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RESEARCH ARTICLE

# An Improved MCDM Model to Support Smart Energy Management System in Smart Grid Paradigm

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**ABSTRACT** Smart grid development is required to accommodate the integration of renewable generation resources into systems. Energy management is improved by smart devices that allow two-way communication. A multi-criteria decision analysis framework is used in this study to provide a model for decision making. Prior to communicating with the energy market aggregator, it considers the human-oriented viewpoint to offer an interface with a smart device within smart grid system. In this research, the proposed framework is utilized for decision-making optimization based on six criteria, evaluated using three multi-criteria decision-making techniques. To assess criteria, a thorough investigation has been undertaken across five load classes aiming at demand side management (DSM) options from high load class to lowest load class and concerned load-generation balance. The findings of this research make it convenient for the framework that communicates the actual results of the energy system and the energy markets aggregator for an energy management plan. The findings of this study support the development of a framework that effectively communicates the actual performance of the energy system and the energy markets aggregator for an energy management plan. The results have been evaluated using sensitivity analysis across five DSM options, and trade-off studies have been conducted to support effective decision-making in practice. Finally, this research offers a cost-effective, clean, and efficient system configuration aimed at consumer preferences.

**INDEX TERMS** Demand side management, energy management system, multi-criteria decision-making (MCDM), preference ranking organization method for enrichment of evaluations (PROMETHEE), smart grid, technique for order of preference by similarity to ideal solution.

## I. INTRODUCTION

Renewable energy sources (RESs) use is increasing exponentially across the globe. Many nations use RES technologies to serve a range of goals, including energy security, the diversification of economies and energy sources, meeting rising demand, and promoting social and environmental welfare [1]. The reliability and stability of electric networks are put at risk by the intermittent characteristics of some RES i.e., PV and wind generation [2]. In comparison to conventional counterparts like hydropower, there is also a lack of controllability over the generation [3]. The concept of Demand side management (DSM) is used in the literature to explain this enhancement on the user side [4]. A

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higher integration of intermittent RESs, while maintaining voltage stability, can be enabled through a gradual shift from heavy reliance on load following toward enhanced generation-following strategies [5]. DSM programs have considerable potential subjected to their reliance on consumer behavior and can only be successful considering consumer incentives [6].

## II. LITERATURE REVIEW

Smart grid offers modernization to deliver a compact solution under many conflicting criteria, that encompasses several factors that call for decision-making tools and approaches, across several criteria that belong to different genres [7], [8]. The geographic increase of the new mechanism necessitates consideration of environmentally benevolent and socially suitable solutions in addition to technological and financial considerations. To create a win-win situation, the quantity of potential solutions (alternatives) must be assessed across multiple criteria [9]. Such approaches have been utilized to achieve home energy management allowing consideration of consumer preferences along with dynamic pricing, aimed at improving demand side management (DSM) across distribution side of the grid [10]. Rather than increasing power generation, congestion management systems for dynamic pricing programs along with demand response (DR) solutions, require decision making under competing criteria [11].

Several research propose an interesting idea that focuses on smart homes for a smart grid, by interacting with their surroundings rather than serving as passive system components, proactive clients can negotiate and collaborate in an intelligent network [12]. An information and communication technology (ICT) architecture has suggested accomplishing the aims of the smart home, smart building, and smart grid [13]. The methodical review in [14] offers an in-depth discussion regarding the importance of meteorological data, load profiles, component modelling, and cost and reliability factors in size optimization. Different methods for size optimization, such as analytical, iterative, and artificial intelligence approaches. Notably, computational costs have been reduced, and optimal global solutions were obtained using artificial intelligence approaches including genetic algorithm (GA), particle swarm optimization (PSO), and ant colony optimization (ACO). The work in [15] offers insights into several important areas, including the system configuration, future prospects, improvements to improve their utilization, and economic feasibility. The paper also covers methods for creating efficient storage systems. Additionally, it provides a succinct overview of improvements made in cost analysis methods, reliability indices, and optimization strategies specifically for hybrid renewable energy systems.

The work in [16] focuses on the application of DSM schemes in distributed generation system development and building energy management (BEM). The study highlights that DSM strategies, primarily implemented through utility-initiated demand response (DR) programs, are geared towards real estate sectors encompassing residential, commercial, institutional, and industrial buildings. It emphasizes the economic implications of power generation curtailments and argues that the disposal of excess energy is not as cost-effective as it may seem, as it incurs additional costs and power losses. The paper [17] presents a metric system based on multiple criteria decision analysis (MCDA) to quantitatively measure Building Information Modeling (BIM) effects in BEM, specifically for existing housing. The key performance indicators (KPIs) is used to evaluate the optimization aspects of cost and interoperability, for prioritizing optimization aspects during BIM implementation. The study in [18] employs a model-based MCDA framework that aids in choosing the very efficient measures for sustainable growth depending on their macroeconomic, environmental, and social consequences. The hybrid PROMETHEE and SIMOS methods emphasize the importance of prioritizing the efficiency pillar to further decarbonize the energy system while maximizing health benefits, quality of life, resilience, and competitiveness.

The study in [19] offers an innovative method for integrating technological, economical, and environmental aspects into energy planning. The goal is to find the best system configuration among several off-grid power supply system alternatives using universal priority criteria. This strategy combines multi-criteria decision analysis based on the Analytical Hierarchy Approach (AHP) with system optimization to develop a planning strategy for off-grid power supply systems. The study in [20] aims to offer a model that maximizes the use of locally accessible RESs while minimizing electricity prices and reducing the probability of load loss. The C-DEEPSO technique is used for optimization, and the AHP-TOPSIS model then makes use of the resulting data. The AHP-TOPSIS model evaluates and identifies the best alternative by using expert weights. The paper in [21] presents MCDA model to enhance the energy efficiency of public buildings. The suggested model incorporates energy efficiency, financial viability, and environment preservation requirements. By employing the ELECTRE approach, the model effectively categorizes energy retrofitting actions based on their overall performance. By categorizing energy retrofitting activities, decision-makers can prioritize and allocate financial resources accordingly.

TOPSIS framework considers six distinct energy resources have employed in order to develop low-carbon energy solutions for residential buildings [22]. This framework utilizes various engineering tools, including residential building energy analysis, renewable energy analysis, MCDA techniques, and cost-benefit analysis, to provide valuable insights. The proposed model in [23] combines the identification, definition, and evaluation of decision criteria and utilizes MCDA framework. A case study involving the use of an intelligent decision system demonstrates how the evidential reasoning approach is used to aggregate evaluation information. Sensitivity and trade-off studies have been useful in aiding decision-making procedures in practice. The application of an analytic hierarchy process (AHP) analysis is used in [24] encapsulating key ecosystem stakeholders to identify major challenges and formulate policies to foster an effective BEMS industry ecosystem. The survey assesses elements of the ecosystem including economic, institutional, technological, and social systems, assigning weights to each element in decreasing order.

The work in [25] incorporates social, environmental, and economic criteria into decision-making models for energy projects. It acknowledges the limitations of cost-benefit and life cycle cost analyses in capturing complex social impacts and expressing them in monetary terms. To address these limitations, the study emphasizes the use of MCDA as a family of decision-making protocols that evaluate and prioritize multi-objective problems. The research highlights the advantages of MCDA approaches over traditional cost-benefit analyses in the context of sustainable energy planning and decision-making. The research in [26] introduces a DSM approach to an institutional building, integrating the concept of user satisfaction. Fuzzy-AHP and Fuzzy-TOPSIS models are utilized to select the best configuration. The research offers a cost-effective, clean, and reliable energy configuration with sensitivity analysis. An approach is presented in [27] for evaluating sustainable energy consumption in the industrial sector of selected European countries, study employs four MCDA methods (TOPSIS, VIKOR, COMET, and PROMETHEE II) to assess energy consumption sustainability based on criteria. Optimal energy source arrangement among the six options is evaluated using TOPSIS approach [28]. Five criteria are modelled and computed using a historical demand side dataset. To build a comprehensive dataset, the TOPSIS approach is used, and outcomes are integrated with demand side data.

