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Computational Modeling and Fuzzy Evaluation of Energy Efficiency in Public and Commercial Buildings Based on End-Use Energy Categories

Imam Arif Rahardjo[1], Iwa Garniwa[2*], Budi Sudiarto[3], Pranda M.P. Garniwa[4]

[1,2,3] *Department of Electrical Engineering, Faculty of Engineering, Universitas Indonesia, Indonesia*
[4] *Department of Geography, Universitas Indonesia, Indonesia*

***Corresponding Author:** iwa@eng.ui.ac.id

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ABSTRACT

Energy efficiency assessment in public and commercial buildings plays a pivotal role in supporting sustainable development and energy conservation strategies. However, traditional evaluation approaches often fall short in accommodating the inherent uncertainty and subjectivity associated with building energy performance indicators. This study proposes a computational modeling framework based on fuzzy logic to assess energy efficiency using end-use energy consumption categories. Energy use data were categorized into six primary types: appliances & others, lighting, cooling, cooking & water heating, distributed heating, and central heating, which were normalized and processed through fuzzification, rule-based inference, and defuzzification stages. The proposed model was tested on a dataset from various building types in China, and validated through expert judgment. The results demonstrated that the fuzzy logic approach effectively captures nuanced energy consumption patterns and provides a more adaptable and interpretable evaluation metric compared to conventional binary classifications. The model offers insights into energy optimization potentials specific to different usage patterns. This research contributes a flexible and scalable methodology that can be implemented across various building typologies and geographies. The findings also highlight the potential for integrating fuzzy-based assessments into future smart energy management systems.

Keywords: Energy efficiency, fuzzy logic, public and commercial buildings, energy performance evaluation, computational modeling.

INTRODUCTION

The building sector accounts for a significant portion of global energy use and greenhouse gas emissions, with estimates indicating that it represents approximately 30% of total final energy consumption and nearly 28% of energy-related CO_2 emissions worldwide (*Global Status Report for Buildings and Construction :Towards a Zero-Emissions, Efficient and Resilient Buildings and Construction Sector*, 2022). Public and commercial buildings, in particular, exhibit complex usage patterns and high-intensity energy consumption across multiple end-use systems such as lighting, HVAC (Heating, Ventilation, and Air Conditioning), and plug-in appliances. Improving energy efficiency in this segment is thus considered vital for achieving global energy sustainability targets and national decarbonization strategies aligned with the Paris Agreement and net-zero emission roadmaps (Ürge-Vorsatz et al., 2015).

Traditional methods for evaluating building energy performance—such as Energy Use Intensity (EUI), benchmarking, and building energy simulations—have served as essential tools in performance assessment (Crawley et al., 2008; González-Torres et al., 2022). However, these approaches often rely on deterministic assumptions and fail to account for the heterogeneity and uncertainty present in real-world building operations. Influences such as occupant behavior, fluctuating operational schedules, and environmental variability introduce complexities that cannot be adequately captured through conventional deterministic frameworks (Yan et al., 2015).

Recent research has explored the integration of computational and data-driven methods into energy performance analysis, including statistical learning (Amasyali & El-Gohary, 2018), clustering algorithms (Chou & Tran, 2018), and hybrid modeling techniques (Diao et al., 2017). These approaches have demonstrated promising improvements in predictive accuracy and anomaly detection. Nevertheless, their widespread adoption is often hindered by interpretability challenges, particularly in the context of decision-making among building managers and policymakers (Ribeiro et al., 2016). Moreover, existing models rarely focus on disaggregated end-use consumption data or consider the vagueness inherent in classifying building energy efficiency.

Fuzzy logic-based models offer a robust alternative for handling imprecise, uncertain, and linguistically defined variables in energy analysis (Zadeh, 1965). Their ability to model non-binary decision rules and incorporate expert knowledge makes them especially well-suited to energy efficiency classification problems. However, most prior applications of fuzzy logic in this field are limited in scale and often do not differentiate between specific end-use systems (Doukas et al., 2007), nor do they incorporate spatial heterogeneity across diverse building types or regions (Pazouki et al., 2021).

