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Review Article

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Visualization and Assessment of Energy Efficiency Drivers and Solution Practices for Temperature-controlled Supply Chain Operations

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Abstract

The higher energy consumption in temperature-controlled supply chains (cold supply chains where lower ambient temperature is required to keep the product fresh) causes a rise in financial burden and negative environmental and social impacts. As natural energy resources are limited, therefore, the necessity is to realize the significance of the driving factors responsible for higher energy efficiency in temperature-controlled supply chains. Therefore, the presented study aims to explore and analyze the driving characteristics (factors) that leverage energy efficiency in cold supply chain (CSC) operations. The research work explores 12 key drivers for higher energy efficiency in CSC based on the literature review and the opinions of the domain professionals. In addition, the research work also proposed six best effective solution practices to raise the driving characteristic of energy efficiency in CSC operations. A new hierarchical model comprised of driving factors and proposed practices has been developed and analyzed using a hybrid methodology based on the Best Worst method (BWM) and Preference Ranking Organization Method for Enrichment of Evaluation (PROMETHEE-II) methods. The BWM method has been used to analyze the significance of the driving factors while the PROMETHEE method has been used to prioritize the proposed practices for improved environmental efficiency of CSC. The discoveries of the work might help the management and decision makers to identify the core drivers and best suitable solutions for improving the energy efficiency of their organizational CSC operations.

Keywords

Cold supply chain, Temperature control, Energy efficiency, BWM, PROMETHEE

Introduction

The perishables have a short life cycle and get contaminated, or quality decay takes place as soon as they come in contact with a temperature above the permissible sustainable range [1]. Therefore, their storage and movement are carried out under a temperature-controlled environment to keep the temperature below the surrounding temperature [2, 3]. Examples of perishables include fruits and vegetables, dairy items, seafood, meat, raw and baked food items, beverages and soft drinks, and pharmaceuticals and vaccines. Agricultural and pharmaceuticals are considered as the most sensitive to environmental conditions [4]. The journey of these perishable items from production to end consumer under a temperature-controlled environment is commonly known as cold supply chain (CSC) [5]. The preservation of perishable items in temperature-controlled environment in CSC is performed using refrigeration systems which consume a huge amount of energy to drive refrigeration units [6]. A substantial increase in refrigerated storage and transportation requirements have raised the amount of energy consumption and negative environmental effect of the supply chain operations [7, 8]. In a study, it was presented that around 40 percent of the food items required refrigeration to keep their quality and potency for a given time period [9]. Coulomb [10] presented that refrigeration in CSC consumes around 15 percent of the total electricity consumed worldwide. As per the observations [11, 12], the total electricity consumption in CSC holds to around 30 percent of the total electricity consumed worldwide. The use of a larger amount of energy results in an economic burden on the CSC and a substantial rise in greenhouse gas emissions and climatic changes [13 - 15]. If the energy used comes from primary energy resources such as coal-operated thermal power plants, the situation becomes worse as it causes higher carbon dioxide emissions and degradation of natural energy resources for future generation [1, 16, 17]. Continuously increasing demand for refrigerated food and beverage items and continuously increasing the number of freight transport have also mounted the additional load of energy consumption [18 - 21]. The higher energy consumption, its environmental load, and continuous degradation of natural energy resources create a challenge against the whole world and mounted a massive pressure on players of the CSC to reduce the energy consumption [22 - 25]. In addition, use of traditional refrigeration technologies and irregularities in distribution facilities also create a serious challenge to reduce the energy consumption in subsequent CSC operations [26]. To reduce the energy consumption in CSC, it is the prime requirement to explore the driving factors and model them to improve energy efficiency.

From the above motivation, the presented study aims to identify and analyze the key driving factors for improving energy efficiency in CSC. In addition, the study also aims to explore the most effective practices which might help the management to improve the energy efficiency of their CSC.

Experimentation

Development of the proposed model

To achieve the aim of the study, based on an extensive literature survey and discussion which the domain experts, twelve key driving factors of improving the energy efficiency of the CSC operation were identified which were further categorized into three core categories namely: economic drivers, knowledge and motivation-based drivers, and organizational and managerial drivers. Each core category of drivers consists of four sub drivers, the summary of which is given in table 1.