The MCDA framework in [29] is based on personal preferences and sustainability criteria, where the scenarios are scored and evaluated. MCDA platform incorporates life-cycle assessment, energy and economic modules, and multi-criteria decision analysis. It empowers decision-makers to gain a thorough understanding of the technical, environmental, economic, and social dimensions associated with decarbonizing energy systems. The study in [30] proposes a method for assisting investment decisions regarding smart shading devices in office buildings. The approach combines PROMETHEE-II with EnergyPlus, enabling the examination of smart building aspects, considering criteria encompassing energy, finance, environment, and occupants' well-being. The analysis reveals that although smarter options may come at a higher cost, the increased comfort and energy savings they provide compensate for the additional expenditure. The paper in [31] presents a systematic literature review focused on passive strategies for optimizing energy consumption in buildings. The review employs multiple criteria decision-making techniques to identify the most suitable passive strategies and the relevant criteria for their selection.

The study in [32] employs a MCDA framework for determining the best mix of energy efficiency and indoor air quality strategies. The framework considers criteria such as educational attainment, health, energy performance, and costs. By comparing various combinations of energy retrofit and indoor environment quality schemes, the MCDA results provide insights into the trade-offs between energy efficiency and indoor environmental quality while reducing carbon emissions. The article in [33] analyzes and compares various options for renewable electricity storage, ranging from small batteries to large-scale storage systems, utilizing MCDA and TOPSIS. The solution is evaluated considering nine criteria, including investment requirements, power density, efficiency, and duration of operation. The study in [34] explores the application of GIS technology, including machine learning, deep learning, and multiple criteria decision analysis, to estimate the energy-saving potential and investment energy value of photovoltaic systems. The research in [35] proposes a system dynamics approach for evaluating the techno-economic, environmental, and social indicators associated with sustainable power systems where MCDA methods are employed to assess the sustainability of different scenarios and policies. Research effort in [36] presents a sustainability framework for benchmarking the life cycle performance on environmental axis across modular buildings. The framework aims to develop sustainability index and benchmarks based on residential buildings. A TOPSIS based model in [37] is presented to support smart appliances such as dish washer is presented across six criteria across decision energy management in smart grid paradigm.

Besides the above literature, recent literature (2023-2025) has increasingly concentrated on the use of multi-criteria decision-making (MCDM) and multi-objective optimization techniques for demand-side management (DSM), with a special emphasis on including both consumer preferences and generation characteristics. Uzair and Kazmi [38] used traditional MCDM methods such as TOPSIS and multi-criteria evaluation (MCE) to optimize building energy management by balancing generation and load based on parameters such as energy efficiency, cost savings, and interior comfort. Zabala et al. [39] suggested an agent-based optimizer for DSM in energy communities that schedules appliance and EV charging depending on user preferences and availability, thereby optimizing PV self-consumption. Similarly, Rollo et al. [40] simulated different load-shifting solutions in renewable energy communities and assessed their influence on economic efficiency, social cohesion, and environmental sustainability.

Elavarasan et al. [26] used fuzzy AHP and fuzzy TOPSIS to integrate technical, economic, and social parameters for DSM in institutional buildings while stressing user happiness. AHP, fuzzy AHP, TOPSIS, fuzzy TOPSIS, ELECTRE, PROMETHEE, and MCE are examples of popular MCDM techniques used in these investigations. The researchers in [41] reviewed and emphasized the importance of power system flexibility in incorporating renewable energy sources such as wind and solar into the grid. Because these resources vary, innovative solutions are required to maintain grid stability and reliability. Energy storage devices, demand response programs, grid expansion, enhanced forecasting techniques, and variable generation sources were among the key options proposed. The fuzzy MCDM is used in [42] for selection of biomass resources considering various objective weights across four alternatives.

In this paper, bridging the limitations left in the literature serves as the very novel aspects. The additional costs with high power usage and use of application of DSM strategies to reduce the load equating the optimal generation is one aspect of this study. To propose a model that maximizes the use of locally accessible renewable energy sources while minimizing electricity prices and reducing user discomfort. To entitle the consumers with the optimal solutions across contradicting criteria that might negatively affect traditional market conditions. To allow decision-makers as per prioritization and allocation of available resources accordingly. This study offers use of MCDA protocols for decision-making considering MCE, TOPSIS and PROMETHEE as hybrid scheduling problem, which evaluates and prioritize multi-criteria problems across various load classes and finding out a tradeoff solution amongst the conflicting criteria. The results have been evaluated with sensitivity analysis and trade-off studies have been carried out usefulness in aiding effective decision-making procedures.

The paper has been arranged as follows. Literature review has presented in section II. Methodology is illustrated in section III. Section-IV includes MCDA techniques used in hybrid scheduling problems. Section-V encapsulates test setup. The results and simulations are shown in section VI. The paper is concluded in section VII.

## III. METHODOLOGY

The methodology is illustrated in Fig 1. This study's technique is designed to address qualitative intuitive client inputs and transfer them so that the aggregator algorithm can deal with them in an organized and quantitative manner. In a hybrid model, three MCDM techniques were used. Projects involving energy planning are complex and involve a variety of stakeholders, necessitating the use of many objective functions. The steps of the applied methodology are as follows:

1. To define decision criteria and customer alternatives, data must first be collected. The granular load classification and service prioritization across classes is such that it varies from critical Class 1 (C1) down to highly flexible Class (C5) loads. The four seasonal variations are considered with respective load curves.
2. There are five classes considered in the methodology according to consumer options with DSM that includes,

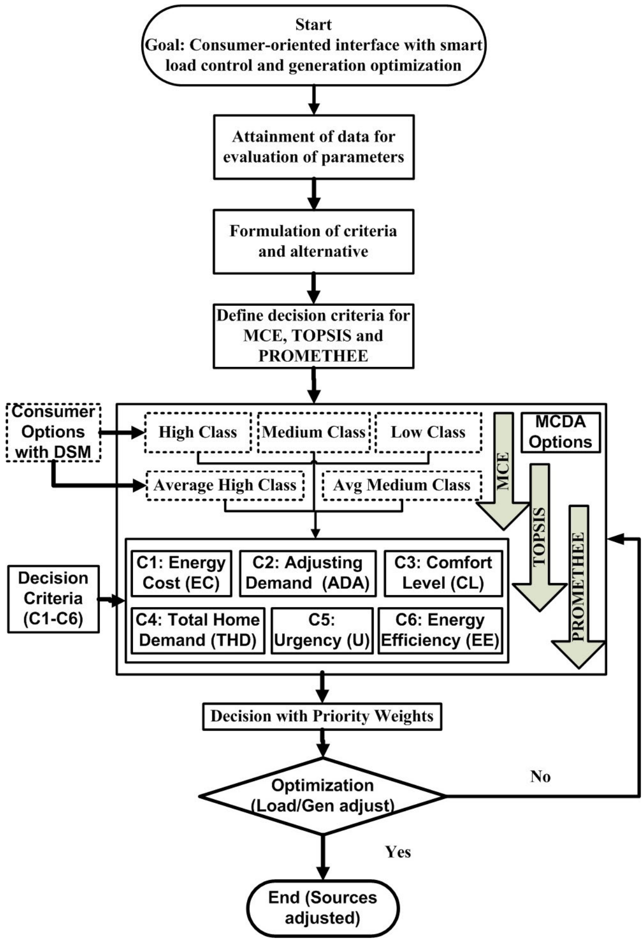


**FIGURE 1. Flowchart of the proposed approach.**

high, average high, medium, average medium and low classes as per load and generation balance, respectively. However, to keep the discussion pertinent and to the point, only high, medium, and low load classes will be discussed in detail.

