Multi-Criteria Decision-Making for Energy Management in Smart Homes Using Hybridized Neuro-Fuzzy Approach

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Abstract

The necessity for smart energy oversight solutions has arisen in response to the rising popularity of energy-efficient home automation and other energy-saving technologies. Optimizing smart home energy use using multi-criteria decision-making (MCDM) is a proven methodology. However, the procedure

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for making decisions and MCDM's capacity to handle various criteria are typically limiting factors. Hybrid methods, which integrate multiple decision-making approaches like Fuzzy Logic (FL) and Modular Neural Networks (MNN), could potentially be able to circumvent these restrictions and boost energy management systems' efficacy and precision. This investigation presents a hybrid Neuro-Fuzzy (H-NF) method for MCDM in regulating energy for smart homes by combining FL with an MNN. The suggested approach would optimize energy use in smart homes by considering several parameters, notably cost, ease of use, and environmental effects. In addition, this study aims to examine how the H-NF model fares in comparison to other methods of making important decisions in terms of several performance metrics. The suggested hybridized approach has the potential to deliver more precise and effective decision-making processes for energy management in smart homes, allowing users to optimize their energy consumption while preserving comfort and lowering environmental impact.

Keywords: Neural network, decision accuracy, fuzzy logic, inference, hybridization, decision-making, sustainability.

1 Introduction

Smart houses have been developed and used in response to the rising worldwide demand for energy and concerns about environmental sustainability. Smart homes optimize energy use, increase comfort, and boost productivity using cutting-edge technology like the Internet of Things (IoT), artificial intelligence (AI), and automation. In addition, smart homes have prioritized energy management in recent years to meet their goals of decreased energy use, a more stable energy grid, more energy efficiency, and outstanding environmental friendliness.

Making well-informed decisions based on various factors is crucial for successful energy management in smart homes. However, this procedure might be complicated because of the presence of unknowns and competing goals. Multi-Criteria Decision-Making (MCDM) is one strategy in which the optimal action is chosen from a pool of possibilities using several criteria [11]. Homeowners may make well-informed choices that reflect their values and preferences with the help of MCDM methods, which provide a standardized framework for assessing and ranking various energy management measures. To this end, a hybrid neuro-fuzzy (H-NF) approach has been developed for optimizing smart home energy use.

1.1 Overview of MCDM

MCDM is a computational approach for determining whichever among several alternatives meets the most criteria. It considers the priorities of decision-makers and evaluates options based on how well they meet the specified criteria. Since MCDM allows for the consideration of various elements, it has found widespread application in the realm of energy management, where it is employed to make decisions about energy usage and conservation [3].

1.2 Overview of H-NF Approach

The H-NF method integrates elements of both neural networks and fuzzy logic. Using the input data, the neural network trains its neurons to identify patterns and formulate predictions. In contrast, fuzzy logic is used when exact information is lacking, and assessments must be made using approximate criteria [8, 13].

By considering factors including energy usage, cost, convenience, and ecological effect, the H-NF Strategy for Energy Management may help smart homes make the most of their energy use. Selecting inputs, extracting features, and making a call are the three major procedures that make up the methodology. First, data is gathered from various sensors and smart actuators in the input selection phase. Next, the data is prepared for the decision-making step by being transformed and preprocessed in the feature extraction phase. Finally, in the decision-making phase, the H-NF method is utilized to choose the optimal action given the available options.

1.3 Motivation

Significant research efforts have been made to optimize energy usage, decrease expenses, and promote sustainability in light of the rapid proliferation of smart houses and the increased emphasis on energy management in residential environments. However, there are significant obstacles to overcome due to the complexity and ambiguity of energy-related decision-making procedures. Energy management solutions may be evaluated and chosen using the practical framework MCDM methods provide, which considers several factors simultaneously. In this light, investigating how to combine FL and MNN into an H-NF strategy is an intriguing area of inquiry [14].

Fuzzy logic is a computational approach for representing and working with uncertain, imprecise, and subjective information [9]. Conventional crisp reasoning fails to represent the inconsistencies and uncertainty commonly associated with energy management choices due to considerations like evolving energy costs, varied customer preferences, and unexpected weather. To work around such issues, fuzzy logic makes use of linguistic factors and membership mechanisms to determine and reason with subjective material that is prone to ambiguity [12]. As a result, decisions that consider subjective and inaccurate criteria can be conducted with more precision and adaptability with the help of fuzzy logic.

However, MNN is a valuable tool for modeling complicated systems and capturing subtle connections between different variables. Utilization patterns, alternative energy outlets, storage facilities, and individual preferences are all interconnected in the management of smart home energy. These dependencies can be encapsulated in an MNN topology, which facilitates the examination of various data sources and the recognition of actionable insights. The H-NF methodology, which is the outcome of integrating MNN with fuzzy logic, takes advantage of the positive aspects of both methods to provide better and more accurate decisions.

The potential of the H-NF technique to overcome the shortcomings of conventional approaches is what drives its use in the context of MCDM for regulating energy in automated residences. Traditional decision-making methods often use oversimplified models that fail to account for the nuances and unknowns of today's smart home ecosystems. The use of fuzzy logic and modular neural networks enhances the suggested approach by enabling the modeling of intricate connections and the provision of highly customized suggestions in response to changing data.

The H-NF strategy may also increase consumer happiness and participation in energy management. Convenience, accessibility, and management are two significant features that smart homes aim to provide for their inhabitants. The suggested method may personalize energy management techniques by considering user preferences and comfort-related parameters within the decision-making frame. This tailored strategy encourages users to take an active role in conserving energy and boosts user satisfaction.

1.4 Advantages of the Hybridized Neuro-Fuzzy Approach

The hybridized neuro-fuzzy method boasts various benefits compared to the existing approaches, such as [2]:

- The FL part of the technique allows it to deal with the frequently encountered imprecise and unpredictable information found in the field of energy governance.

- Because of its malleability, the method can be adapted to meet the demands of a wide variety of smart homes.
- The technique considers numerous criteria when evaluating energy-related decisions, allowing stakeholders to make educated decisions according to a variety of considerations.

Implementing an H-NF technique to optimize energy consumption in smart homes is an exciting new frontier. In addition to being versatile and adaptive, the method may be used to consider several factors and deal with imperfect or incomplete information. As a result, H-NF techniques, like those employed in energy management, are predicted to gain popularity as the importance of sustainable and efficient energy consumption expands.

