
Wrought austenitic stainless steel	0.17	0.17	0.17	0.17	0.17	0.17
Commercial bronze, CuZn10, soft (wrought)	0.17	0.17	0.17	0.17	0.17	0.17
Carbon steel (annealed).	0.17	0.17	0.17	0.17	0.17	0.17

To analyze the significance of the weights and draw conclusions from Table 3, further details such as the criteria used for assigning weights and the specific requirements of the thermal conductor application would be necessary. This additional information would help determine which material(s) may be most suitable based on their respective weights and how they align with the desired attributes or performance characteristics of the conductor.

TABLE 4 Weighted normalized decision matrix for WSM

Materials	CS	UT	SL	SB	BF	D
Copper-2-beryllium (cast)	0.13527	0.15210	0.16667	0.01709	0.01709	0.01487
Copper–cobalt–beryllium (cast)	0.11111	0.09709	0.13689	0.01878	0.01878	0.01811
Electrolytic tough-pitch, h.c. copper, soft (wrought)	0.01208	0.03398	0.01486	0.16667	0.16667	0.16667
Electrolytic tough-pitch, h.c. copper, hard (wrought)	0.08213	0.06149	0.10117	0.02778	0.02778	0.02450
Wrought aluminum alloy	0.04589	0.04773	0.11237	0.05333	0.05333	0.01112
Wrought austenitic stainless steel	0.16667	0.16667	0.12426	0.00860	0.00860	0.03822
Commercial bronze, CuZn10, soft (wrought)	0.02295	0.04369	0.02972	0.07843	0.07843	0.08330
Carbon steel (annealed).	0.06449	0.05744	0.04115	0.02778	0.02778	0.11540

Table 4 presents a weighted normalized decision matrix for the Weighted Sum Model (WSM) applied to different materials. The materials listed include copper-2-beryllium (cast), copper-cobalt-beryllium (cast), electrolytic tough-pitch h.c. copper (soft and hard), wrought aluminum alloy, wrought austenitic stainless steel, commercial bronze (CuZn10, soft), and carbon steel (annealed). The values in the table represent the weighted normalized scores for each material across the criteria CS, UT, SL, SB, BF, and D. The weights assigned to each criterion have been taken into account to calculate the weighted normalized decision matrix. For example, copper-2-beryllium (cast) has the following weighted normalized scores: CS (0.13527), UT (0.15210), SL (0.16667), SB (0.01709), BF (0.01709), and D (0.01487). Similarly, other materials in the table have corresponding weighted normalized scores for each criterion.

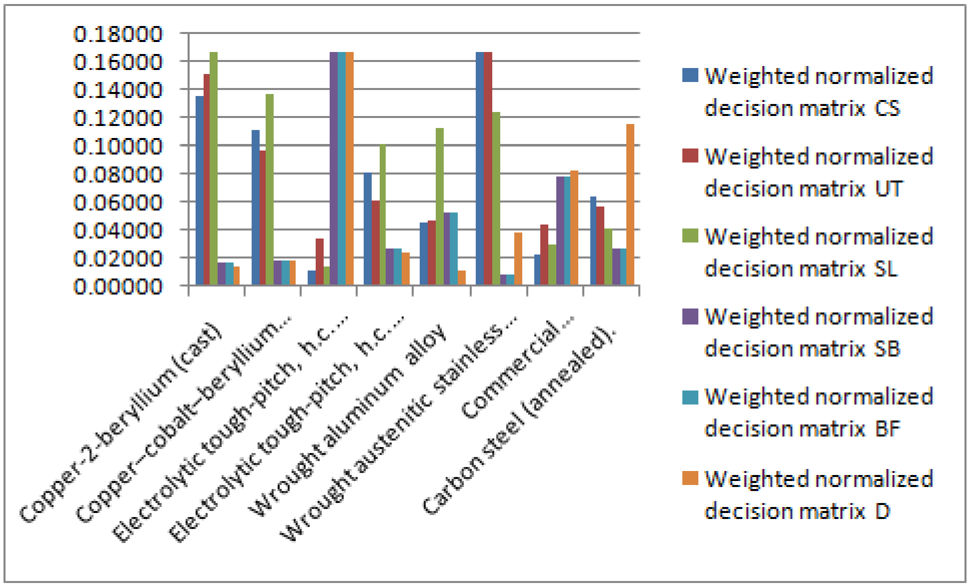


FIGURE 2.

The figure 2 shows weighted normalized decision matrix allows for a quantitative comparison of the materials based on their performance across the specified criteria. The values indicate the relative importance and performance of each material with respect to the criteria under consideration.