3. There are six decision criteria, across which, all the evaluations are carried out:

$$\mathrm{C1} = \text{Energy cost (EC)} = \text{To Decrease } (-\mathrm{ve})$$
$$\mathrm{C2} = \text{Adjusting (load) demand(ALD)} = \text{To Increase } (+\mathrm{ve})$$
$$\mathrm{C3} = \text{Comfortlevel(CL) of consumer} = \text{To Increase } (+\mathrm{ve})$$
$$\mathrm{C4} = \text{Total home/building demand (THD)}$$
$$= \text{To Decrease } (+\mathrm{ve})$$
$$\mathrm{C5} = \text{Urgency(U)} = \text{To Decrease } (-\mathrm{ve})$$
$$\mathrm{C6} = \text{Energy Efficiency(EE)} = \text{ToIncrease } (+\mathrm{ve})$$

4. It is assumed that the real-time data integration and forecasting is provided, where smart meters and IoT Sensors can provide sub-hourly measurements of home/building demand (THD), comfort indices (e.g., temperature, etc.), and instantaneous energy costs (real-time tariffs for energy cost). The load forecasting:

Short-term predictions feed back into adjusting weights $w_i$, for example, if a cold front is forecast, urgency (C5) and comfort (C3) weights rise preemptively.

- High-criticality classes see minimal THD (C4 ↓) and Urgency (C5 ↓) at the expense of peak Energy Cost (C1).
- Low-criticality classes allow more aggressive load adjustments (C2 ↑) to reduce overall cost (C1 ↓) and improve Efficiency (C6 ↑).

5. The effect on six criteria C1–C6 is as follows:
   - **Energy Cost (C1↓):** Shifting flexible loads (C2 ↑) to low-tariff periods and peak shaving via automated DR events.
   - **Adjusting Demand (C2↑):** Provided real-time signaling and automated control of thermostats, EV chargers, and appliances.
   - **Consumer Comfort (C3↑):** Minimum comfort thresholds encoded as constraints—no DSM event can breach a user's comfort band.
   - **Total Home/Building Demand (C4↓):** Coordinated load shedding and peak clipping across classes reduces peak draw without violating comfort or urgency constraints.
   - **Urgency (C5↓):** Critical loads flagged with low urgency weights are never deferred; less urgent tasks (e.g., dryer cycles) can be postponed.
   - **Energy Efficiency (C6↑):** Continuous monitoring of device efficiency and preferring modes (e.g., heat-pump low-rate operation) that maximize output per kWh.
6. To prioritize and optimize the best solutions in light of consumer restrictions, MCE, TOPSIS and PROMETHEE are used. Cross-validation is conducted via multiple MCDM techniques, where all score DSM options against C1–C6. It will result in collaborative decision: Final action chosen through majority ranking or a weighted consensus of the three methods, ensuring robustness against any one method's bias.
7. For the load-generation scheduling algorithms, the framework's output provides a foundation. Where the weights are either objective or they are equal weights.
8. This model can be employed for various consumer needs and equipment across system optimization and their contribution towards grid operations.
9. The proposed model can-be scalable and adaptable across following dimensions and will be explored in detail in future studies.

Each aggregation node (e.g., building energy manager) runs the MCDM engine locally on its fleet of devices, passing only summarized flexibility bids and aggregated demand to the grid operator. This feature aims at decentralized execution.

Grid-level controller reconciles bids by selecting those that best improve system-wide C1 (minimized cost), C4 (flattened demand), and C6 (maximized efficiency), while respecting local priorities on C2, C3, and C5. This feature refers to hierarchical coordination. By considering these six criteria into a dynamic, class-aware, and cross-validated MCDM framework, supported by real-time data and decentralized coordination, the proposed strategy scales to millions of heterogeneous users while ensuring each user's power supply needs and preferences are met subjected to high computation power, by incorporating this feature C1–C6 to be met across thousands of users.

## IV. MULTI-CRITERIA DECISION TECHNIQUES

### A. MULTI-CRITERIA EVALUATION (MCE)

The technique has application for calculating rank of the best among multiple solutions like m alternatives evaluated across n criteria, with highest score and other solutions are ranked as per following scores. where $i = 1, 2, \ldots m$, $S_{MCE}$ shows the score for weighted sum, $s_{ij}$ is the normalized score of i$^{th}$ alternative/solution from the reference of j$^{th}$ criterion, and $w_j$ is the weight associated with j$^{th}$ criterion.

$$S_{MCE} = \sum_{i=1}^{m} s_{ij} w_j \tag{1}$$

where, $\sum_{C=1}^{C=6} w_j$ are the weights across six criterion and sum of all weights is equal to 1.

$$\sum_{C=1}^{C=6} w_j = w_{EC} + w_{ALD} + w_{CL} + w_{THD} + w_U + w_{EE} = 1 \tag{2}$$

### B. TECHNIQUE FOR ORDER PREFERENCE BY SIMILARITY TO IDEAL SOLUTION (TOPSIS)

It is based on determining the optimum option given all potential tradeoffs. It depends on increasing advantages and choosing the greatest options as those that are the furthest from the least acceptable ones, also referred to as the negative ideal solutions. Developed normalized decision matrix follows definition of $i = 1, ..n$ criteria ($c_{ij}$) and $j = 1, ..m$ choices ($A_j$).

$$n_{ij} = \frac{c_{ij}}{\sqrt{\sum_{j=1}^{m} c_{ij}^2}} \tag{3}$$

Normalized weighted values $T_{ij}$ in the decision matrix is then calculated.

$$T_{ij} = n_{ij} w_j \tag{4}$$

Positive ideal $A^+$ and negative ideal solution $A^-$ are then derived, where $I'$ and $I''$ are related to benefit and cost criteria (positive and negative variables).

$$\begin{aligned} A^+ &= \{T_1^+, \ldots, T_1^+\} = \{(MAX_j T_{ij} | i \in I'), (MIN_j T_{ij} | i \in I'')\} \\ A^- &= \{T_1^-, \ldots, T_1^-\} = \{(MIN_j T_{ij} | i \in I'), (MAX_j T_{ij} | i \in I'')\} \end{aligned} \tag{5}$$

From n-dimensional Euclidean distance, $D_j^+$ and $D_j^-$ are calculated as separation of every alternative from the positive/negative ideal solutions.

$$D_j^+ = \sqrt{\sum\nolimits_{i=1}^{n} \left(Tij - T_i^+\right)^2}\,; D_j^- = \sqrt{\sum\nolimits_{i=1}^{n} (Tij - T_i^-)^2} \tag{6}$$

Relative closeness $C_j$ to ideal solution of each alternative is calculated, where $C_j = 1$ is positive ideal solution and $C_j = 0$ is negative ideal solution, larger index shows better performance and closeness to the ideal solution, as the optimal solution.

$$C_j = \frac{D_j^-}{(D_j^+ + D_j^-)} \tag{7}$$

### C. PREFERENCE RANKING ORGANIZATION METHOD FOR ENRICHMENT OF EVALUATIONS (PROMETHEE)

The method has designated as follows.

Step 1: Decision matrix has to be normalized:

$$P_{ij} = \left\{R_{ij} - \min\left(R_{ij}\right)\right\} / \{\max(R_{ij}) - \min\left(R_{ij}\right) \quad (i = 1, 2, \ldots, n, j = 1, 2, \ldots, m) \tag{8}$$

where $R_{ij}$ is routine performance quantity of $i^{th}$ alternative with $j^{th}$ criterion. The non-beneficial criteria, Equation (19) is shown as follows:

$$P_{ij} = \left\{max(R_{ij}) - \left(R_{ij}\right)\right\} / \{\max(R_{ij}) - \min\left(R_{ij}\right) \tag{9}$$

Step 2: Calculate the differences of $i^{th}$ alternative from other alternatives pairwise.