The study also explores the six most effective managerial practices based on the literature review and the expert's suggestions as per their experience. The proposed managerial practices are namely: Organization of load capacity (minimizing overheating or overcooling) (P1), Proper maintenance of refrigeration equipment (P2), Implementation of energy saving strategies and plans (P3), Reducing transportation distance and exposure time (P4), Adoption of energy-efficient refrigeration technologies (P5), and Proper training and education of the employees for energy saving (P6). In order to provide insights of the mutual association among the driving factors and the proposed solution practices, the study also develops a hierarchical model which consists of the identified driving factors and the practices. The analysis of the developed model has been performed using a hybrid methodology based the BWM and the PROMETHEE-II methods. Figure 1 has been elucidated to demonstrate the structure of the developed model.

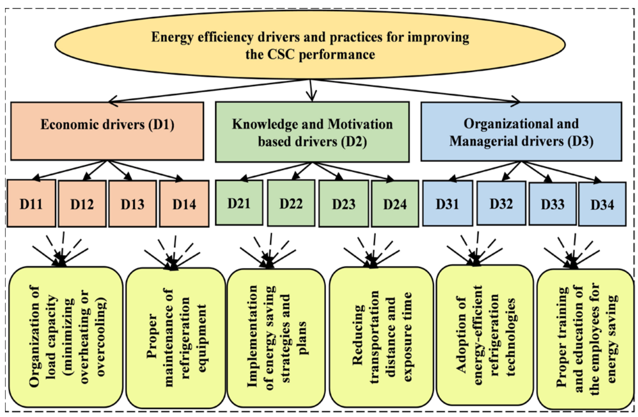

Figure 1: Hierarchical model for mutual assessment of the drivers and practices.

Table 1: Summary of driving factors.

Driver	Core category	Driving factor	Abbreviation
D1	Economic drivers	Cost saving due to reduced energy consumption	D11
		Cost saving due to possible penalties for higher energy consumption	D12
		Exemption from possible penalties and punishments due to higher GHG emissions	D13
		Tax relaxation and subsidies	D14
D2	Knowledge and Motivation based drivers	Training for energy saving and its benefits to our ecosystem	D21
		Adequate information and knowledge flow among the competitors	D22
		Employees morale and incentives benefits	D23
		Conducting audits and conferences	D24
D3	Organizational and Managerial drivers	Effective coordination between CSC members	D31
		Effective and robust CSC infrastructure	D32
		Long-term energy saving plans and strategies	D33
		Commitment and support toward energy saving	D34

Solution methodology

This section has been introduced to discuss the research methodology for achieving the desired objectives of the research. The research methodology adopted in the presented research work integrates the BWM and PROMETHEE-II methods to achieve the targeted objective of the research. The BWM method has been used to govern the relative significance of the explored driving factors of improving the energy efficiency of CSC. On the other hand, the PROMETHEE method has been used to develop the preference hierarchy of the proposed solution practices for adding the driving power to the identified factors. The graphical presentation of the stepwise procedural structure of research work has been shown in figure 2.

Empirical assessment of the proposed model

The aim of the study is to explore and visualize the significant driving factors for enhancing the energy efficiency of CSC. In addition, it has also been aimed to propose the best effective solution practices that might help the management to boost the driving power of identified factors for improving their organizational performance. For the same, twelve driving factors and six most appropriate solution practices have been identified as discussed above. In order to develop a healthier basis for the assessment of the explored driving factors and the proposed solution practices, the empirical assessment of the same has been performed gathering the relevant information from the domain professionals. For the same, a questionnaire containing the supportive intimations about the driving factors and the solution practices was structured on google doc and discussed with the academic experts for its relevancy. In the questionnaire, the experts were asked to provide information about the factors and practices as per their experience in a well-structured format. The questionnaire contained the questions such as what the best and worst factors should be as per their opinion, how they would rate the factors relative the best and worst factors, and preferably they would like to choose the proposed practices towards improving the energy efficiency of their CSC. Followed by a group of 186 domain professionals were selected from the various cold chain handling industries and academia of the Punjab region of India. Then, the structured questionnaire was dispatched to selected professionals through emails out of which 59 responses (with a response rate of 31.72 percent) were received and analyzed for their information appropriateness. After checking the relevancy of all the responses, the significance of the driving factors and priorities of the solution practices were assessed by implementing the BWM and PROMETHEE-II methods.