1.5 Research Scope

The research scope encompasses the development and application of a hybridized Neuro-Fuzzy approach for multi-criteria decision making in energy management in smart homes. The research will focus on integrating fuzzy logic and modular neural networks, identifying relevant criteria, developing a decision-making model, evaluating alternative strategies, developing a user-friendly decision support system, and validating the effectiveness of the proposed approach [18].

1.6 Objectives

The prominent objectives of this study are delineated as follows:

- Develop a comprehensive framework for energy management in smart homes: The research aims to design a holistic framework that encompasses various aspects of energy management, including energy generation, consumption, storage, and distribution. This framework will consider multiple criteria, such as cost, comfort, environmental impact, and user preferences, to facilitate optimal decision making.
- Implement a hybridized Neuro-Fuzzy approach: The research proposes the integration of artificial neural networks and fuzzy logic to develop a hybridized Neuro-Fuzzy system. This approach will enable effective modeling, analysis, and decision making within the context of energy management in smart homes. The hybridized system will leverage the strengths of both techniques, such as neural networks' ability to handle complex data patterns and fuzzy logic's capability to handle imprecise and uncertain information.

- Provide a user-friendly decision support system: The research aims to develop a user-friendly decision support system that enables homeowners to interact with the proposed framework easily. This system will provide intuitive visualizations, recommendations, and insights based on the analysis conducted using the hybridized Neuro-Fuzzy approach. By incorporating user preferences and feedback, the system will empower homeowners to make informed decisions and actively participate in energy management processes.

The layout of the research work is structured as follows: Section 2 delineates the literature reviews of recent research works that exhibit the proposed methodology's significance in filling the gap. Section 3 briefs the dataset utilized and core methodology with computations and Section 4 highlights the observed outcomes with appropriate discussions. Finally, Section 5 put an end note to the research study with future work and analyzed vital points.

2 Related Work

Wang et al. offer a novel method for selecting appropriate locations for wind power projects in Vietnam, which combines the Fuzzy Analytic Hierarchy Process (FAHP) and The Technique for Order of Preference by Similarity to the Ideal Solution (TOPSIS) [20]. This study makes an impact by suggesting a multi-criteria decision-making (MCDM) strategy inside a fuzzy setting for the installation of wind farms in Vietnam. Initially, the FAHP model is used to provide a relative importance score to each candidate site based on various qualitative as well as quantitative criteria. Finally, we use TOPSIS to determine the ranking of the remaining options. TOPSIS's subjective nature in the decision-makers' evaluation of weights is one of the system's flaws. Consequently, how can lapses be handled when data collected by decision-makers is inadequate or the subjective awareness of the decision-makers is robust?.

For efficient supply chain procurement, Chen zeroes emphasis the difficulties of making informed choices among viable options throughout the supplier selection process [4]. The study emphasizes that depending entirely on subjective or objective criteria weights in various choice procedures might lead to biased findings and draws attention to the contrast between the two. As a result of integrating the entropy significance, the analytic hierarchy process (AHP) weight, and the methodology for choosing an order through resemblance to an optimal approach (TOPSIS), this research has developed an MCDM solution. By substituting entropy-AHP factors for qualitative weights, the TOPSIS approach is improved. The most suitable supplier can be chosen with the help of this innovative decision-making technique. The decision-making process on construction material suppliers is employed to demonstrate the suggested method's efficacy in the study. The benefits of integrating the TOPSIS technique with entropy-AHP factors in correctly choosing the best supplier are shown via sensitivity assessment.

Dymova et al. provided a synthesis of more than four decades of research and practice on establishing and resolving MCDM issues in diverse domains of human endeavor in the face of various forms of uncertainty [5]. For practical reasons, the authors don't describe the many decision-making procedures already known to man, opting instead to zero down on the most widely used computational tools and approaches. Consequently, the work may be seen as a kind of illustrated survey of the most prevalent mathematical techniques used to address MCDM issues, emphasizing applications. For demonstration purposes, we apply these methods and techniques to the seemingly straightforward "buying a cat" issue, which has all the hallmarks of a multilayered fuzzy MCDM assignment. The primary element of the approach and actual entropy-weighing approach is often carried out using the actual data, yielding more trustworthy conclusions; nevertheless, using incorrect data may also lead to biased evaluations.

To aid manufacturing enterprises in selecting appropriate locations for industrial parks, He et al. proposed an MCDM methodology [6]. The approach starts with an examination of the literature to create assessment criteria. Next, we present a fuzzy optimization model by fusing the fuzzy-TOPSIS with the fuzzy-VIKOR (VlseKriterijumska Optimizacija I Kompromisno Resenje) approaches which can be expressed as FT-FV. The optimization model employs a Lagrange mechanism to compute the significance of choice criteria, and Fuzzy-TOPSIS is used to establish their relative importance. In addition, the fuzzy-VIKOR technique is used to evaluate potential locations and choose the most advantageous one. Finally, the suggested methodology is used for a quantitative investigation that compares and rates five potential sites for a production business. The research shows how the framework could be used in the real world. The study also provides a thorough evaluation of alternative approaches, as well as sensitivity studies, to account for uncertainty in the relative importance of criteria and decision-makers. These studies validate the framework's applicability to the issue of choosing locations for intelligent and environmentally friendly manufacturing complexes.

This study examines hydroelectricity, solar power, wind, biomass, and geothermal power energies in Pakistan, among additional sources of renewable sources. The researchers use a unified approach that merges the AHP, the Delphi technique, and the Fuzyy-TOPSIS methodologies. In the first process, the most critical criteria for picking renewable energy (RE) resources are defined and selected using the Delphi technique. The four primary factors are financial, environmental, technological, and social and political considerations. Twenty more criteria enhance these main ones. The AHP is then used to care for each factor in the selection paradigm. According to the report, wind power is probably the most practical option out of all the potential alternative energy resources for electricity production in Pakistan. The study's findings are significant, reliable, and resilient, as shown by the sensitivity assessment performed on the selection process. The study's findings help prioritize renewable energy sources for power production, which may inform policy choices and promote long-term energy sustainability in Pakistan.