Step 3: Calculate the preference function, $T_j\left(i, i'\right)$.

$$\begin{aligned} &T_j\left(i, i'\right) = 0 \; if \; P_{ij} \leq P_{i'j} \\ &T_j\left(i, i'\right) = (P_{ij} - P_{i'j}) \; if \; P_{ij} \geq P_{i'j} \end{aligned} \tag{10}$$

Step 4: Find accumulated preference function considering criteria weights ($w_j$) of $j^{th}$ criterion.

$$Pi\left(\pi\right), \left(i, i'\right) = \left[\sum_{j=1}^{m} w_j T_j\left(i, i'\right)\right] / \sum_{j=1}^{m} w_j \tag{11}$$

Step 5: Find leaving (or positive) / entering (or negative) outranking flows for $i^{th}$ alternative.

$$Fi(\varphi)^+\left(i\right) = \frac{1}{n-1} \sum_{i'=1}^{n} Pi\left(\pi\right)\left(i, i'\right), \left(i \neq i'\right) \tag{12}$$

$$Fi(\varphi)^-\left(i\right) = \frac{1}{n-1} \sum_{i'=1}^{n} Pi\left(\pi\right)\left(i', i\right), \left(i \neq i'\right) \tag{13}$$

Step 6: Calculate net outranking flow for every alternative.

$$Fi(\varphi)\left(i\right) = Fi(\varphi)^+\left(i\right) - Fi(\varphi)^-\left(i\right) \tag{14}$$

Step 7: Find rank of alternatives that depends on values of $Fi(\varphi)\left(i\right)$. When the value of $Fi(\varphi)\left(i\right)$ is higher, the alternative is preferred in terms of the best solution.

## V. TEST SETUP

Consumer behavior has a significant impact on demand-shifting model under DSM and it is essential to incorporate consumers' needs. This model incorporates consumer preferences by providing a simple and intuitive user interface for typical users, translating their inputs into a quantitative framework that supports the development of algorithms aligned with customer needs.

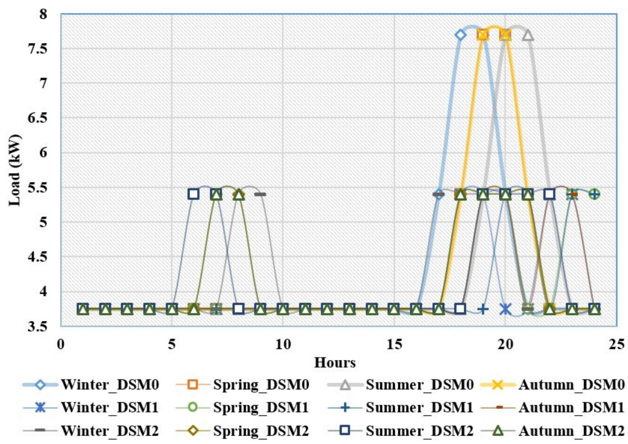


**FIGURE 2.** Load curves across seasons in a year and anticipated DSM adjustments.

For that purpose, the season variations of the load and generation needs to be incorporated because it has direct impact on consumer trends. The test setup is taken from [43], where in simulations and benchmarking, miniature scaled down version of IEEE 33 bus system is considered at 0.1 % scaling for home automation level. It must have been shown and it will be shown in author's action. The 3750 kW of complete scaled version of IEEE 33-bus test feeder (Baran and Wu) is considered at 0.1 % scaled level at 1 pf that is 3.75 kW, to provide a fully reproducible benchmark. That level is considered normal load level and medium and high load level is the scaled version of it. This scaled load gives the average house hold load. The loads have considered from U.S residential energy splits, categorizations and energy demands, as shown in Table -1 with respective classes, devices and their ratings. The test setup includes three-load levels i.e., normal load 3.75 kW, medium load 5.4 kW and high load of 7.7 kW is considered in this study. The overall load distribution varies between these three levels. The load without DSM and two variations of DSM like load shifting and valley clipping is utilized as shown in Fig. 2, along with four seasonal variations are considered with respective load curves or simply considered load profiles, as aforementioned in step-1 of the methodology. The load profile-1 is shown as DSM_0 across four seasons (winter, spring, summer and autumn). Similarly, load profile_2 and load profile_3 have designated as DSM_1 and DSM_2, respectively. The snapshot of load profiles has shown across 24 hours, as shown in figure 2.

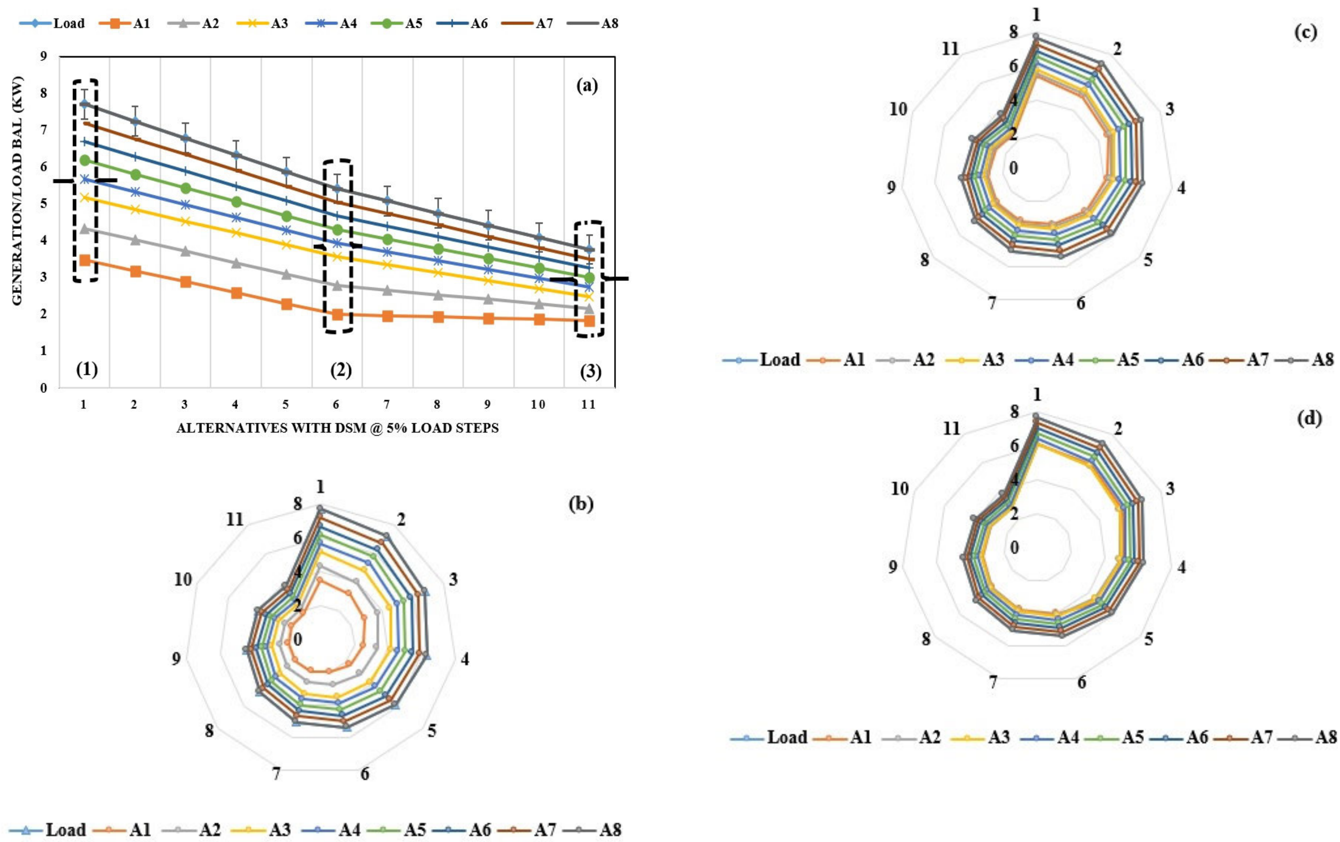

**FIGURE 3.** The alternatives across five classifications of load-generation balance, load-generation balance across (b) Low load, (c) Medium load, (d) High loa.