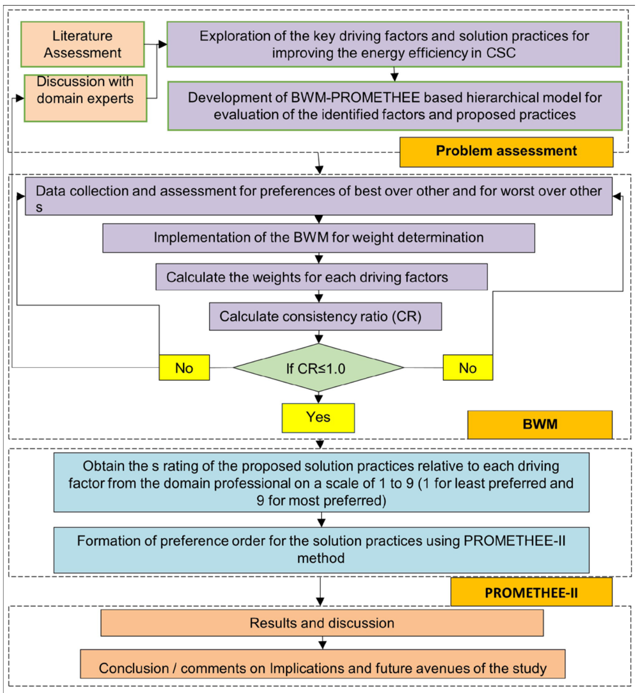

Figure 2: Stepwise procedural structure of the research work.

Determination of significance index using BWM

The BMW is a novel multi-criteria decision making (MCDM) technique to determine the weights of the set of criteria or attributes. The BWM was first introduced by Rezaei in 2015 [27] and was first used for real case problem by Rezaei et al. [28] to analyze the significance of various segments of supplier likings. The BWM determines the weights of the criteria or attributes based on the pairwise comparisons. The pairwise comparisons in BWM are established relative to the best and worst criteria respectively. The lesser and easy computational steps of BWM make it more popular among the researchers and practitioners to form the solution to the problem [29]. The stepwise procedure of determine the significance index for the driving factors from BWM as presented by Rezaei [27] can be summarized in the following steps:

Step 1

First, the set of criteria (in our case the driving factors) are determined based on the literature assessment or opinions of the decision makers. The summary of the explored driving factors is given in table 1.

Step 2

To form the pairwise comparisons, the decision experts are asked to select the best significance and worst significant criteria from the set of chosen criteria as per their own perspectives or liking. Followed, the decision makers are asked to provide the significance rating for all the other criteria relative to the best one and worst one respectively on 1 to 9 Likert scale. While providing the rating of the other criteria relative to the most preferred criterion, the best criteria is given significance index as 1 while the others from 1 to 9 scale (1 for best and highest for worst criterion). Similarly, the rating of the criteria relative to worst is also gathered on a 1 to 9 scale (1 for worst and highest for the best criterion). An example of such type of pairwise comparisons is given in table 2, table 3, and table 4.

Step 3

Determination of optimal significance weights for the driving factors. The optimal weights are formed in such a way that the absolute deviation of the weights relative to the best and worst relative to the others is minimum. The following steps are followed for achieving the desired objective.

Table 2: Selection of best and worst criteria.

Criteria Number	Criterion 1	Criterion 2	Criterion 3
Names of Criteria	Economic drivers	Knowledge and Motivation based drivers	Organizational and Managerial drivers
Select the Best	Economic drivers		
Select the Worst	Knowledge and Motivation based drivers		

Table 3: Significance index of the criteria relative to best.

Best to others (Economic drivers)	Economic drivers	Knowledge and Motivation based drivers	Organizational and Managerial drivers
	1	5	3

Table 4: Significance index of the criteria relative to worst.

Others to the Worst (Knowledge and Motivation based drivers)	Knowledge and Motivation based drivers
Economic drivers	4
Knowledge and Motivation based drivers	1
Organizational and Managerial drivers	3

Objective: Minimize Δ_L

Subject to; $\left|W_b - x_{Bj}W_j\right| \le \Delta_L$, for all j (1)

$$\left|W_j - x_{jw}W_w\right| \le \Delta_L \text{, for all j} \quad (2)$$

$$\sum W_j = 1 \quad (3)$$

$$Wj \ge 1 \text{, for all j} \quad (4)$$

Where, Δ_L represents objective function of the formed linear problems which aims to minimize the deviations of weights from the best and worst solutions. W_b shows the significance index assigned by the decision experts for the most preferred (best) driving factors and W_w represents the same for the (worst) preferred driving factor. x_{Bj} denotes the weight factor for most preferred and x_{jw} for least preferred driving factor. W_j is the significance weight for j^{th} driving factor.