This study proposes a computational framework that integrates end-use energy disaggregation with fuzzy inference systems (FIS) to evaluate the energy efficiency of public and commercial buildings. Drawing on a large-scale dataset comprising 11,073 buildings across multiple administrative jurisdictions, the model classifies energy efficiency based on the relative contributions of four major end-use categories: lighting, centralized heating, distributed heating, and miscellaneous appliances. The novelty of this work lies in three primary contributions: (1) a detailed end-use disaggregation approach to enable more nuanced performance evaluation, (2) the implementation of an interpretable fuzzy classification system that reflects the non-linear and uncertain nature of energy efficiency, and (3) a spatial analysis of inefficiency patterns across different institutional and regional contexts.

The findings reveal that higher proportions of appliance and lighting consumption are strongly associated with inefficient performance, especially in buildings managed by central government agencies. These results underscore the importance of targeting behavioral and operational drivers of energy waste, in addition to technical retrofitting measures. Overall, this research contributes to the development of more transparent, scalable, and adaptable models for evaluating building energy efficiency.

MATERIAL AND METHODS

This study presents a computational framework for evaluating building energy efficiency based on categorized end-use energy consumption using a fuzzy logic approach. The model is developed and executed within the MATLAB R2024a environment, utilizing the Fuzzy Logic Toolbox to construct a Mamdani-type Fuzzy Inference System (FIS). The FIS is designed to process qualitative judgments and linguistic variables, which are appropriate for modeling uncertainties inherent in energy consumption behavior across building sectors, as shown in Figure 1.

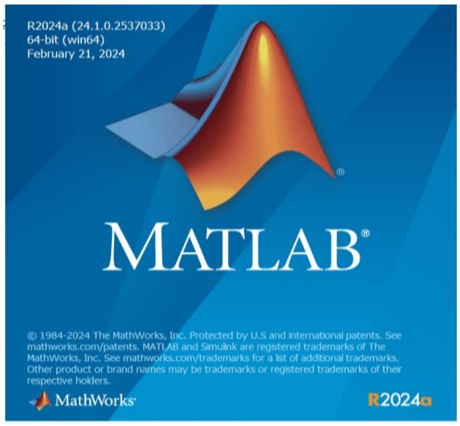

Figure 1. MATLAB R2024a environment used for fuzzy modeling implementation

Six critical energy end-use categories are identified as input variables: appliances & others, lighting, cooling, cooking & water heating, distributed heating, and central heating. Each input is assigned a corresponding fuzzy membership function to represent low, medium, and high consumption levels. These inputs are fuzzified and then processed through a rule-based inference engine constructed from expert knowledge and relevant literature. The system synthesizes the input variables through fuzzy rules to generate a single output variable representing Energy Efficiency, which is expressed as a linguistic variable with fuzzy sets such as *low*, *moderate*, and *high*. Finally, the fuzzy output is defuzzified to yield a crisp efficiency index, providing a holistic evaluation of building energy performance.

The operational workflow of the fuzzy inference model applied in this study is illustrated as shown in Figure 2. The process begins with six input variables representing energy consumption across major end-use categories. Each of these inputs is assigned a fuzzy membership function, enabling the transformation of quantitative values into qualitative linguistic terms. These inputs are then fed into the Mamdani-type FIS, which consists of a fuzzification interface, a rule base, an inference engine, and a defuzzification unit. The system evaluates the inputs using predefined fuzzy rules and produces an output that reflects the overall energy efficiency of the building. This output is then defuzzified to provide a measurable efficiency score that facilitates comparative and diagnostic analysis of building energy performance

This study utilized a comprehensive dataset comprising 11,073 public and commercial buildings across China. To establish an initial benchmark of energy efficiency, the input of each building was calculated and classified into three categories: low (bottom 25% of the distribution), medium (middle 50%), and high (top 75%). While this method provides a statistical foundation, it does not capture the nuanced influence of individual end-use patterns, particularly under operational uncertainty. To address this limitation, a fuzzy inference system (FIS) based on the Mamdani approach was developed to model energy efficiency using the proportion of energy allocated to the six main end-use categories.