## VI. RESULTS AND DISCUSSIONS

The load and generation balance is shown in Fig 3(a). The load is shown in the distribution (1). Now there are two ways, either high load is balanced with high generation or load is reduced to the decreased generation. The distribution (1) also shows a high load at 7.7 kW with a step of 5% decreased till 3.75 kW. Between distributions (1) to (2), the average high load with generation via respective alternatives has been shown. Also, the distribution (2) shows reduced load till 5.4 kW that is medium load and balanced generation via each alternative. Between distributions (2) to (3), the average medium load with generation via respective alternatives has been shown. Similarly, the distribution (3) shows reduced load till 3.75 kW that is low/normal load and balanced generation via each alternative, respectively.

Firstly, (left side top to bottom in (1) of Fig 3(a)), the load is increased and generation needs to be increased i.e. load of 7.7 kW is met by generation starting from 3.47 kW in alternative A1 and completely 7.7 kW by alternative A8, as shown in Fig 3(a)-3(b). Secondly, (top left to right side of Fig 3(a)), load is decreased and generation is decreased throughout the distribution (1) till (3). Thirdly, (Right side top to bottom in (1) of Fig 3(a)), load is decreased and generation is increased. Fourthly, (bottom left to right side of Fig 3(a)), both load and generation are increase simultaneously in balanced way from low to high value throughout the distribution (3) until (1). Fig 3(c) is aimed at medium load following and medium generation for optimal solution. Likewise, Fig 3(d) is aimed at high load following and high generation for optimal solution.

It can be observed in Fig 3(b) that the load-generation margin is highest for the case of low load-generation optimization

whereas it is reduced in Fig 3(c) for medium counterpart and least in Fig 3(d) for high load-generation balance (i.e., higher loads and higher generation).

There are six criteria considered in the proposed methodology, as aforementioned in the methodology section. The methodology is initially applied across MCE as shown in Fig 4. Fig 4(a) shows the alternatives trends across five load classes. The highest standard deviation is observed across alternative A1, A2, A6 and the least across A8, A7 and A4, respectively. It can be observed in Fig 4(b) for lowest class of load, evaluation with MCE across the contradictory objectives, A8, A5 and A7 are the top alternatives. Similarly, in Fig 4(c), across medium load class, A8, A6 and A7 are the most feasible alternatives. Finally, in Fig 4(d), across high load class, A5, A8 and A6 are the feasible trade-off solutions.

**TABLE 1. U. S. Residential energy splits, categorization and energy demand.**

| Category (cat.) | CL | Energy KWh | A cat. kW | B cat. kW | C cat. kW | LL kW (MF=3) | ML kW (MF=4.32) | HL kW (MF=6.16) |
|---|---|---|---|---|---|---|---|---|
| **Lighting** | A | 2.6535 | 0.0000 | 0.1106 | 0.0000 | 0.3318 | 0.4778 | 0.6813 |
| **Refrigeration** | A | 2.7138 | 0.1131 | 0.0000 | 0.0000 | 0.3393 | 0.4886 | 0.6967 |
| **Wet Cleaning** | A | 1.7144 | 0.0714 | 0.0000 | 0.0000 | 0.2142 | 0.3084 | 0.4398 |
| **Electronics** | B | 2.1027 | 0.0000 | 0.0876 | 0.0000 | 0.2628 | 0.3784 | 0.5396 |
| **Cooking** | B | 0.7449 | 0.0000 | 0.0000 | 0.0310 | 0.093 | 0.134 | 0.190 |
| **Computers** | B | 1.3445 | 0.0000 | 0.0560 | 0.0000 | 0.168 | 0.242 | 0.345 |
| **Space Heating** | C | 2.6192 | 0.0000 | 0.1091 | 0.0000 | 0.3273 | 0.4713 | 0.672 |
| **Water Heating** | C | 2.9944 | 0.0000 | 0.0000 | 0.1248 | 0.3744 | 0.5391 | 0.769 |
| **Space Cooling** | C | 6.3427 | 0.0000 | 0.2643 | 0.0000 | 0.7929 | 1.1418 | 1.628 |
| **Others** | C | 6.7697 | 0.0940 | 0.0940 | 0.0940 | 0.846 | 1.218 | 1.737 |
| **Total** | - | 30 | 0.2785 | 0.7216 | 0.2498 | 3.75 kW 90 kWh | 5.4 kW 130 kWh | 7.7 kW 185 kWh |
| | | | Total Averaged kW = 1.25 kW | | | | | |

[a.]Note: CL: Category Load Class, LL = Low Load, ML = Medium Load; HL = High Load, MF = Multiplying Factor.

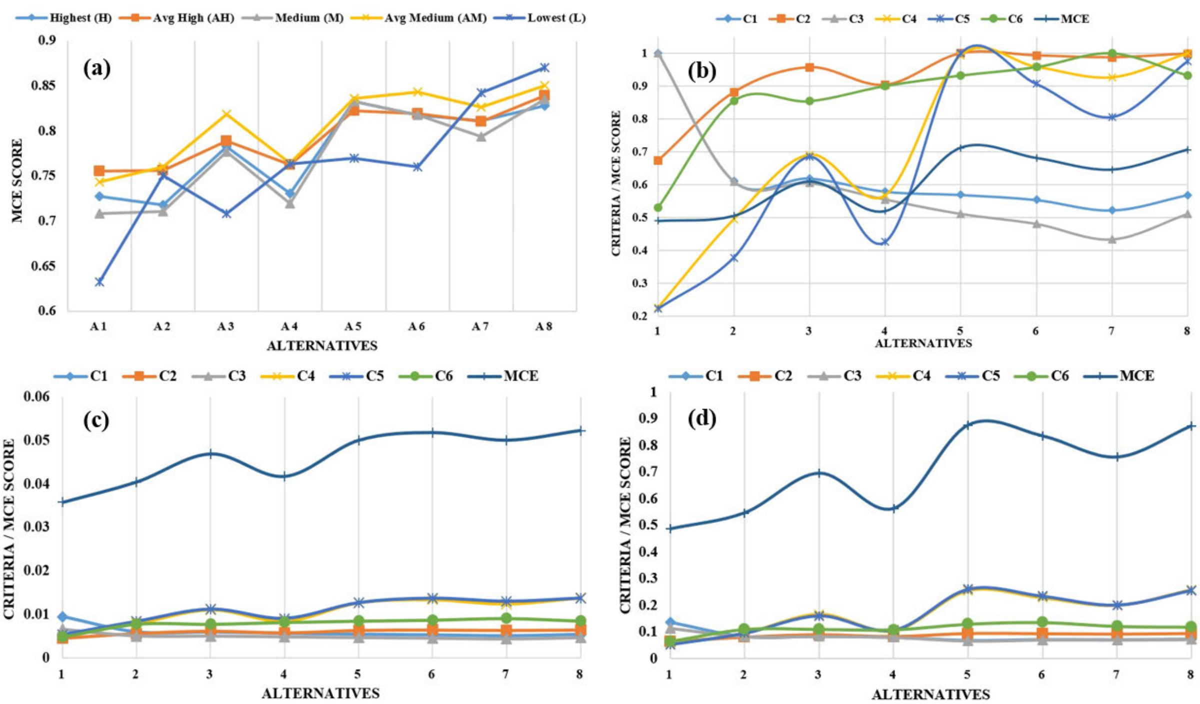


**FIGURE 4. The alternatives evaluation with MCE based analysis.**

The methodology is later applied across TOPSIS, across load classes and six criteria, as shown in Fig 5. Fig 5(a) shows alternatives trends via evaluations across five load classes. The highest value of Pi via TOPSIS evaluation is observed across alternative A8, A3 and the least across A1, in Fig 5(b) respectively. In Fig 5(c) and 5(d), for medium and high class of load, TOPSIS evaluation across conflicting objectives, results in the same feasible trade-off solutions as correlated by Fig 5(b) for lowest class of load.