Followed by the formation of significance weights consistency ratios are calculated to check the reliability of pairwise comparisons using equation 5.

$$C.R. = \frac{\Delta_L}{CI} \quad (5)$$

Where, the C.I. denotes the consistency index which is formed using consistency index table as shown in table 5.

Table 6 summarizes the significance of the weights of the driving factors on improving the energy efficiency of CSC as obtained from the implementation of BWM.

In order to check the reliability of the pairwise comparisons of the core drivers and their driving factors, consistency checks have been conducted and for each pairwise comparison consistency ratio (C.R.) has been determined using equation 5. From the analysis, it has been observed that for pairwise comparisons among the core category of drivers, economic drivers, knowledge and motivation-based drivers, and organizational and managerial drivers, the values of C.R. are 0.125, 0.117, 0.116, and 0.09, respectively, which satisfy the consistency boundary condition of Rezaei [27]. Therefore, it is perceived that all the comparisons are reliable to proceed with formed significance weights. The significance weights obtained from BWM are considered as the base weights for establishing the significance preference order of the proposed solution practices.

Table 5: C.I. values for the x_{BW} value [27].

a_{BW}	1	2	3	4	5	6	7	8	9
CI	0	0.44	1	1.63	2.3	3	3.73	4.47	5.23

Table 6: The summary of significance index of the driving factors as obtained from the BWM.

Core category of driver	Significance index	Driving factor	Driving factor weight	Global weight
Economic drivers	0.625	Cost saving due to reduced energy consumption	0.471	0.294
		Cost saving due to possible penalties for higher energy consumption	0.088	0.055
		Exemption from possible penalties and punishments due to higher GHG emissions	0.294	0.184
		Tax relaxation and subsidies	0.147	0.092
Knowledge and Motivation based drivers	0.125	Training and energy saving and its benefits to our ecosystem	0.395	0.049
		Adequate information and knowledge flow among the competitors	0.256	0.032
		Employees morale and incentives benefits	0.256	0.032
		Conducting audits and conferences	0.093	0.012
Organizational and Managerial drivers	0.25	Effective coordination between CSC members	0.091	0.023
		CSC infrastructure	0.273	0.068
		Long-term energy saving plans and strategies	0.455	0.114
		Commitment and support toward energy saving	0.182	0.045

Establishment of importance order of the solution practices using PROMETHEE method

The PROMETHEE is a MCDM method commonly used to determine the ranking or priorities of the criteria or alternatives. It is an outranking method and was first presented by Brans in 1982 [30]. From the literature analysis of the past research, it has been observed that many developments have been done to the original PROMETHEE method such as PROMETHEE-I (1982), PROMETHEE-II (1982), PROMETHEE-III and PROMETHEE-IV (1988), PROMETHEE-V and PROMETHEE-VI (1992 and 1994, respectively) [30]. PROMETHEE-I provides a partial order of the alternatives, therefore, in the current research work, PROMETHEE-II method has been used due to its capability to provides complete order of the priorities. In PROMETHEE method, the order of the alternatives is established by considering the negative and positive outranking flows [31]. Stepwise procedure to determine the importance order of the proposed solution practices is given in the following steps.

Step 1

The formation of pairwise decision matrix. For this, the alternatives (solution practices) are compared relative to each criterion (driving factors) on a scale of 1 to 9. For example, the 1 should be assigned for least important alternative and 9 for most important. Then, followed by, the max-min method, normalization of the pairwise decision matrix (table 7) is done using the following equations 6 and 7.

$$Z_{ij} = \frac{\left[a_{ij} - \min\left(a_{ij}\right)\right]}{\left[\max\left(a_{ij}\right) - \min\left(a_{ij}\right)\right]};\ \{\text{for profit criteria}\} \tag{6}$$

$$Z_{ij} = \frac{\left[\max\left(a_{ij}\right) - a_{ij}\right]}{\left[\max\left(a_{ij}\right) - \min\left(a_{ij}\right)\right]};\{\text{for cost criteria}\} \tag{7}$$

Where, a_{ij} is the important score of alternative i relative to criteria j.