A new neuro-fuzzy diagnostic system was presented in [23] by combining a non-iterative ANN with a novel fuzzy model, the T-controller. Using a Padé polynomial for improved accuracy and coefficients synthesized using an optimized simulated annealing simulation on a pre-trained SGTM neural-like structure, the system has been tested on actual data to forecast generator power from 13 variables. The system's great performance is proved via a number of measures, and the findings are made more understandable by the use of polynomial coefficients.

An innovative concept of mathematical transformations from [24] was introduced the basis for information modeling, opens up possibilities for solving problems in areas as diverse as pattern identification, estimation, categorization, basic distinct elements selection, optimization, retrieving information or reorganization, and security. Employing space-time parallelization methods, it employs neural-like components that serve as general approximator, facilitating both supervised and unsupervised learning via algorithmic or hardware representations. The model enables a standardized approach across a broad spectrum of purposes, provides fast non-iterative learning with a fixed amount of computation steps, and guarantees reproducibility and good results with both big and minor instruction samples.

From all the recent reviews, it's been noticed that none has included an optimal strategy to address the energy management problem concerning essential factors like user preferences. Thus, this study incorporated a novel management technique to optimize energy management barriers.

3 H-NF Methodology

3.1 Problem Statement

The primary challenge this research aims to address is the optimization of energy management in smart homes, considering multiple criteria such as cost, comfort, environmental impact, and user preferences. This involves the integration of artificial neural networks and fuzzy logic into a hybrid Neuro-Fuzzy system for effective modeling and decision-making. Moreover, the research seeks to develop a user-friendly decision support system that empowers homeowners to actively participate in energy management processes.

In the context of energy management in smart homes, the problem can be formulated as follows:

Given a set of alternative energy management strategies, $E = \{e_1, e_2, \ldots, e_n\}$, and a set of criteria $ɰ = \{ɰ_1, ɰ_2, \ldots, ɰ_m\}$, the objective is to determine the optimal energy management strategy that maximizes the overall satisfaction and minimizes the energy cost while considering multiple criteria simultaneously. Each alternative strategy E_i can be represented by a vector of decision variables:

$$\boldsymbol{E_i} = \langle \boldsymbol{x_1}, \boldsymbol{x_2}, \ldots, \boldsymbol{x_j} \rangle \tag{1}$$

where, x_j represents the degree of adoption or utilization of a particular energy management option or component, such as renewable energy sources, energy storage systems, consumption patterns, or control strategies.

Let $L = \{l_1, l_2, \ldots, l_n\}$ represent the set of linguistic terms associated with each criterion, $ɰ_m$. The linguistic terms define the qualitative levels or linguistic variables that describe the evaluation of the criteria. For example, in the case of energy cost, the linguistic terms could be “low,” “medium,” and “high,” representing different levels of energy cost. The problem involves the following components which are represented in Table 1.

3.2 Dataset

The Smart* Data Set (Smart – UMass Trace Repository, n.d) for sustainability is a dataset available in the UMass trace repository that was collected as part of the Smart* project, which targets to optimize home energy consumption [1]. Unlike previous work that focused on collecting data from a large number of homes, the Smart* project prioritized collecting a comprehensive set of data from each home, referred to as “sensing depth.” The dataset

Table 1 Problem components and descriptions

Problem Components	Description
Fuzzy Logic Modelling	Fuzzy sets and membership functions will be defined to represent the linguistic variables associated with each criterion, $ɰ_m$. Let $\mu[ɰ_m, l_n, x_j]$ denote the membership function that represents the degree of membership of decision variable x_j to the linguistic term l_n associated with criterion $ɰ_m$.
Modular Neural Network Modelling	A modular neural network structure will be developed to capture the complex relationships between decision variables x_j and criteria $ɰ_m$. The neural network will consist of interconnected modules, each module responsible for modelling the relationships within a specific criterion $ɰ_m$. The output of each module will be the aggregated evaluation for the corresponding criterion.
Weight Assignment	Weights will be assigned to each criterion $ɰ_m$ to reflect their relative importance in the decision-making process. Let ϖ_j denote the weight assigned to criterion $ɰ_m$. The weights will be determined based on the preferences and priorities of smart home occupants.
Aggregation and Decision Making	The fuzzy outputs from each module of the modular neural network will be aggregated using fuzzy aggregation operators, such as weighted averaging or weighted maximum. The result of the aggregation will provide an overall evaluation for each alternative strategy ai. The alternative with the highest overall evaluation will be selected as the optimal energy management strategy.

captures multiple aspects of the home environment. Overall, the Smart* Data Set for sustainability provides a rich collection of actual information from real homes, encompassing various aspects of energy consumption and environmental factors.

3.3 Architecture

The architectural components of the proposed H-NF method for energy management in smart homes are depicted in Figure 1. The component of the architecture integrates the outputs of the FL and MNN components to form the hybrid Neuro-Fuzzy approach. It combines the fuzzy logic-based reasoning with the neural network-based learning and adaptation to leverage the strengths of both approaches, resulting in a more robust and accurate energy management system.

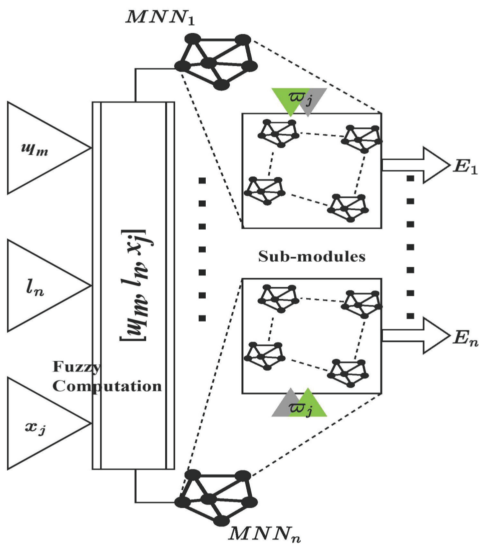

Figure 1 H-NF architecture.

3.4 Computational Process

The computational procedure for multi-criteria decision making for energy management in smart homes using an H-NF approach involves the following steps which are diagrammatically represented in Figure 2:

Figure 2 Computational procedures of H-NF.