Finally, methodology is evaluated with PROMETHEE, as shown in Fig 6. Fig 6(a) shows alternatives trends via evaluations across five load classes, with the highest standard deviation found across alternative A2 and A4. The leaving and entering flow with respective difference

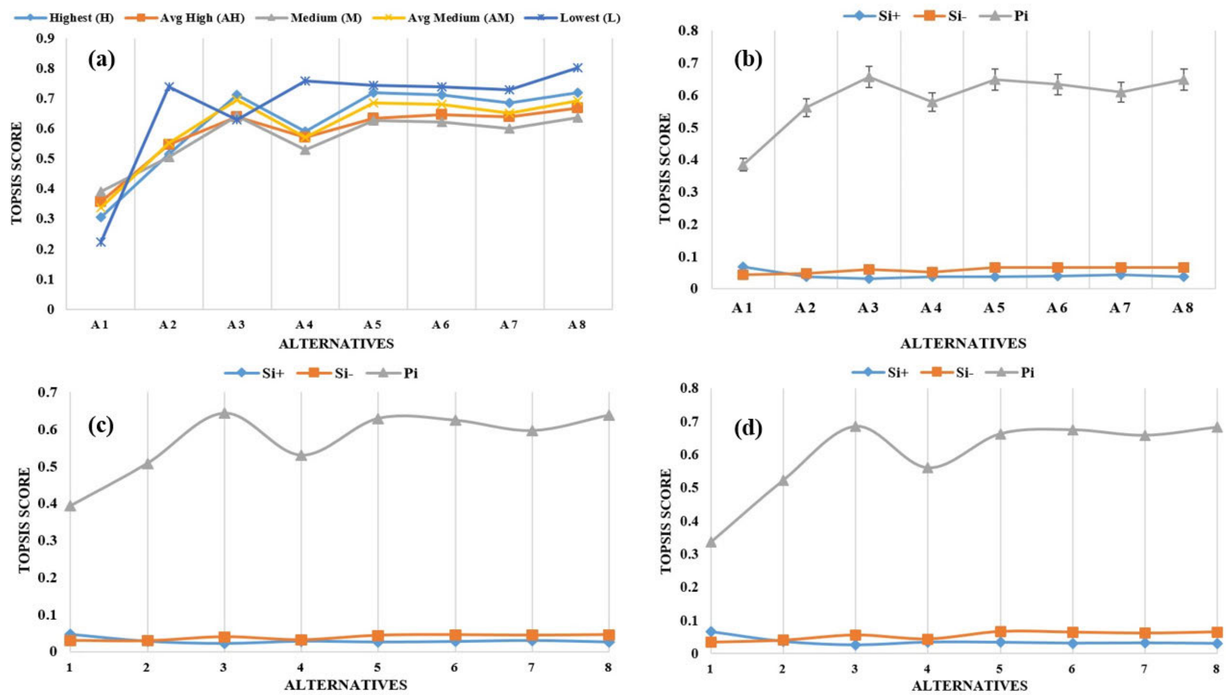


**FIGURE 5.** The alternatives evaluation with TOPSIS based analysis.

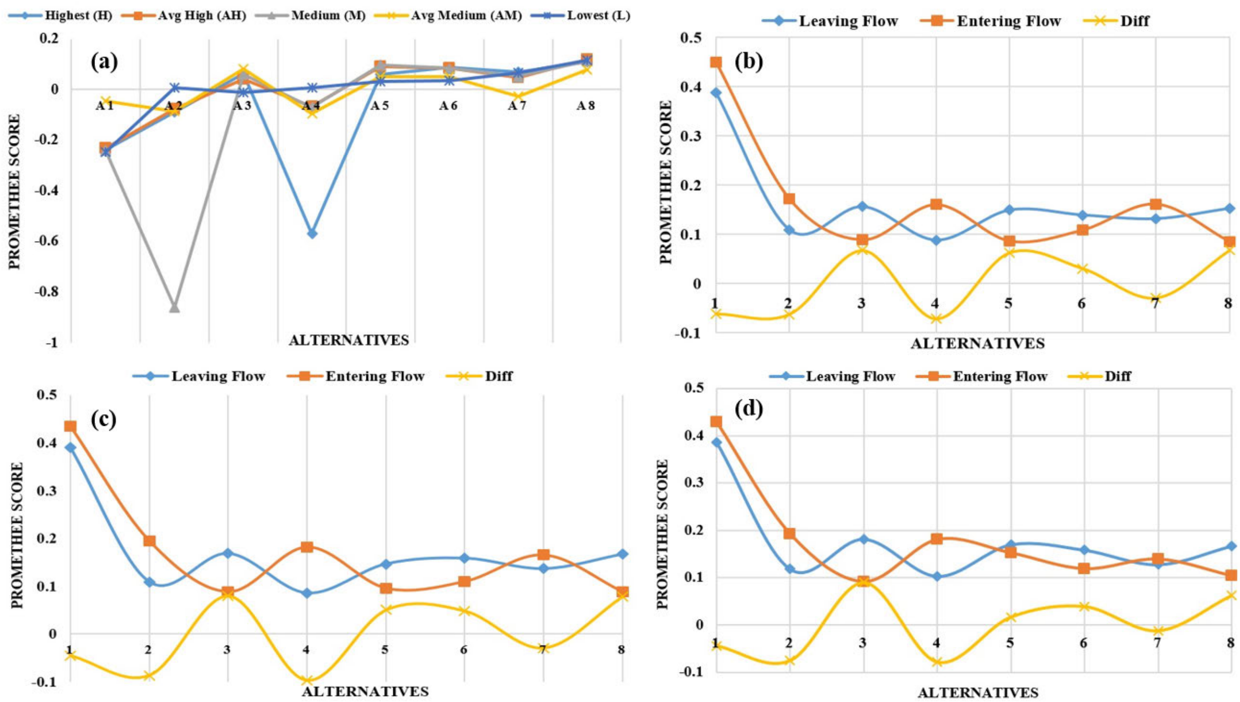


**FIGURE 6.** The alternatives evaluation with PROMETHEE based analysis.

(diff) is demonstrated across lowest load class as shown in Fig 6(b), medium load class in Fig 6(c) and highest load class across6(d), respectively. Where A8 is the optimal trade-off alternative and A1 to be the worst amongst all alternatives across lowest load class, as shown in Fig 6(b). Whereas, in medium and high load class across Figs 6(c) and 6(d) results in the A3 to be the optimal trade-off solution with A1 amongst the worst solution. The suggested model can be