Step 2

Determination of relative deviation distance of each solution practice with respect to other using equation 8.

$$D_{(u,v)} = z_j\left(u\right) - z_j\left(v\right) \tag{8}$$

For example, the deviation distance of P1 and P2 for driving factor D11, D12, and D13 can be calculated as:

$$D_{P_1-P_2} = (0.667-0.333),(0.250-0.000),(0.333-0.333) = 0.333, 0.250, 0.00 \text{ respectively}$$

Step 3

Multi-criteria preference index (PI) is formed for each deviation. The PI matrix is formed putting the positive deviation at their respective pairwise comparison spot and for all the negative deviation, the PI scores are considered as zero. Followed by the global PI scores were determined for each solution practice computing the summation of the weighted PI scores for each solution practice.

Step 4

Followed, positive flow ($\frac{\sum \Pi(a,x)}{n-1}$, superiority of alternative a over others) and negative flow ($\frac{\sum \Pi(x,a)}{n-1}$, inferiority of alternative a over other) are determined. Finally, the solution practices were ranked based on their net leaving (outranking) flow scores. The net flow for the alternative is the difference between the positive flow and negative flow of the respective alternative. The solution with the highest net outranking flow is considered as the most preferable solution practice. On the other hand, the practice with least outranking net flow is least preferable or can preferred at last. The following equations ca be used to determine the net flow of the solution practices. Table 8 shows the summary of results obtained from the PROMETHEE method.

From table 8, it can be observed that among the six proposed solution practices, P5 (Adoption of energy-efficient refrigeration technologies) is the most effective practice to add the driving power of the identified driving factors to improve the energy efficiency of CSC.

Results and Discussion

To perform the empirical assessment of the developed model (Figure 1), the research work proposed an integrative

Table 8: The summary of the results obtained from the PROMETHEE method.

Solution practice	Positive flow	Negative flow	Net flow	Rank
P1	0.126	0.301	-0.175	5
P2	0.119	0.242	-0.122	4
P3	0.347	0.105	0.242	2
P4	0.056	0.473	-0.417	6
P5	0.509	0.029	0.480	1
P6	0.213	0.222	-0.009	3

Table 7: Normalized pairwise decision matrix for the proposed solution practices.

	D11	D12	D13	D14	D21	D22	D23	D24	D31	D32	D33	D34
P1	0.667	0.250	0.333	0.000	1.000	0.000	0.200	0.000	0.333	0.667	0.000	0.000
P2	0.333	0.000	0.333	0.500	0.800	0.667	0.400	0.400	0.000	1.000	0.500	0.333
P3	0.333	0.750	1.000	1.000	0.800	1.000	0.600	0.800	1.000	0.667	1.000	0.667
P4	0.000	0.000	0.000	0.500	0.000	0.000	0.000	0.000	0.333	1.000	0.500	0.000
P5	1.000	1.000	1.000	1.000	0.600	0.667	0.400	0.200	0.333	1.000	1.000	1.000
P6	0.667	0.500	0.333	1.000	1.000	0.333	1.000	1.000	1.000	0.000	0.000	0.333

approach based on the BWM and PROMETHEE-II methods. The key findings observed from the BWM analysis (Table 6) demonstrate that among the three identified core category of driving factors, the *economic*, and *organizational and managerial* drivers (significance weight 0.625 and 0.25, respectively) are the two most significant drivers for improving the energy efficiency of CSC operations. On the hand, although the *knowledge and motivation-based driver* form the least significant weight (0.125), have a significant driving power of improving the energy efficiency of CSC. The results show that improving the driving characteristics of the economic drivers is the most suitable way for energy efficiency improvement and energy consumption in CSC operations. The figure 3 shows the summary of the significance weights of the core category of drivers. Figure 4a, 4b, and 4c demonstrate the significance weights of economic, knowledge and motivation-based, and organizational and managerial drivers, respectively.

From the analysis (figure 4a, figure 4b, and figure 5), it has been observed that among the economic drivers, *cost saving due to reduced energy consumption* has the most influencing power (with significance weight of 0.294) for improving the energy efficiency of CSC. Results also show that *training and energy saving and its benefits to our ecosystem* might reduce the overall consumption of energy and possible hazards to the environment with significance weight of 0.049. Among driving factors of organizational and managerial drivers, *long-term energy saving plans and strategies* have the highest driving power for improving the energy efficiency of CSC with a global significance weight of 0.114.

The preference order from the PROMETHEE method is based upon the net dominating power (net flow) relative to the others. Therefore, to establish the priority through PROMETHEE method, the net flows are calculated for each solution practice, the results of which are summarized in table 8. Figure 6 has been formed to provide graphical visualization of the results of the PROMETHEE method.