Problem Formulation and Data Collection: Define the set of alternative energy management strategies $E = \{e_1, e_2, \ldots, e_n\}$ and the set of criteria $ɯ = \{ɯ_1, ɯ_2, \ldots, ɯ_m\}$. Collect relevant data for each strategy and criterion, including energy consumption patterns, renewable energy availability, user preferences, and cost factors.

FL Modelling: Define the linguistic terms $L = \{l_1, l_2, \ldots, l_n\}$ for each criterion ɰ_m develop membership functions $\mu[\text{ɰ}_m, l_n, x_j]$ to represent the degree of membership of decision variable (Ross, 1994) x_j to each linguistic term l_n associated with criterion ɰ_m. These membership functions will capture the qualitative evaluation of each criterion.

Energy Cost (ɰ_1):

$$\boldsymbol{L}\text{: } \boldsymbol{\mu}(\text{ɰ}_{\mathbf{1}}, \boldsymbol{L}, \boldsymbol{x}) = \mathbf{1} - \boldsymbol{\mu}(\text{ɰ}_{\mathbf{1}}, \boldsymbol{M}, \boldsymbol{x}) - \boldsymbol{\mu}(\text{ɰ}_{\mathbf{1}}, \boldsymbol{H}, \boldsymbol{x}) \tag{2}$$

$$\boldsymbol{M}\text{: } \boldsymbol{\mu}(\text{ɰ}_{\mathbf{1}}, \boldsymbol{M}, \boldsymbol{x}) = \mathbf{1} - \boldsymbol{\mu}(\text{ɰ}_{\mathbf{1}}, \boldsymbol{L}, \boldsymbol{x}) - \boldsymbol{\mu}(\text{ɰ}_{\mathbf{1}}, \boldsymbol{H}, \boldsymbol{x}) \tag{3}$$

$$\boldsymbol{H}\text{: } \boldsymbol{\mu}(\text{ɰ}_{\mathbf{1}}, \boldsymbol{H}, \boldsymbol{x}) = \mathbf{1} - \boldsymbol{\mu}(\text{ɰ}_{\mathbf{1}}, \boldsymbol{L}, \boldsymbol{x}) - \boldsymbol{\mu}(\text{ɰ}_{\mathbf{1}}, \boldsymbol{M}, \boldsymbol{x}) \tag{4}$$

Here, *x* represents the decision variable associated with energy cost. *L*, *M*, and *H* denote low, moderate, and high, respectively.

User Comfort(ɰ_2):

$$\boldsymbol{P}\text{: } \boldsymbol{\mu}(\text{ɰ}_{\mathbf{2}}, \boldsymbol{P}, \boldsymbol{x}) = \mathbf{1} - \boldsymbol{\mu}(\text{ɰ}_{\mathbf{2}}, \boldsymbol{M}, \boldsymbol{x}) - \boldsymbol{\mu}(\text{ɰ}_{\mathbf{2}}, \boldsymbol{G}, \boldsymbol{x}) - \boldsymbol{\mu}(\text{ɰ}_{\mathbf{2}}, \boldsymbol{\xi}, \boldsymbol{x}) \tag{5}$$

$$\boldsymbol{M}\text{: } \boldsymbol{\mu}(\text{ɰ}_{\mathbf{2}}, \boldsymbol{M}, \boldsymbol{x}) = \mathbf{1} - \boldsymbol{\mu}(\text{ɰ}_{\mathbf{2}}, \boldsymbol{P}, \boldsymbol{x}) - \boldsymbol{\mu}(\text{ɰ}_{\mathbf{2}}, \boldsymbol{G}, \boldsymbol{x}) - \boldsymbol{\mu}(\text{ɰ}_{\mathbf{2}}, \boldsymbol{\xi}, \boldsymbol{x}) \tag{6}$$

$$\boldsymbol{G}\text{: } \boldsymbol{\mu}(\text{ɰ}_{\mathbf{2}}, \boldsymbol{G}, \boldsymbol{x}) = \mathbf{1} - \boldsymbol{\mu}(\text{ɰ}_{\mathbf{2}}, \boldsymbol{P}, \boldsymbol{x}) - \boldsymbol{\mu}(\text{ɰ}_{\mathbf{2}}, \boldsymbol{M}, \boldsymbol{x}) - \boldsymbol{\mu}(\text{ɰ}_{\mathbf{2}}, \boldsymbol{\xi}, \boldsymbol{x}) \tag{7}$$

$$\boldsymbol{\xi}\text{: } \boldsymbol{\mu}(\text{ɰ}_{\mathbf{2}}, \boldsymbol{\xi}, \boldsymbol{x}) = \mathbf{1} - \boldsymbol{\mu}(\text{ɰ}_{\mathbf{2}}, \boldsymbol{P}, \boldsymbol{x}) - \boldsymbol{\mu}(\text{ɰ}_{\mathbf{2}}, \boldsymbol{M}, \boldsymbol{x}) - \boldsymbol{\mu}(\text{ɰ}_{\mathbf{2}}, \boldsymbol{G}, \boldsymbol{x}) \tag{8}$$

Here, *x* represents the decision variable associated with user comfort. *P*, *G*, and ξ represent the poor, good, and excellent, respectively.

Environmental Impact(ɰ_3):

$$\boldsymbol{L}\text{: } \boldsymbol{\mu}(\text{ɰ}_{\mathbf{3}}, \boldsymbol{L}, \boldsymbol{x}) = \mathbf{1} - \boldsymbol{\mu}(\text{ɰ}_{\mathbf{3}}, \boldsymbol{M}, \boldsymbol{x}) - \boldsymbol{\mu}(\text{ɰ}_{\mathbf{3}}, \boldsymbol{H}, \boldsymbol{x}) \tag{9}$$

$$\boldsymbol{M}\text{: } \boldsymbol{\mu}(\text{ɰ}_{\mathbf{3}}, \boldsymbol{M}, \boldsymbol{x}) = \mathbf{1} - \boldsymbol{\mu}(\text{ɰ}_{\mathbf{3}}, \boldsymbol{L}, \boldsymbol{x}) - \boldsymbol{\mu}(\text{ɰ}_{\mathbf{3}}, \boldsymbol{H}, \boldsymbol{x}) \tag{10}$$

$$\boldsymbol{H}\text{: } \boldsymbol{\mu}(\text{ɰ}_{\mathbf{3}}, \boldsymbol{H}, \boldsymbol{x}) = \mathbf{1} - \boldsymbol{\mu}(\text{ɰ}_{\mathbf{3}}, \boldsymbol{L}, \boldsymbol{x}) - \boldsymbol{\mu}(\text{ɰ}_{\mathbf{3}}, \boldsymbol{M}, \boldsymbol{x}) \tag{11}$$

Here, *x* represents the decision variable associated with environmental impact.