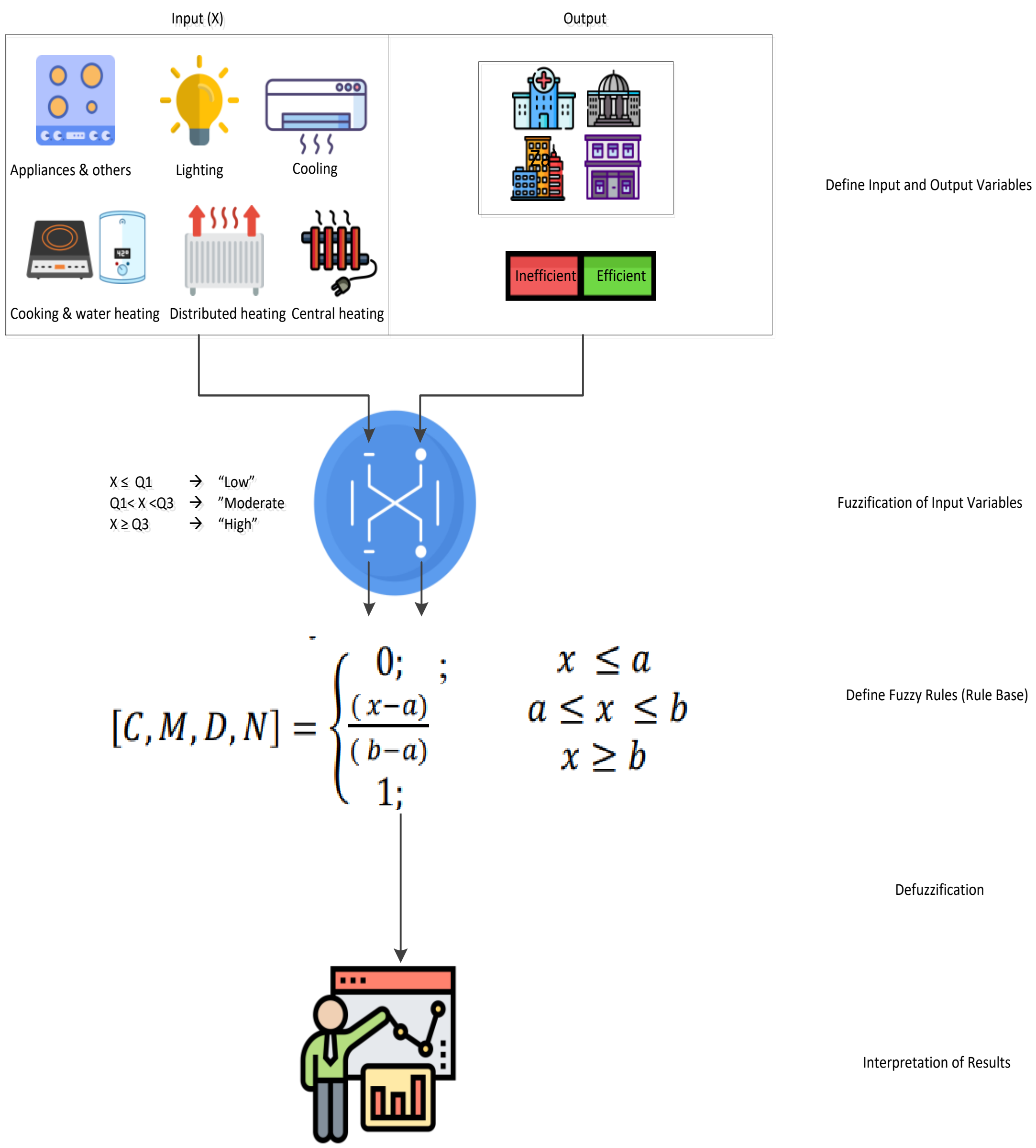

Figure 2. Flowchart of fuzzy-based energy efficiency evaluation framework

The fuzzy logic-based energy efficiency evaluation model in this study was developed using a Mamdani-type fuzzy inference system. The model takes six categories of end-use energy consumption as input variables: appliances and others, lighting, cooling, cooking and water heating, distributed heating, and central heating. Each input was represented using triangular membership functions to capture qualitative states such as low, medium, and high. The fuzzification process converts normalized quantitative values into fuzzy linguistic variables, which are then processed through a rule-based inference engine. The rule base was designed based on expert knowledge and empirical observations, covering various combinations of input conditions. The defuzzification stage was implemented using the centroid method to generate a crisp value of energy efficiency. The overall output of the model is a linguistic and numerical assessment of the building's energy efficiency. This method enables flexible, interpretable, and context-sensitive evaluation, especially under conditions where precise data is limited or uncertainty is present. The schematic diagram of the Mamdani fuzzy logic model for evaluating energy efficiency based on end-use energy consumption categories is illustrated as shown in Figure 3.