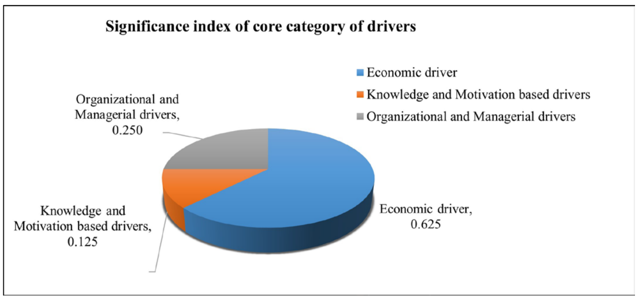

Figure 3: Significance index of the core category of drivers.

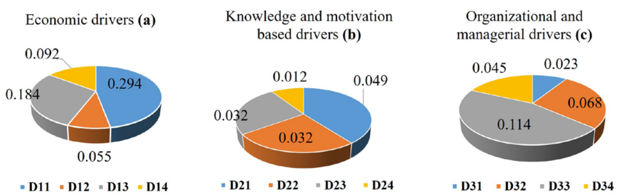

Figure 4: Significance weights for economic drivers, **(b)** for knowledge and motivation-based drivers, and **(c)** for organizational and managerial drivers.

From table 8 and figure 6, it has been observed that among the six proposed solution practices, P5 (*adoption of energy-efficient refrigeration technologies*) obtained the highest net flow value and therefore is the most effective practice to reduce the energy consumption in CSC operations. The adoption of technologies such as tri-generation technology in integration with solar energy applications might be an example of such type of refrigeration technology [32 - 34]. The results also demonstrate that *implementation of energy saving strategies and plans* appeared as the second most effective solution practice that might be considered as second preference priority for reducing the energy consumption in CSCs. The other solution practices P1 (organization of load capacity (minimizing overheating or overcooling)), P2 (proper maintenance of refrigeration equipment), P4 (reducing transportation distance and exposure time), and P6 (proper training and education of the employees for energy saving) are formed their preference priorities as five, four, six, and three, respectively.

Conclusion

The aim of the study was to explore and analyze the most significant drivers for energy efficiency improvement in CSC. In addition, it was also targeted to propose the most effective solution practices for reducing energy consumption with improved energy efficiency of CSC. To achieve the objective, twelve key drivers of improving energy efficiency and six most effective solution practices were explored and modeled into a hierarchical framework as shown in figure 1. The assessment of structured framework was performed using an integrative approach based on BWM and PROMETHEE methods. The BWM was used to form the significance weights of the driving factors and the PROMETHEE method was used to establish the priorities of the proposed solution practices. The key findings of the research reveals that the economic drivers *cost saving due to reduced energy consumption* and *exemption from possible penalties and punishments due to higher GHG emissions* are the two most significant drivers for adding the energy efficiency in CSC. The third most effective driver *long-term energy saving plans and strategies* comes from the organizational and managerial category of drivers. The findings also demonstrate that among the six proposed solution practices, *adoption of energy-efficient refrigeration technologies* and *implementation of energy saving strategies and plans* are the two most significant discoveries of the research which might be adopted to add the driving power of the factors for improving the energy efficiency of CSC. Findings demonstrate that to improve energy efficiency, the management must focus on developing long-term strategies and plans of energy saving. In addition, the management should adopt advanced refrigeration technologies which are energy efficient and produce minimum environmental effect of their emissions

Managerial Implications and Future Avenues

From the implication sides, the research work forms wide theoretical and managerial implications. On one side, by enriching the literature content in the subject domain, it broadens the knowledge domain of the researchers and practitioners, on the other side, by providing the practical application evidence of the proposed MCDM methods (BWM and PROMETHEE) it supports their adoption for the solution of MCDM problems of weight and priority determination. As far as the managerial implications side, it helps the management to explore the most significant driving factors for improving the energy efficiency of CSC. The key discoveries of the work (proposed solution practices) might help the management to take decisions for developing strategies for reducing the energy consumption in their CSC operations.

From the future scope perspectives, the interested researchers might extend the analysis considering the uncertainty and vagueness in the decision making. In addition, the results of the study can also be validated gathering the data from the other geographical regions of the world other than India.

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None.

Conflict of Interest

The authors declare no competing interests that are relevant to the content of this article.