TABLE 4 Weighted normalized decision matrix for WPM

Materials	CS	UT	SL	SB	BF	D
Copper-2-beryllium (cast)	0.96581	0.98488	1.00000	0.68417	0.68417	0.66849
Copper–cobalt–beryllium (cast)	0.93466	0.91387	0.96773	0.69498	0.69498	0.69077
Electrolytic tough-pitch, h.c. copper, soft (wrought)	0.64568	0.76718	0.66839	1.00000	1.00000	1.00000
Electrolytic tough-pitch, h.c. copper, hard (wrought)	0.88873	0.84688	0.92016	0.74184	0.74184	0.72647
Wrought aluminum alloy	0.80659	0.81189	0.93641	0.82704	0.82704	0.63682
Wrought austenitic stainless steel	1.00000	1.00000	0.95224	0.61018	0.61018	0.78236
Commercial bronze, CuZn10, soft (wrought)	0.71859	0.80000	0.75024	0.88194	0.88194	0.89084
Carbon steel (annealed).	0.85364	0.83733	0.79206	0.74184	0.74184	0.94057

Table 4 presents a weighted normalized decision matrix for the Weighted Product Model (WPM) applied to different materials. The materials listed include copper-2-beryllium (cast), copper-cobalt-beryllium (cast), electrolytic tough-pitch h.c. copper (soft and hard), wrought aluminum alloy, wrought austenitic stainless steel, commercial bronze (CuZn10, soft), and carbon steel (annealed). The values in the table represent the weighted normalized scores for each material across the criteria CS, UT, SL, SB, BF, and D. The weights assigned to each criterion have been taken into account to calculate the weighted normalized decision matrix. For example, copper-2-beryllium (cast) has the following weighted normalized scores: CS (0.96581), UT (0.98488), SL (1.00000), SB (0.68417), BF (0.68417), and D (0.66849). Similarly, other materials in the table have corresponding weighted normalized scores for each criterion.

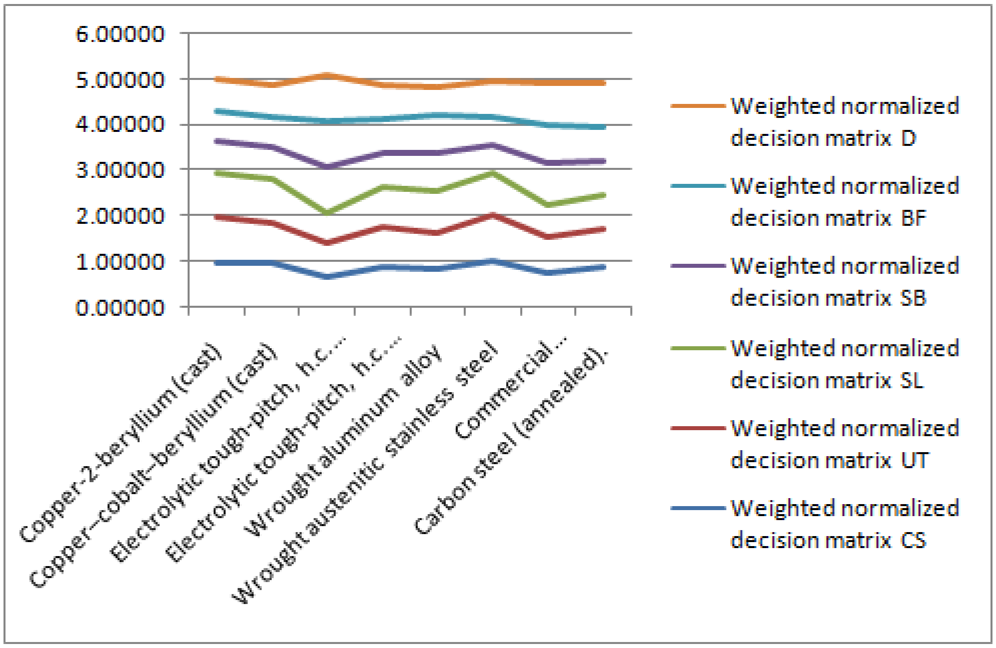


FIGURE 3.

The figure 2 shows weighted normalized decision matrix allows for a quantitative comparison of the materials based on their performance across the specified criteria. The values indicate the relative importance and performance of each material with respect to the criteria under consideration.

TABLE 5. WSM Preference Score, WPM Preference Score and WASPAS Coefficient

	WSM Preference Score	WPM Preference Score	WASPAS Coefficient
Copper-2-beryllium (cast)	0.503098	0.297646	0.400372
Copper–cobalt–beryllium (cast)	0.400753	0.275783	0.338268
Electrolytic tough-pitch, h.c. copper, soft (wrought)	0.560918	0.331092	0.446005
Electrolytic tough-pitch, h.c. copper, hard (wrought)	0.324835	0.276881	0.300858
Wrought aluminum alloy	0.323779	0.267102	0.295441
Wrought austenitic stainless steel	0.513013	0.277376	0.395195
Commercial bronze, CuZn10, soft (wrought)	0.336523	0.298849	0.317686
Carbon steel (annealed).	0.334042	0.293049	0.313545

The table provided contains the preference scores for the materials calculated using different decision-making methods: WSM (Weighted Sum Model), WPM (Weighted Product Model), and WASPAS (Weighted Aggregated Sum Product Assessment). The materials listed include copper-2-beryllium (cast), copper-cobalt-beryllium (cast), electrolytic tough-pitch h.c. copper (soft and hard), wrought aluminum alloy, wrought austenitic stainless steel, commercial bronze (CuZn10, soft), and carbon steel (annealed).