Other Energy Utilization(ɰ_4):

$$\boldsymbol{L}\text{: } \boldsymbol{\mu}(\text{ɰ}_{\mathbf{4}}, \boldsymbol{L}, \boldsymbol{x}) = \mathbf{1} - \boldsymbol{\mu}(\text{ɰ}_{\mathbf{4}}, \boldsymbol{M}, \boldsymbol{x}) - \boldsymbol{\mu}(\text{ɰ}_{\mathbf{4}}, \boldsymbol{H}, \boldsymbol{x}) \tag{12}$$

$$\boldsymbol{M}\text{: } \boldsymbol{\mu}(\text{ɰ}_{\mathbf{4}}, \boldsymbol{M}, \boldsymbol{x}) = \mathbf{1} - \boldsymbol{\mu}(\text{ɰ}_{\mathbf{4}}, \boldsymbol{L}, \boldsymbol{x}) - \boldsymbol{\mu}(\text{ɰ}_{\mathbf{4}}, \boldsymbol{H}, \boldsymbol{x}) \tag{13}$$

$$\boldsymbol{H}\text{: } \boldsymbol{\mu}(\text{ɰ}_{\mathbf{4}}, \boldsymbol{H}, \boldsymbol{x}) = \mathbf{1} - \boldsymbol{\mu}(\text{ɰ}_{\mathbf{4}}, \boldsymbol{L}, \boldsymbol{x}) - \boldsymbol{\mu}(\text{ɰ}_{\mathbf{4}}, \boldsymbol{M}, \boldsymbol{x}) \tag{14}$$

Here, x represents the decision variable associated with other energy utilization.

User Preferences($ɰ_5$):

$$\boldsymbol{L}\text{:}\ \boldsymbol{\mu}(ɰ_{\mathbf{5}}, \boldsymbol{L}, \boldsymbol{x}) = \mathbf{1} - \boldsymbol{\mu}(ɰ_{\mathbf{5}}, \boldsymbol{M}, \boldsymbol{x}) - \boldsymbol{\mu}(ɰ_{\mathbf{5}}, \boldsymbol{H}, \boldsymbol{x}) \tag{15}$$

$$\boldsymbol{M}\text{:}\ \boldsymbol{\mu}(ɰ_{\mathbf{5}}, \boldsymbol{M}, \boldsymbol{x}) = \mathbf{1} - \boldsymbol{\mu}(ɰ_{\mathbf{5}}, \boldsymbol{L}, \boldsymbol{x}) - \boldsymbol{\mu}(ɰ_{\mathbf{5}}, \boldsymbol{H}, \boldsymbol{x}) \tag{16}$$

$$\boldsymbol{H}\text{:}\ \boldsymbol{\mu}(ɰ_{\mathbf{5}}, \boldsymbol{H}, \boldsymbol{x}) = \mathbf{1} - \boldsymbol{\mu}(ɰ_{\mathbf{5}}, \boldsymbol{L}, \boldsymbol{x}) - \boldsymbol{\mu}(ɰ_{\mathbf{5}}, \boldsymbol{M}, \boldsymbol{x}) \tag{17}$$

Here, *x* represents the decision variable associated with user preferences.

In each equation, the membership function $\mu[ɰ_m, l_n, x_j]$ represents the degree of membership of the decision variable x to the linguistic term l_n associated with criterion, $ɰ_m$. These equations define the fuzzy sets and membership functions that capture the qualitative evaluation of each criterion. The values of the membership functions will depend on the specific fuzzy logic techniques and membership function shapes chosen for the application.

MNN Modeling: Design an MNN structure to model the complex relationships between decision variables x_j and criteria $ɰ_m$. Divide the network into interconnected modules, with each module responsible for modeling the relationships within a specific criterion $ɰ_m$. Train each module using appropriate learning algorithms, such as backpropagation or radial basis function networks, to capture the interdependencies between decision variables and criteria.

Let's assume we have 'n' decision variables represented by the vector $\langle x_1, x_2, \ldots, x_j \rangle$, and m criteria represented by the vector $ɰ = \{ɰ_1, ɰ_2, \ldots, ɰ_m\}$. We want to model the complex relationships between these decision variables and criteria using a Modular Neural Network (MNN).

The MNN is divided into interconnected modules, with each module responsible for modeling the relationships within a specific criterion, $ɰ_m$. Let's denote the module for the criterion $ɰ_m$ as μ_j. Each module μ_j takes the input vector x as its input and produces an output, O_j.

The output O_j of module μ_j is calculated by applying a set of weight parameters ϖ_j and activation function $f()$ to the inputs x. The computation can be represented as,

$$\boldsymbol{O_j} = \boldsymbol{f}[\boldsymbol{e_j} + (\boldsymbol{\varpi_j} * \boldsymbol{x})] \tag{18}$$

where, $\boldsymbol{\varpi_j}$ is the weight matrix for the module μ_j, * denotes matrix multiplication, and $\boldsymbol{e_j}$ denote the bias vector for the module μ_j.

To train each module μ_j, an appropriate learning algorithm, such as backpropagation, is utilized. Backpropagation is a commonly used algorithm for training neural networks. It involves iteratively adjusting the $\boldsymbol{\varpi_j}$ and $\boldsymbol{e_j}$ of the module relied on the gradient of the error with respect to the network parameters. The specific details of the training process depend on the chosen algorithm.

Weight Assignment: Assign weights $\boldsymbol{\varpi_j}$ to each criterion ɰ_m to reflect their relative importance in the decision-making process. These weights can be determined based on the preferences and priorities of smart home occupants. The weights should be normalized to ensure their sum is equal to 1.

The weights $\varpi_j = \{\varpi_1, \varpi_2, \ldots, \varpi_m\}$ is determined based on the preferences and priorities of the smart home occupants. There are several methods to determine the ϖ_j, such as direct user input, pair-wise comparisons, or Analytic Hierarchy Process (AHP). In this study, we employed AHP to determine the weights.