Credit Author Statement

Neeraj Kumar: Conceptualization, Methodology, Resources, Formal analysis, Investigation, Writing - original draft preparation, Writing - review and editing; Mohit Tyagi: Writing - original draft preparation, Writing - review and editing, Supervision; Anish Sachdeva: Writing - review and editing, Supervision; Manish Gupta: Writing - review and editing. All the authors read and approved the manuscript.

References

1. Adekomaya O, Jamiru T, Sadiku R, Huan Z. 2016. Sustaining the shelf life of fresh food in cold chain–a burden on the environment. Alexandria Eng J 55(2): 1359-1365. https://doi.org/10.1016/j.aej.2016.03.024
2. Khan AU, Ali Y. 2021. Sustainable supplier selection for the cold supply chain (CSC) in the context of a developing country. Environ Dev Sustain 23: 13135–13164. https://doi.org/10.1007/s10668-020-01203-0
3. Zhao H, Liu S, Tian C, Yan G, Wang D. 2018. An overview of current status of cold chain in China. Int J Refrig 88: 483-495. https://doi.org/10.1016/j.ijrefrig.2018.02.024
4. Vaghasiya TP, Kumar A, Nakum K. 2022. A review on wide range application of nanoparticles in agriculture and its implications in plant disease management. NanoWorld J 8(2): 55-65. https://doi.org/10.17756/nwj.2022-100
5. James SJ, James C. 2010. The food cold-chain and climate change. Food Res Int 43(7): 1944-1956. https://doi.org/10.1016/j.foodres.2010.02.001
6. Li X, Campana PE, Li H, Yan J, Zhu K. 2017. Energy storage systems for refrigerated warehouses. Energy Procedia 143: 94-99. https://doi.org/10.1016/j.egypro.2017.12.653
7. Chandran R, Hasanuzzaman M, Arıcı M, Kumar L. 2022. Energy, economic and environmental impact analysis of phase change materials for cold chain transportation in Malaysia. J Energy Storage 55: 105481. https://doi.org/10.1016/j.est.2022.105481
8. Marchi B, Bettoni L, Zanoni S. 2022. Assessment of energy efficiency measures in food cold supply chains: a dairy industry case study. Energies 15(19): 6901. https://doi.org/10.3390/en15196901
9. Meneghetti A, Monti L. 2015. Greening the food supply chain: an optimisation model for sustainable design of refrigerated automated warehouses. Int J Prod Res 53(21): 6567-6587. https://doi.org/10.1080/00207543.2014.985449
10. Coulomb D. 2008. Refrigeration and cold chain serving the global food industry and creating a better future: two key IIR challenges for improved health and environment. Trends Food Sci Technol 19(8): 413-417. https://doi.org/10.1016/j.tifs.2008.03.006
11. Kayfeci M, Keçebaş A, Gedik E. 2013. Determination of optimum insulation thickness of external walls with two different methods in cooling applications. Appl Therm Eng 50(1): 217-224. https://doi.org/10.1016/j.applthermaleng.2012.06.031
12. Neusel L, Hirzel S. 2022. Energy efficiency in cold supply chains of the food sector: an exploration of conditions and perceptions. Clean Logist Supply Chain 5: 100082. https://doi.org/10.1016/j.clscn.2022.100082
13. Calati M, Zilio C, Righetti G, Longo GA, Hooman K, et al. 2022. Latent thermal energy storage for refrigerated trucks. Int J Refrig 136: 124-133. https://doi.org/10.1016/j.ijrefrig.2022.01.018
14. Tyagi M, Kumar P, Kumar D. 2015. Analysis of interactions among the drivers of green supply chain management. Int J Bus Perform Supply Chain Model 7(1): 92-108. https://doi.org/10.1504/IJBPSCM.2015.068137
15. Kumar N, Tyagi M, Sachdeva A. 2023. A sustainable framework development and assessment for enhancing the environmental performance of cold supply chain. Manag Environ Qual 34(4): 1077-1110. https://doi.org/10.1108/MEQ-03-2022-0046
16. Agarwal S, Tyagi M, Garg RK. 2023. Conception of circular economy obstacles in context of supply chain: a case of rubber industry. Int J Product Perform Manag 72(4): 1111-1153. https://doi.org/10.1108/IJPPM-12-2020-0686
17. Kumar N, Tyagi M, Sachdeva A. 2022. Depiction of possible solutions to improve the cold supply chain performance system. J Adv Manag Res 19(1): 106-138. https://doi.org/10.1108/JAMR-10-2020-0285
18. Sharma J, Tyagi M, Bhardwaj A. 2020. Parametric review of food supply chain performance implications under different aspects. J Adv Manag Res 17(3): 421-453. https://doi.org/10.1108/JAMR-10-2019-0193
19. Estrada-Flores S. 2010. Achieving temperature control and energy efficiency in the cold chain. In Proceedings of the 1st IIR International Cold Chain Conference, Cambridge, UK.
20. Tyagi M, Kumar P, Kumar D. 2015. Analyzing CSR issues for supply chain performance system using preference rating approach. J Manuf Technol Manag 26(6): 830-852. https://doi.org/10.1108/JMTM-03-2014-0031
21. Heard BR, Miller SA. 2018. Potential changes in greenhouse gas emissions from refrigerated supply chain introduction in a developing food system. Environ Sci Technol 53(1): 251-260. https://doi.org/10.1021/acs.est.8b05322
22. Saif A, Elhedhli S. 2016. Cold supply chain design with environmental considerations: a simulation-optimization approach. Eur J Oper Res 251(1): 274-287. https://doi.org/10.1016/j.ejor.2015.10.056 .
23. Gopal N, Panchal D. 2021. A structured framework for reliability and risk evaluation in the milk process industry under fuzzy environment. Facta Univ Ser Mech Eng 19(2): 307-333. https://doi.org/10.22190/FUME201123004G
24. Leng L, Zhang J, Zhang C, Zhao Y, Wang W, et al. 2020. Decomposition-based hyperheuristic approaches for the bi-objective cold chain considering environmental effects. Comput Oper Res 123: 105043. https://doi.org/10.1016/j.cor.2020.105043