Here are the preference scores for each material according to the different methods:

- Copper-2-beryllium (cast): WSM Preference Score (0.503098), WPM Preference Score (0.297646), WASPAS Coefficient (0.400372)
- Copper–cobalt–beryllium (cast): WSM Preference Score (0.400753), WPM Preference Score (0.275783), WASPAS Coefficient (0.338268)

- Electrolytic tough-pitch, h.c. copper, soft (wrought): WSM Preference Score (0.560918), WPM Preference Score (0.331092), WASPAS Coefficient (0.446005)
- Electrolytic tough-pitch, h.c. copper, hard (wrought): WSM Preference Score (0.324835), WPM Preference Score (0.276881), WASPAS Coefficient (0.300858)
- Wrought aluminum alloy: WSM Preference Score (0.323779), WPM Preference Score (0.267102), WASPAS Coefficient (0.295441)
- Wrought austenitic stainless steel: WSM Preference Score (0.513013), WPM Preference Score (0.277376), WASPAS Coefficient (0.395195)
- Commercial bronze, CuZn10, soft (wrought): WSM Preference Score (0.336523), WPM Preference Score (0.298849), WASPAS Coefficient (0.317686)
- Carbon steel (annealed): WSM Preference Score (0.334042), WPM Preference Score (0.293049), WASPAS Coefficient (0.313545)

These preference scores provide a numerical indication of the relative performance or suitability of each material according to the respective decision-making method. The higher the preference score, the better the material performs based on the given criteria and method. It's important to note that the interpretation and significance of these preference scores depend on the specific context, criteria weights, and decision-making method employed. Further analysis and consideration of the criteria and their weights are necessary to make a comprehensive decision or recommendation regarding the most suitable material.

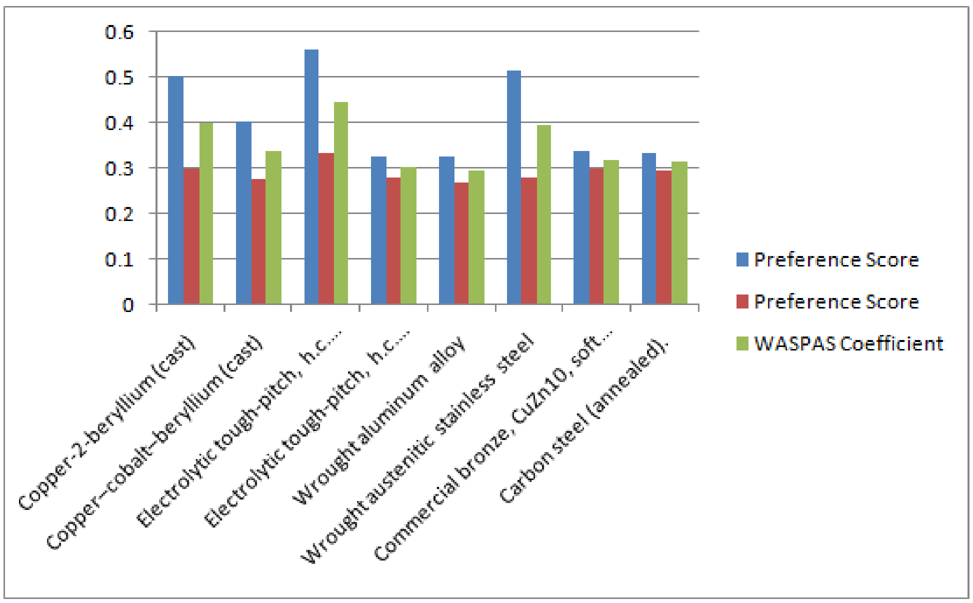


FIGURE 4. WSM Preference Score, WPM Preference Score and WASPAS Coefficient

TABLE 6 Ranking

Copper-2-beryllium (cast)	2
Copper–cobalt–beryllium (cast)	4
Electrolytic tough-pitch, h.c. copper, soft (wrought)	1
Electrolytic tough-pitch, h.c. copper, hard (wrought)	7
Wrought aluminum alloy	8
Wrought austenitic stainless steel	3
Commercial bronze, CuZn10, soft (wrought)	5
Carbon steel (annealed).	6