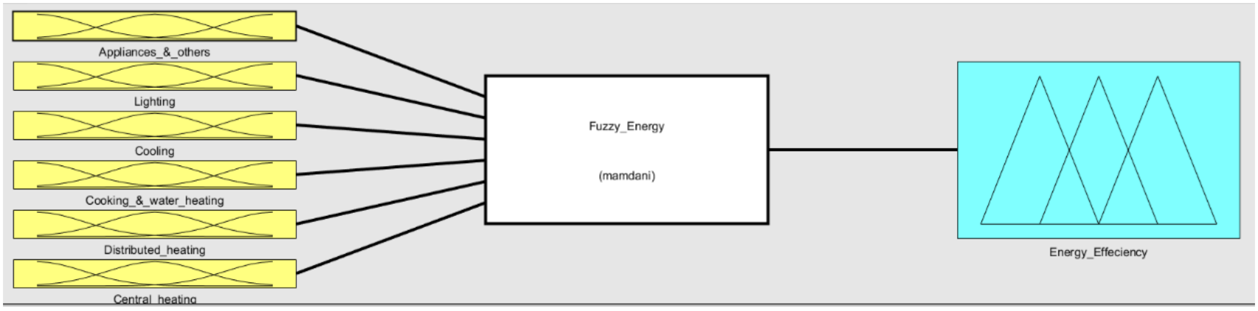

Figure 3. Schematic diagram of the Mamdani fuzzy logic model for evaluating energy efficiency based on end-use energy consumption categories

The model receives six fuzzy inputs representing major energy end-uses and produces a fuzzy output indicating the building's energy efficiency level. Each input variable (appliances & others, lighting, cooling, cooking & water heating, distributed heating, and central heating) was represented using three triangular membership functions, labeled as Low, Medium, and High. The output variable, representing energy efficiency level, also used five linguistic terms: very inefficient, inefficient, moderately efficient, efficient, and very efficient. A total of 729 fuzzy rules were constructed based on combinations of input terms and expert input from certified energy auditors. These rules capture non-linear interactions between energy usage patterns across different systems.

RESULTS AND DISCUSSION

This study utilizes energy consumption data from public and commercial buildings, sourced from the dataset *City-level Building Operational End-use Carbon Emissions in China*. The dataset provides operational carbon emission information categorized by various end-use energy sectors, including central heating, distributed heating, cooling, lighting, appliances and miscellaneous uses, as well as cooking and water heating. Prior to further analysis, the available carbon dioxide (CO_2) emissions—originally reported in kilograms—were converted into electrical energy consumption in kilowatt-hours (kWh), applying a standard carbon-to-energy conversion factor ($kgCO_2/kWh$). This conversion process enables a more precise quantification of electricity usage, allowing for a more accurate distributional analysis and categorization of energy use intensity in the context of energy efficiency and sustainable planning.

The electricity consumption patterns in these public and commercial buildings were analyzed using annual consumption data over a six-year period, from 2015 to 2020. As illustrated in Figure 4, the data reflect varying proportions of electricity use across different end-use categories, providing a basis for deeper evaluation of energy efficiency levels and modeling of demand-side energy behavior.