Once the weights are assigned, it is important to normalize them to ensure their sum is equal to 1. Normalization is performed by dividing each ϖ_j by the sum of all $\{\varpi_1, \varpi_2, \ldots, \varpi_m\}$. The normalized weights $\varpi_{norm_j} = \langle \varpi_{norm_1}, \varpi_{norm_2}, \ldots, \varpi_{norm_m} \rangle$ can be computed as follows:

$$\boldsymbol{\varpi_{norm_j} = \varpi_j / (\varpi_1 + \varpi_2 + \cdots + \varpi_m)} \tag{19}$$

The normalized weights $\boldsymbol{\varpi_{norm_j}}$ represent a valid probability distribution, where each weight represents the relative importance or priority of the corresponding criterion ɰ_m in the decision-making process.

By combining the MNN modeling and ϖ_j assignment, the H-NF approach can effectively capture the complex relationships between decision variables and criteria while incorporating the relative importance of each criterion in the decision-making process. This enables intelligent energy management in smart homes based on multiple criteria and user preferences.

Aggregation and Decision Making: For each alternative strategy E_i, calculate the overall evaluation value (E_i) by aggregating the fuzzy outputs from each module of the MNN. This is performed using fuzzy aggregation operators, such as weighted averaging or weighted maximum. The aggregation process is represented as follows:

$$\boldsymbol{\phi(E_i) = \sum [\varpi_j * O_j(E_i)]} \tag{20}$$

where, $O_j(E_i)$ represents the outcome of the jth module for the alternative strategy E_i.

Rank and Selection: Rank the alternative strategies based on their overall evaluation values $O_j(E_i)$. The strategy with the highest evaluation value is selected as the optimal energy management strategy for the smart home.

Visualization and Decision Support: A user-friendly decision support system that provides visualizations (Kim et al., 2020), recommendations, and insights based on the analysis conducted using the H-NF approach is evolved. The system is supposed to enable homeowners to interact with the decision-making process, adjust criteria weights, and explore the impact of different strategies on energy consumption, cost, and user comfort.

Validation and Performance Analysis: The developed H-NF approach and decision support system using real-world data and scenarios are validated. Evaluate the performance of the approach in terms of decision and inference accuracy, efficiency, scalability, and usability. Analyze the effectiveness of the approach in optimizing energy consumption, enhancing user comfort, and promoting sustainable practices in smart homes.

The computational procedure outlined above combines the strengths of FL and MNN to enable multi-criteria decision-making for energy management in smart homes. By integrating these techniques, homeowners can make informed decisions that consider various criteria and lead to energy-efficient, comfortable, and sustainable smart homes. The algorithm of proposed H-NF is depicted in Table 2.

Table 2 Algorithm of proposed H-NF

Input: $\text{ɰ} = \{\text{ɰ}_1, \text{ɰ}_2, \ldots, \text{ɰ}_m\}$, $L = \{l_1, l_2, \ldots, l_n\}$, $\langle x_1, x_2, \ldots, x_j \rangle$	
Output: $E = \{e_1, e_2, \ldots, e_n\}$	
1: $\mu[\text{ɰ}_m, l_n, x_j]$	*//fuzzy modelling*
2: $\forall(\mu_j \leftarrow x)$	
2.1: $O_j \leftarrow f[e_j + (\varpi_j * x)]$	*//relationships within a specific criterion*, ɰ_m
2.2 Adjust (ϖ_j, e_j)	*//backpropagation*
2.3 $\forall(\text{ɰ}_m)$	
Assign ϖ_j	
2.4 ϖ_j *Normalization*:	
$\varpi_{norm_j} = \varpi_j/(\varpi_1 + \varpi_2 + \cdots + \varpi_m)$	
3: $\phi(E_i) = \sum[\varpi_j * O_j(E_i)]$	*//Aggregation and Decision-making*

4 Performance Analysis

The proposed approach's evaluation is compared to the performance of a few recent existing approaches like TOPSIS-AHP, TOPSIS-FAHP, FT-FV, and H-NF approaches, which are discussed in Section 2. A variety of performance indicators and their accompanying mathematically computable equations are utilized for assessing the study, as mentioned earlier on MCDM for energy management in smart homes using an H-NF approach.

Mean Square Error (MSE): The MSE calculates the typical squared disparity between the expected and actual results [21]. The performance of the H-NF technique in modeling the connections between choice factors and criterion is evaluated. For any data point, i, we can record the projected result as Υ_i and the actual result as ψ_i. Then, we can calculate the MSE as,

$$\boldsymbol{MSE} = [\mathbf{1}/\boldsymbol{N}] \times \sum(\boldsymbol{\Upsilon_i} - \boldsymbol{\psi_i})^{\mathbf{2}} \tag{21}$$

The observed MSE values for different methods (TOPSIS-AHP, TOPSIS-FAHP, FT-FV, and H-NF) at varying training-to-testing ratios indicate the performance of each method in terms of prediction accuracy. A lower MSE value indicates better prediction accuracy, while a higher value suggests less accurate predictions.

Based on the observed values from Figure 3, it can be seen that the H-NF method consistently achieves the lowest MSE values across

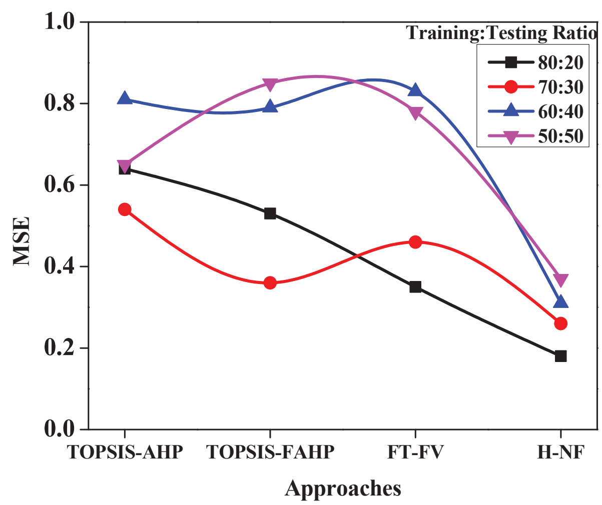

Figure 3 Analysis of MSE.

all training-to-testing ratios. This indicates that the hybrid Neuro-Fuzzy approach outperforms the other methods (TOPSIS-AHP, TOPSIS-FAHP, and FT-FV) in terms of prediction accuracy for energy management in smart homes. The decreasing trend of MSE values as the training set size increases suggests that increasing the training data helps improve the prediction accuracy of the models. These observed values indicate that the H-NF method shows promise for delivering more precise and effective decision-making processes for energy management in smart homes, as it consistently achieves lower MSE values and therefore demonstrates better prediction accuracy compared to the other methods. It is significant to observe that the interpretation of MSE values should be considered in the context of the specific dataset and problem domain.