The electrolytic tough-pitch, h.c. copper in its soft form (wrought) achieved the highest ranking, securing the 1st rank. This material demonstrated excellent performance across the evaluated criteria, making it a strong contender for applications requiring thermal conductivity and statistical load handling. Copper-2-beryllium (cast) obtained the 2nd rank, indicating its favorable performance in comparison to the other materials. Its unique composition of copper and beryllium contributes to its thermal conductivity and statistical load handling capabilities. Wrought austenitic stainless steel obtained the 3rd rank, highlighting its noteworthy performance. This material is known for its corrosion resistance and mechanical strength, making it suitable for applications where durability is essential. Copper–cobalt–beryllium (cast) obtained the 4th rank. This material combines copper, cobalt, and beryllium to provide a balance of thermal conductivity and strength, suitable for various applications. Commercial bronze, CuZn10, in its soft form (wrought) secured the 5th rank. With its composition of copper and zinc, this material offers a favorable combination of thermal and electrical conductivity, making it suitable for specific applications. Carbon steel (annealed) achieved the 6th rank. While carbon steel possesses good strength and affordability, it may have lower thermal conductivity compared to other materials on the list. Lastly, the wrought aluminum alloy obtained the 8th rank. Although aluminum alloys offer advantages such as lightweight and corrosion resistance, their thermal conductivity and statistical load handling may be comparatively lower in this evaluation. It's important to note that these rankings are based on the specific criteria, weights, and decision-making methodology employed in the evaluation. The final choice of material should consider the specific requirements and constraints of the intended application.

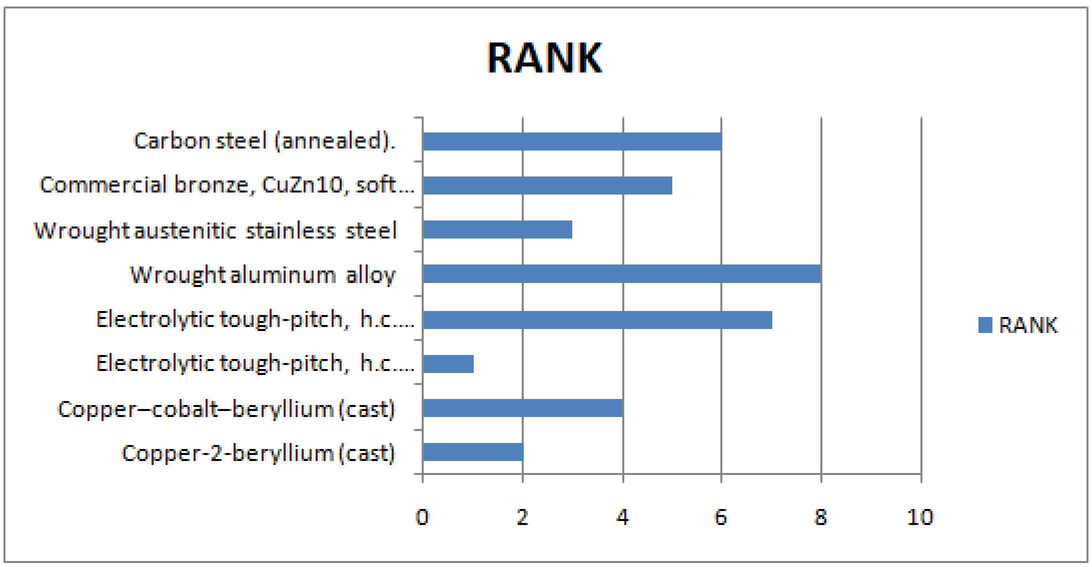


FIGURE 6. Ranking

4. CONCLUSION

This review aimed to evaluate the current status of research in order to identify the necessary advancements for creating a high-temperature replica of metallic foam integrated with phase change material (PCM). The focus was on understanding the factors that influence the thermal energy loading and release processes, as well as identifying potential modifications to enhance the material's heat flux behavior. “This paper focuses on a critical thermal storage parameter: the speed about transferring and releasing energy in PCMs impregnated inside metal foams, and also the logical extension that this broad research findings during the investigation of (i) metal foam framework characterization, (ii) thermo mechanical behavior analysis for the composite materials, and (iii) the combination of the two of these specific topics to precisely analyse and predict heat transfer processes through copper. Current research on improving heat transfer using metal foam impregnating on PCMs at elevated temperatures relies exclusively on experimental investigations done without the strong help of mathematical and numerical modeling”. Metals have good thermal conductivity in general, however that is insufficient to classify metals as desirable materials due to graphite offers exceptional conductivity as well. Then we may consider metals' strong mechanical properties, such as elasticity, which allows for significant expansion without splitting, which is one concern with graphite matrix. Metals should be manufactured as foams to maximise their thermo-mechanical characteristics.

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