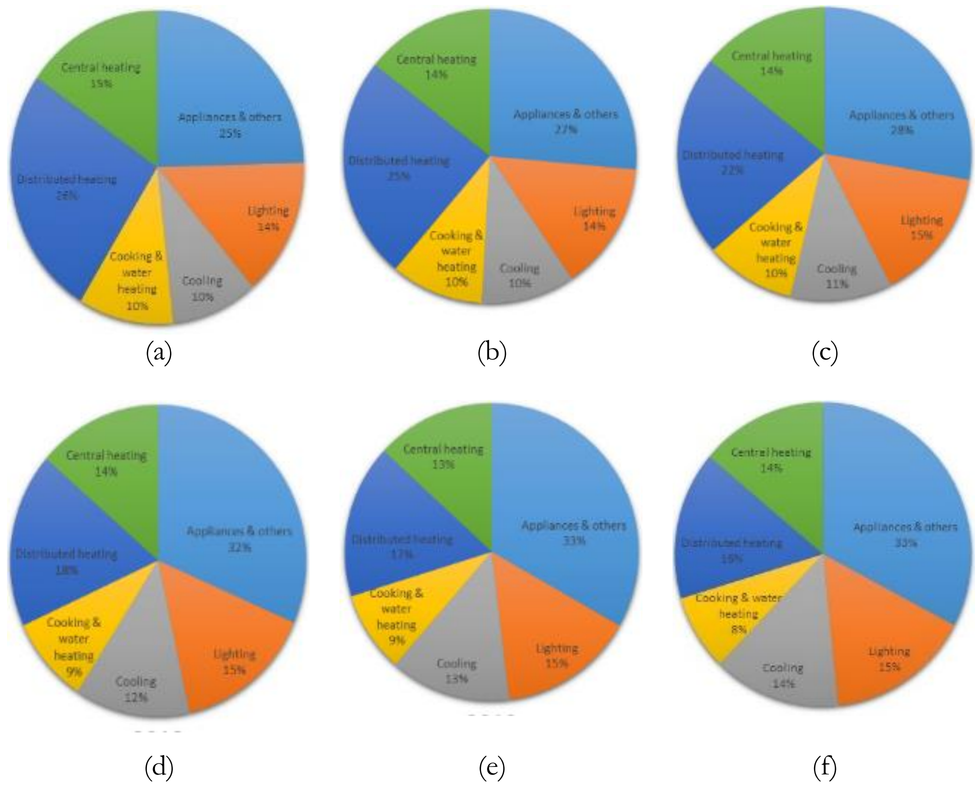

Figure 4. Annual distribution of electricity consumption by end-use category in public and commercial buildings (2015–2020), listed as: (a) 2015; (b) 2016, (c) 2017, (d) 2018, (e) 2019, (f) 2020.

The analysis reveals that the category "Appliances & Others" consistently accounted for the largest share of total electricity use, with proportions ranging from 25% in 2015 to 33% in 2020. This category exhibited a progressive increase over the years, indicating a growing demand for miscellaneous electrical devices and plug-in equipment in building operations. In contrast, "Distributed Heating" initially represented a substantial proportion of consumption (26% in 2015 and 25% in 2016), but experienced a gradual decline to 16% by 2020, suggesting potential shifts in heating systems or improvements in efficiency.

Lighting remained relatively stable throughout the period, with annual proportions fluctuating narrowly between 14% and 15%, indicating consistent energy use behavior and lighting technology adoption. Similarly, "Central Heating" showed a relatively steady share across the years, averaging approximately 14%, with minor variations (13%–15%), suggesting limited systemic or technological changes in centralized thermal systems.

The "Cooling" category displayed a modest upward trend, increasing from 10% during 2015–2017 to 13%–14% in 2019 and 2020, possibly reflecting increased cooling demand or higher deployment of air-conditioning systems. Meanwhile, "Cooking & Water Heating" consistently contributed the smallest proportion to total electricity use, maintaining a range between 9% and 10%, which may be attributed to the use of alternative energy sources for these functions or inherently lower consumption intensity.

Overall, the multi-year distribution highlights a shift in the electricity consumption landscape, particularly the rising dominance of non-specific appliances and the reduced share of distributed heating. These trends provide valuable empirical insights for energy efficiency modeling, targeted demand-side management, and the prioritization of retrofit strategies in public and commercial buildings.

End-Use Electricity Consumption Profile and Implications for Modeling Energy Efficiency

The analysis of electricity consumption by end-use category, as depicted in Figure 4, provides foundational insights for constructing a reliable and interpretable model of energy efficiency in public and commercial buildings. The data reveal distinct patterns in electricity usage distribution over a six-year period (2015–2020), which are critical for the formulation of fuzzy rule bases and for identifying priority areas in demand-side modeling.

The "Appliances & Others" category consistently accounts for the highest proportion of electricity consumption across all observed years. Its share rose from 25% in 2015 to 33% in 2020, indicating an increasing reliance on plug-load equipment, digital devices, and miscellaneous electrical systems within building operations. This rising trend suggests a shift toward more distributed and user-controlled electricity use, which inherently introduces variability and complexity into energy consumption profiles. From a modeling perspective, this category warrants higher weighting and granularity in rule development due to its dominant and growing influence on total consumption.