Root Mean Square Error (RMSE): The average prediction error of the H-NF method can be quantified by estimating the RMSE, which is the square root of the MSE [21]. It can be helpful when comparing various strategies. The RMSE formula is expressed as,

$$\boldsymbol{RMSE} = \sqrt{\boldsymbol{MSE}} \tag{22}$$

The outcome from Figure 4 exhibits that the H-NF approach yields the best RMSE results over a wide range of training-to-testing ratios. The H-NF technique improves prediction accuracy for smart home energy

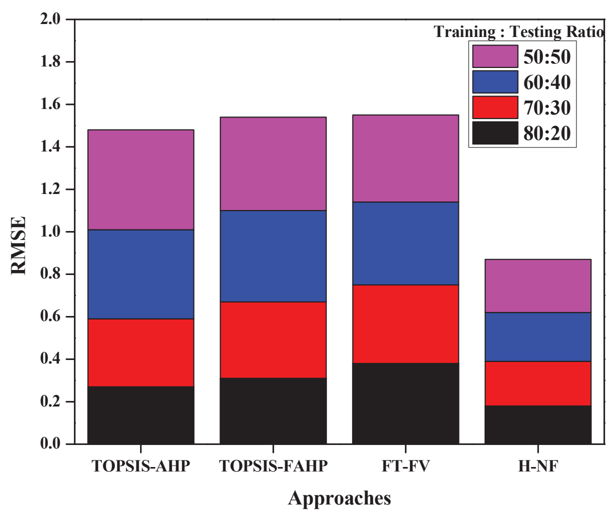

Figure 4 Analysis of RMSE.

management compared to the other approaches (TOPSIS-AHP, TOPSIS-FAHP, and FT-FV). A more extensive training set is associated with better model accuracy, measured by a smaller RMSE. By consistently achieving lower RMSE values, the H-NF method demonstrates better prediction accuracy than the other methods. Thus, the results exhibit promise for delivering more precise and effective decision-making processes for energy management in smart homes. Since the H-NF model has a reduced average prediction error, it may give more accurate estimates of energy usage and help customers better manage their energy consumption without sacrificing comfort or the environment.

Fuzzy Inference Accuracy (FIA): The accuracy of the fuzzy logic inferential process is quantified using a metric called "fuzzy inference accuracy" [22]. It can be calculated the same way as the preceding reasoning, as the mean of the absolute differences between the expected value ranges and the actual ones.

$$FIA = [\mathbf{1}/\boldsymbol{N}] \times \sum |\boldsymbol{\Upsilon_i} - \boldsymbol{\psi_i}| \tag{23}$$

Results from Figure 5 reveal the performance of different methods (TOPSIS-AHP, TOPSIS-FAHP, FT-FV, and H-NF) in optimizing energy management in smart homes. The FIA values at various training-to-testing ratios (94.14% at 80:20, 92.15% at 70:30, 90.11% at 60:50, and 89.67% at 50:50) indicate the improvement achieved by each proposed method compared to the other baseline. The H-NF consistently outperforms the other methods, demonstrating the highest FIA values across all ratios. This suggests that the H-NF model provides more precise and effective decision-making processes, enabling users to optimize their energy consumption while maintaining comfort and reducing environmental impact. The observed improvements in FIA values signify the potential of the hybridized approach to enhance energy management systems' efficacy and precision in smart homes, making it a promising solution for achieving energy efficiency and sustainability.

Energy Savings (ES): The amount of energy conserved or optimized can be estimated when comparing the H-NF method to a baseline or benchmark scenario [19]. It reflects the decrease in energy usage that resulted from adopting the strategy. Let $\boldsymbol{\sigma}$ represent the initial energy consumption, and $\boldsymbol{\vartheta}$ represent the energy consumption after implementing the approach. Then, the amount of energy saved can be determined as follows:

$$\boldsymbol{ES} = \boldsymbol{\sigma} - \boldsymbol{\vartheta} \tag{24}$$

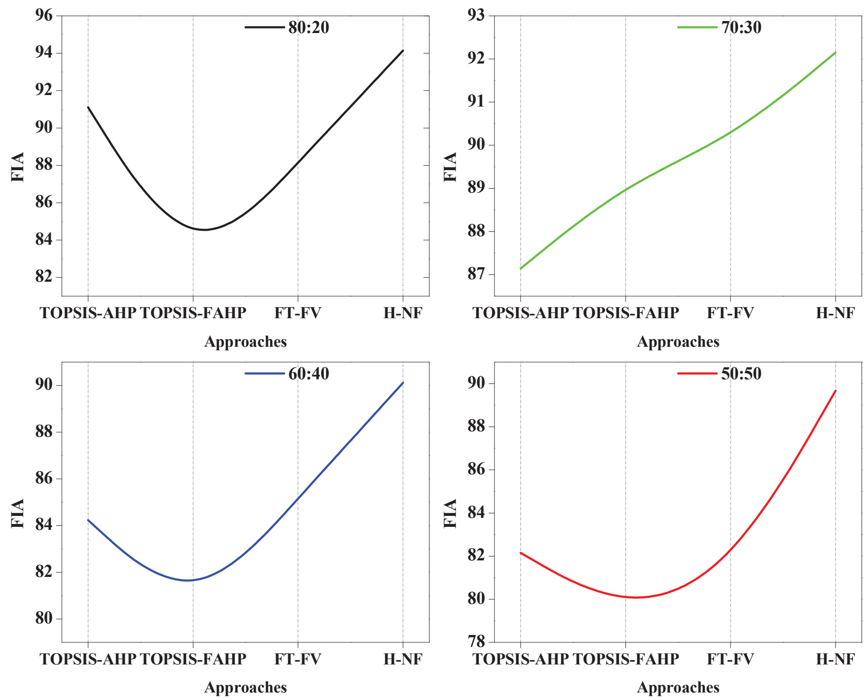

Figure 5 Analysis of FIA.