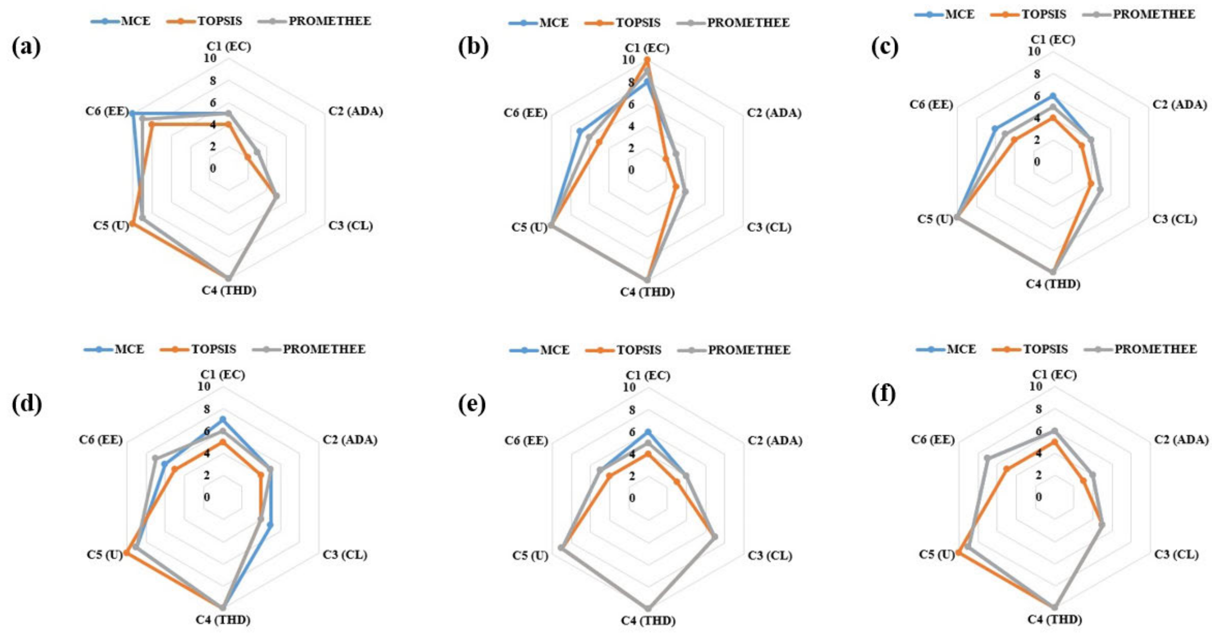


**FIGURE 7.** **Normalized weights of decision criteria for the alternatives across (a) H class; (b) AH class; (c) M class, (d) AM class, (e) Lowest class, (f) Optimal across all load classes.**

used to determine the results using the projected consumer inputs shown in Table 1. The preferences for the DSM application are measured on a Likert scale of 1 to 10, with 1 representing the least desired weight and 10 representing the most desired weight. The preferences and applications can then be modified based on the intended qualitative inputs and the system under investigation to define the algorithm requirements. The score based (MCE), separation metrics (TOPSIS and PROMETHEE) for all the load classes (High to lowest) across respective criteria as sensitivity analysis are shown in Fig-7 (a)-(f). The normalized weights of decision criteria for the alternatives across high load class is presented in Fig 7(a), AH class in Fig 7(b), medium load class in Fig 7(c), AM load class in Fig 7(d), lowest load class in Fig 7(e) and optimal load class across all classes in Fig 7(f), respectively. Moreover, the details of optimal weights are provided in Table II and Table III, respectively.

In the worst optimized load category, the option of switching on the equipment immediately has the highest rating. Because of the lack of flexibility in user preferences, this results in poor energy cost performance. As per highest to lowest load class category, Criteria C4-C5 have the highest scores. This means that the customer pays based on a high rate per kWh when the consumption of electricity peaks, which leads in high charges for the total cost of the electricity bill when the total home/building demand and urgency is coupled with highest weights to serve the consumer under smart grid paradigm. Additionally, this alternative performs poorly in locations where billing is based on highest power usage, the energy efficiency C6 is a sort of trade-off, which contributes to the high score in the negative optimum solution and decrease in C1-C3. Consequently, due to its high ratings for criteria across better trade-off alternatives receives a relatively positive score. This shows that the instant turn-on option provides the greatest level of customer convenience and streamlines the usage of equipment in critical situations.

The overall alternatives performance with MCE, TOPSIS and PROMETHEE across high load class, as sensitivity analysis are shown in Fig 8(a), AH class in Fig 8(b), medium load class in Fig 8(c), AM load class in Fig 8(d), lowest load class in Fig 8(e) and optimal load class across all classes in Fig 8(f), respectively. It can be observed from table-4 and Fig 8 (a)-(f), the alternative A5 as per MCE is the optimal trade-off solution across all load classes except A8 for the AM load class. Similarly, as per TOPSIS, solution A3 is the optimal trade-off solution across all load classes. As per PROMETHEE, A3 is the optimal solution across all classes except A8 as best solution for AH and lowest load class.

Due to its better performance in terms of energy cost, flexibility to change demand, and overall house/building demand, other alternatives rank well in the category of the best beneficial solution. The time of use (ToU) rate structure or critical peak pricing (CPP) can be more economically designed by calibrating the equipment to maximize cost reduction through the facilitation of avoiding peaks and great flexibility. The result in other alternatives to receives a poor score for both energy efficiency and comfort level. Additionally, the safety of the equipment must be carefully.

considered because repeated interruptions might affect energy efficiency, whereas alternatives result in high-energy

**TABLE 2.** Evaluation of decision criteria and alternatives weights.

| Criteria | | Alternates Weights MCE | | | | | | Alternatives Weights TOPSIS | | | | | | Alternatives Weights PROMETHEE | | | | | | +ve /-ve Att. |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | H | AH | M | AM | L | O | H | AH | M | AM | L | O | H | AH | M | AM | L | O | |
| Fig-7 | | (a) | (b) | (c) | (d) | (e) | (f) | (a) | (b) | (c) | (d) | (e) | (f) | (a) | (b) | (c) | (d) | (e) | (f) | |
| **C1** | **EC** | 5 | 8 | 6 | 7 | 6 | 6 | 4 | 10 | 4 | 5 | 4 | 5 | 5 | 9 | 5 | 6 | 5 | 7 | -ve |
| **C2** | **ALD** | 3 | 3 | 4 | 5 | 4 | 4 | 2 | 3 | 3 | 4 | 4 | 4 | 3 | 3 | 4 | 5 | 4 | 4 | +ve |
| **C3** | **CL** | 5 | 4 | 5 | 5 | 7 | 5 | 5 | 3 | 4 | 4 | 7 | 5 | 5 | 4 | 5 | 4 | 7 | 5 | +ve |
| **C4** | **THD** | 10 | 10 | 10 | 10 | 10 | 10 | 10 | 10 | 10 | 10 | 10 | 10 | 10 | 10 | 10 | 10 | 10 | 10 | -ve |
| **C5** | **U** | 9 | 10 | 10 | 9 | 9 | 9 | 10 | 10 | 10 | 10 | 9 | 10 | 9 | 10 | 10 | 9 | 9 | 9 | -ve |
| **C6** | **EE** | 10 | 7 | 6 | 6 | 5 | 7 | 8 | 5 | 4 | 5 | 4 | 6 | 9 | 6 | 5 | 7 | 5 | 6 | +ve |

b.* O= Optimal Weight; Att. = Attribute.