In contrast, "Distributed Heating" demonstrates a steady decline from 26% in 2015 to 16% in 2020, reflecting either an improvement in system efficiency, changes in occupant behavior, or possible replacement with more efficient heating technologies. This decreasing trend provides evidence for potential load-shifting and retrofitting measures that could be modeled in energy policy simulations or scenario-based planning. As a result, its influence on fuzzy classification of efficiency may be declining but still represents a significant portion of historical load.

The shares of "Lighting" and "Central Heating" remained relatively stable, each contributing between 13% and 15% throughout the analysis period. Their consistency implies that these systems are mature and relatively uniform across buildings, allowing for more predictable modeling of their contributions to energy use. These stable categories provide a strong reference frame when evaluating relative efficiency and deviation patterns in other categories.

Meanwhile, "Cooling" shows a moderate upward trend—from 10% in 2015 to 14% in 2020—suggesting increasing cooling demands, possibly due to climate variability, extended usage durations, or occupancy pattern changes. This category's dynamic behavior indicates that it should be treated as a context-sensitive parameter in simulation models, particularly in warmer climatic zones or during seasonal peak analysis. In contrast, "Cooking & Water Heating" consistently accounts for the lowest share of electricity use, ranging from 9% to 10%, implying limited impact on the aggregate efficiency classification. However, its presence remains relevant for modeling total end-use coverage and for buildings that utilize electricity as the primary source for these functions.

Taken together, these proportional patterns and temporal trends serve as a quantitative foundation for defining fuzzy membership functions and designing rule-based classification systems to evaluate electrical energy efficiency. They also inform the construction of input vectors in simulation models, allowing for scenario evaluation, sensitivity testing, and the prediction of efficiency performance under varying end-use load conditions. Moreover, by capturing both stable and dynamic consumption behaviors, the model can be calibrated to better reflect real-world building operations, thereby enhancing its applicability in sustainable energy planning and building performance optimization.

Fuzzy Classification Model Design for Energy Efficiency Evaluation

To enhance the interpretability and flexibility of energy efficiency assessment in public and commercial buildings, a fuzzy logic approach is adopted to categorize annual electricity consumption into three linguistic levels: Low, Medium, and High. This model aims to reflect real-world variability by accommodating uncertainty and gradual transitions in energy usage patterns across diverse buildings and cities.

Fuzzy Classification Model Design for Energy Efficiency Evaluation

Membership functions are constructed based on the statistical distribution of annual electricity consumption data. Consumption levels are classified into three distinct categories based on statistical quartile analysis to facilitate a more structured interpretation of the data. The Low category includes all consumption values that fall below the first quartile (Q1), indicating relatively minimal usage within the observed dataset. The Medium category encompasses values that lie within the interquartile range, specifically between Q1 and the third quartile (Q3), representing typical or average consumption behavior. Lastly, the High category comprises values that exceed the third quartile (Q3), reflecting significantly higher consumption levels. This classification method enables a more nuanced understanding of consumption patterns and supports data-driven decision-making processes.

To represent the linguistic values of the input variables, triangular membership functions were employed due to their simplicity, interpretability, and computational efficiency. Each input—such as electricity consumption in categories like Appliances & Others, Lighting, Cooling, Cooking & Water Heating, Distributed Heating, and Central Heating—was normalized to a common scale ranging from 0 to 100 to enable consistent evaluation across variables with different physical units or magnitudes.

The fuzzification process transforms these normalized crisp input values into degrees of membership for three predefined fuzzy sets: Low, Medium, and High. These categories are defined using overlapping triangular functions, allowing for smooth transitions and partial membership across adjacent classes. This design enables the fuzzy inference system to capture uncertainty and variation in energy consumption intensity, which is particularly relevant for heterogeneous building types and operational behaviors. The structure and parameters of the triangular membership functions used for all input variables are shown in Table 1. Each fuzzy set is defined by its corresponding support and core values, which determine the range and peak of the membership function.