25. Syam MM, Cabrera-Calderon S, Vijayan KA, Balaji V, Phelan PE, et al. 2022. Mini containers to improve the cold chain energy efficiency and carbon footprint. Climate 10(5): 76. https://doi.org/10.3390/cli10050076
26. Liu Z, Guo H, Zhao Y, Hu B, Shi L, et al. 2021. Research on the optimized route of cold chain logistics transportation of fresh products in context of energy-saving and emission reduction. Math Biosci Eng 18(2): 1926-1940.
27. Rezaei J. 2015. Best-worst multi-criteria decision-making method. Omega 53: 49-57. https://doi.org/10.1016/j.omega.2014.11.009
28. Rezaei J, Wang J, Tavasszy L. 2015. Linking supplier development to supplier segmentation using Best Worst Method. Expert Syst Appl 42(23): 9152-9164. https://doi.org/10.1016/j.eswa.2015.07.073
29. Kumar N, Tyagi M, Sachdeva A. 2022. Estimation of best possible solutions for environmental trade-offs in cold supply chain using BWM based ELECTRE-I approach. Int J Six Sigma Compet Advant 14(1): 152-169. https://doi.org/10.1504/IJSSCA.2022.124296
30. Brans JP, De Smet Y. 2016. PROMETHEE Methods. In Greco S, Ehrgott M, Figueira J (eds) Multiple Criteria Decision Analysis. International Series in Operations Research & Management Science. Springer, New York, pp 187-219.
31. Kumar N, Tyagi M, Sachdeva A. 2022. Risk Factor Appraisal in Cold Supply Chain Performance System Through Delphi based Hybrid MCDM Approach. In Panchal D, Tyagi M, Sachdeva A, Pamucar D (eds) Optimization of Industrial Systems. Scrivener Publishing, pp 31-44.
32. Ghorbani B, Mehrpooya M. 2020. Concentrated solar energy system and cold thermal energy storage (process development and energy analysis). Sustain Energy Technol Assess 37: 100607. https://doi.org/10.1016/j.seta.2019.100607
33. Dabwan YN, Pei G, Gao G, Feng J, Li J. 2020. A novel integrated solar tri-generation system for cooling, freshwater and electricity production purpose: energy, economic and environmental performance analysis. Sol Energy 198: 139-150. https://doi.org/10.1016/j.solener.2020.01.043
34. Du W, Li M, Wang Y, Ma X, Hu C, et al. 2021. Dynamic energy efficiency characteristics analysis of a distributed solar photovoltaic direct-drive solar cold storage. Build Environ 206: 108324. https://doi.org/10.1016/j.buildenv.2021.108324