**TABLE 3.** Normalized optimal weights of the decision criteria in MCE, TOPSIS and PROMETHEE.

| Criteria (C1-C5) | Energycost | Adjusting demand ability | Comfort level | Total home demand | Urgency | Energy efficiency |
|---|---|---|---|---|---|---|
| **Weight (MCE)** | 6 | 4 | 5 | 10 | 9 | 7 |
| **Normalized weight MCE** | 0.15 | 0.1 | 0.12 | 0.24 | 0.22 | 0.17 |
| **Weight (TOPSIS)** | 5 | 4 | 6 | 10 | 10 | 6 |
| **Normalized weight TOPSIS** | 0.12 | 0.1 | 0.15 | 0.24 | 0.24 | 0.15 |
| **Weight (PROMETHEE)** | 6 | 4 | 5 | 10 | 9 | 7 |
| **Normalized weight PROMETHEE** | 0.15 | 0.1 | 0.12 | 0.24 | 0.22 | 0.17 |

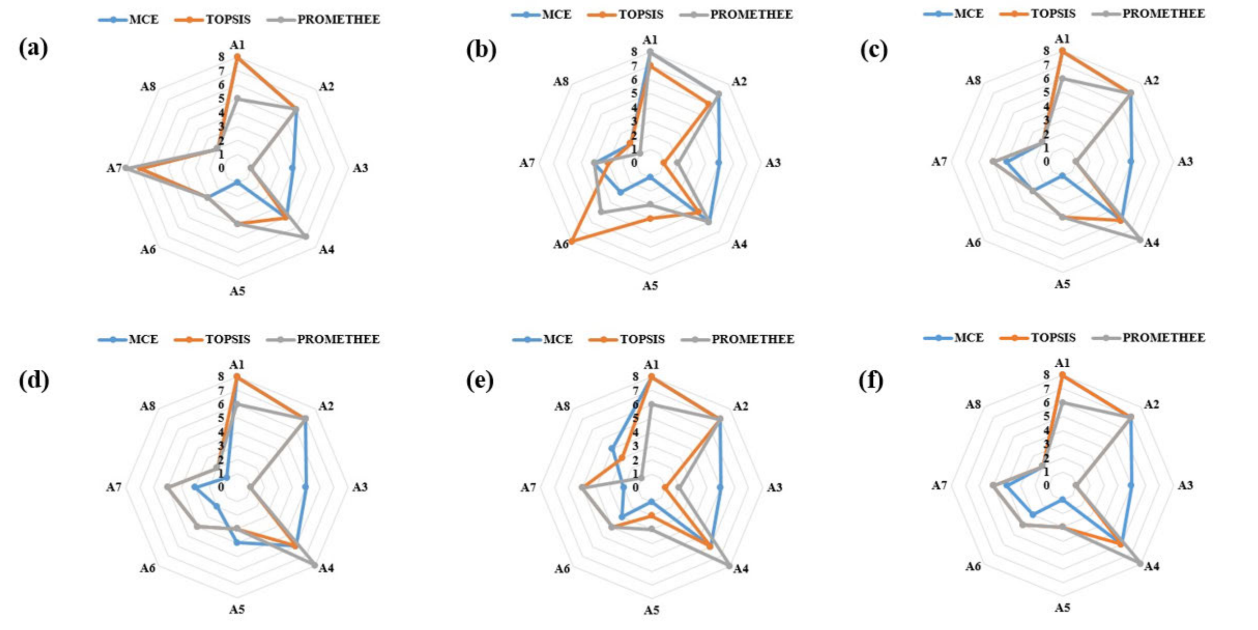


**FIGURE 8.** Overall alternatives performance in MCE, TOPSIS and PROMETHEE across (a) H clas; (b) AH clas; (c) M class, (d) AM class, (e) Lowest class, (f) Optimal across all load classes.

cost and issues in ALD with a bit compromise in comfort level of the consumer.

This demonstrates how crucial it is to consider consumers' needs. To close the gap with the top two alternatives, policymakers in the energy industry might take into account other characteristics that assist the other three-highest alternative. This will encourage consumers to allow for more flexibility. The rest of the alternatives may outperform top two alternative and come closer to the optimal option if incentives are proposed in areas like energy prices (e.g., a significant drop in off-peak usage hours) or urgency (e.g., permitting flexible and dependable equipment modifications of selection at urgent need).

It is important to remember that various consumers may have different preferences, and this could affect the results. Additionally, for every type of equipment and at various times

**TABLE 4.** Evaluation of alternatives across MCE, TOPSIS and PROMETHEE (* O = optimal weight; alt. Ranks = alternative ranks).

| Alt. Ranks | Alternates Rank MCE | | | | | | Alternatives Rank TOPSIS | | | | | | Alternatives Rank PROMETHEE | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | H | AH | M | AM | L | O | H | AH | M | AM | L | O | H | AH | M | AM | L | O |
| **Fig-8** | (a) | (b) | (c) | (d) | (e) | (f) | (a) | (b) | (c) | (d) | (e) | (f) | (a) | (b) | (c) | (d) | (e) | (f) |
| **A1** | 8 | 8 | 8 | 8 | 8 | 8 | 8 | 7 | 8 | 8 | 8 | 8 | 5 | 8 | 6 | 6 | 6 | 6 |
| **A2** | 6 | 7 | 7 | 7 | 7 | 7 | 6 | 6 | 7 | 7 | 7 | 7 | 6 | 7 | 7 | 7 | 7 | 7 |
| **A3** | 4 | 5 | 5 | 5 | 5 | 5 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 2 | 1 | 1 | 2 | 1 |
| **A4** | 5 | 6 | 6 | 6 | 6 | 6 | 5 | 5 | 6 | 6 | 6 | 6 | 7 | 6 | 8 | 8 | 8 | 8 |
| **A5** | 1 | 1 | 1 | 4 | 1 | 1 | 4 | 4 | 4 | 3 | 2 | 3 | 4 | 3 | 4 | 3 | 3 | 3 |
| **A6** | 3 | 3 | 3 | 2 | 3 | 3 | 3 | 8 | 3 | 4 | 4 | 4 | 3 | 5 | 3 | 4 | 4 | 4 |
| **A7** | 7 | 4 | 4 | 3 | 2 | 4 | 7 | 3 | 5 | 5 | 5 | 5 | 8 | 4 | 5 | 5 | 5 | 5 |
| **A8** | 2 | 2 | 2 | 1 | 4 | 2 | 2 | 2 | 2 | 2 | 3 | 2 | 2 | 1 | 2 | 2 | 1 | 2 |

of the year, the needs of the same consumers can change. The mathematical model can be used to calibrate the planned algorithms by considering all these parameter changes. In fact, a user interface that enables option modification for customers is both feasible and helpful for them in finding the balance that best suits their needs. Customers may change their choices and track how those changes affect their electricity bills.

## VII. CONCLUSION

Higher degrees of system management are needed as RESs are increasingly integrated into the distribution grid under the smart grid paradigm. End users must actively participate if the traditional electricity grid is transformed into an intelligent smart grid. Deregulated energy market incentives across various load classes are evolving under demand side management approaches. This study emphasizes the critical importance of considering consumer preferences while creating scheduling algorithms for load-generation balance with DSM across various load classes. The application of DSM strategies is utilized to raise the usage of locally accessible RESs and decrease electricity prices and reduce user discomfort. Consumer entitlement has the optimal solutions across contradicting criteria that might negatively affect traditional market conditions. The hybrid scheduling problem considering MCE, TOPSIS and PROMETHEE evaluates and prioritize multi-criteria problems across various load classes. It is suggested that customer preferences be prioritized and build an interface that aids in decision-making in the context of the deregulated energy market paradigm using a hybrid MCE, TOPSIS and PROMETHEE model. The findings show that consumer preferences can influence a general decision that favors equipment usage right away without considering real-time pricing incentives. The findings of this study make it easier to define the chances to choose between consumer preferences and reduce peak demand and electricity costs. The results have been evaluated with sensitivity analysis and trade-off studies have been carried out usefulness in aiding effective decision-making procedures. The study also offers a realistic solution to achieve while keeping the total home/building demand and urgency like conflicting criteria keeping at the highest values.

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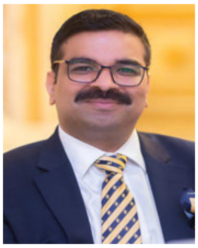

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