The observed results from Figure 6 in terms of energy-saving percentages provide insights into the performance of different methods (TOPSIS-AHP, TOPSIS-FAHP, FT-FV, and H-NF) in optimizing energy management in smart homes. The higher the energy-saving percentage, the more effective the method is in achieving energy efficiency. Among the methods, the H-NF approach demonstrates the highest energy-saving percentage of 93.16%. This indicates that the hybrid Neuro-Fuzzy model outperforms the other methods in terms of energy saving, offering the greatest potential for reducing energy consumption in smart homes. TOPSIS-FAHP follows closely with an energy-saving percentage of 89.14%, indicating its effectiveness in achieving substantial energy savings. The FT-FV method also performs well, with an energy-saving percentage of 87.15%. However, the TOPSIS-AHP method shows a relatively lower energy-saving percentage of 78.18%, suggesting that it is less efficient in optimizing energy use compared to the other methods. Overall, the H-NF method stands out as the most effective approach for achieving significant energy savings in smart homes.

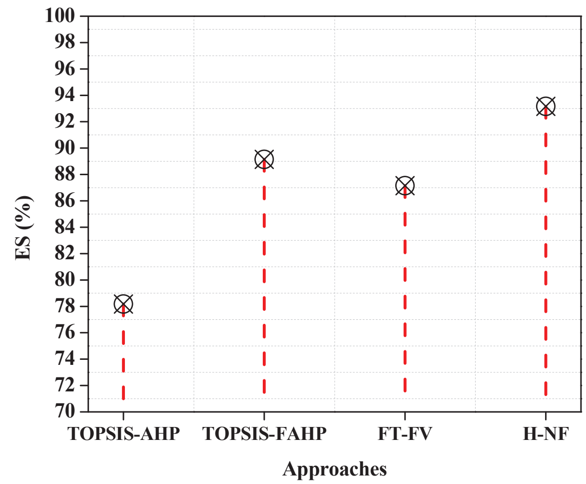

Figure 6 Analysis of ES.

Decision Accuracy (DA): The effectiveness of the decision-making procedure is measured by Decision Accuracy, which uses user-defined criteria [7]. It evaluates the H-NF method's ability to choose the most suitable energy management strategies across a broad spectrum of scenarios. Let Я represent the number of correct decisions made by the approach and $\mathbb{T}$ represent the total number of decisions. The accuracy of the resulting evaluation can then be calculated as

$$\boldsymbol{DA} = Я/\mathbb{T} \tag{25}$$

Figure 7 shows the findings of a value-based examination of four alternative approaches (TOPSIS-AHP, TOPSIS-FAHP, FT-FV, and H-NF) to optimize energy management in smart homes, as measured by the proportion of correct decisions made by each approach. Each approach's correct decision ratio shows how well it does its job. The H-NF technique has the most significant percentage of decision accuracy (94.17%) among the approaches. As a result, the H-NF model provides the most exact and accurate decision-making procedures for energy management in smart homes, showing its superiority over the other techniques regarding decision correctness. TOPSIS-FAHP follows suit, demonstrating efficacy in decision-making with an accuracy percentage of 88.17%. With an estimated accuracy rate of 85.17%, the FT-FV approach likewise does well. Compared to the other approaches, TOPSIS-AHP's comparatively low decision accuracy percentage of 83.12% suggests it makes less-than-optimal decisions. When optimizing

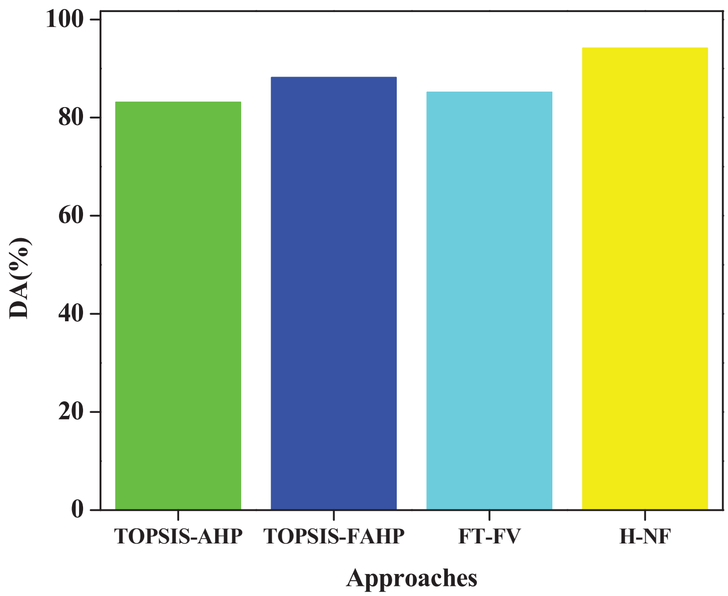

Figure 7 Analysis of DA.

energy usage, maintaining comfort, and reducing environmental effects, the H-NF technique stands out as the most accurate way to decision-making in energy management for smart homes.

5 Conclusion and Future Work

The hybrid Neuro-Fuzzy (H-NF) method proposed in this study offers a promising solution for optimizing energy management in smart homes. By integrating Fuzzy Logic (FL) with Modular Neural Networks (MNN), the H-NF approach considers multiple criteria and parameters to enhance the precision and efficacy of decision-making processes. The comparison of the H-NF model with other methods demonstrated its superior performance in terms of energy savings (>90%), decision accuracy (94.17%), and overall effectiveness. The suggested approach has the potential to empower users in optimizing energy consumption, ensuring comfort, and reducing environmental impact. Future work is focused on several aspects to further enhance the effectiveness of energy management in smart homes. Firstly, exploring the integration of additional decision-making approaches or algorithms could potentially enhance the H-NF model's performance. This could involve incorporating machine learning techniques or advanced optimization algorithms to better handle complex and dynamic energy management scenarios. However, the system's complexity could be a challenge, especially with integrating additional decision-making approaches or algorithms. Its performance might also rely heavily on the quality and quantity of input data.

Our future work involves testing the model with a broader and more diverse set of data, including different types of households and varying patterns of energy usage, could help validate its effectiveness and generalizability.

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