Table 1. Linguistic Terms and Membership Function Ranges for Input Variables Based on Quartile Distribution

Linguistic term	Range (based on quartile)	Membership shape
Low	[Min, Q1]	Triangular
Medium	[Q1, Median, Q3]	Triangular
High	[Q3, Max]	Triangular or Trapezoidal

This design enables a smooth transition between categories, avoiding abrupt thresholding and better capturing the nuanced differences in energy intensity across building types.

The development of the fuzzy classification model begins with the construction of membership functions for both input and output variables. The membership functions were defined and visualized using MATLAB's Fuzzy Inference System (FIS) editor, which provides an intuitive environment for designing fuzzy logic structures.

For the input variables, which represent annual electricity consumption data disaggregated by end-use categories (such as lighting, cooling, appliances & others, distributed heating, central heating, and cooking & water heating), each variable was classified into three linguistic categories: Low, Medium, and High. These categories were determined based on the empirical distribution of the data, particularly utilizing the quartile method to ensure data-driven segmentation. Triangular membership functions were adopted to represent the gradual transition across these categories, allowing for smooth fuzzification of input values and avoiding sharp thresholding.

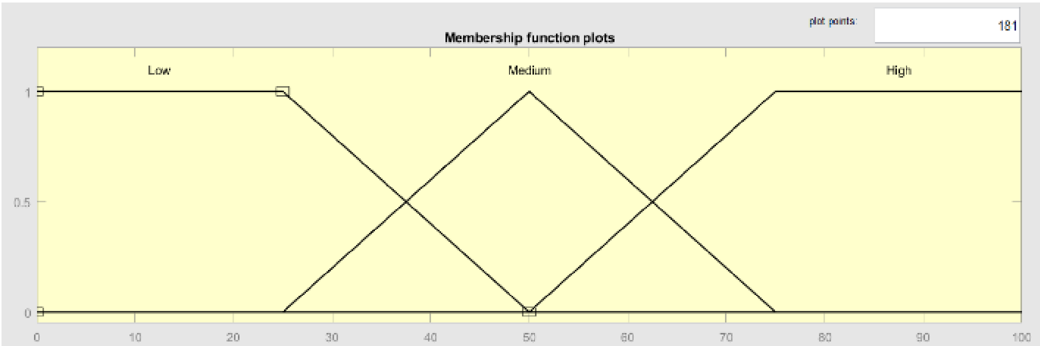

Figure 5. Membership function plot for the input variable "appliances & others" in the fuzzy inference system

As shown in Figure 5, the membership function plot represents the fuzzy input variables Appliances & Others, Lighting, Cooling, Distributed Heating, Central Heating, and Cooking & Water Heating which quantify the proportion of electricity consumption allocated to each end-use category within a building. The input range is normalized between 0 and 100, and the membership function is divided into three linguistic categories: Low, Medium, and High. These categories are implemented using triangular membership functions (trimf) in MATLAB's Fuzzy Logic Toolbox. The "Low" category spans from 0 to 50, with full membership ($\mu = 1$) for values below 25, declining linearly to zero at 50. The "Medium" category peaks at 50, covering a symmetric range from approximately 25 to 75, while the "High" category begins increasing at 50 and reaches full membership at 75 and beyond. The overlapping structure of these fuzzy sets allows input values to have partial membership in multiple categories, enabling smooth and realistic transitions between different usage levels. This fuzzification approach accommodates uncertainty and variability in consumption patterns and forms the basis for robust rule-based reasoning in the fuzzy inference system. Similar membership function structures are constructed for all other input variables in the model, ensuring consistency across the system's input layer.

In contrast to the input variables, the output variable, which reflects the energy efficiency level of a building, was defined with a finer resolution to support more precise classification and interpretability. The output was partitioned into five linguistic terms: Very Inefficient, Inefficient, Moderately Efficient, Efficient, and Very Efficient. The linguistic terms and the corresponding membership function characteristics are shown in Table 2. The table summarizes the core (peak) values and the membership function shape for each category, providing a clear representation of the output variable configuration used in this study.

Table 2. Linguistic Terms and Membership Function Ranges for Output Variables Based on Quartile Distribution

Linguistic term	Core (peak)	Membership shape
Very efficient	0	Triangular
Efficient	25	Triangular
Moderately efficient	50	Triangular
Inefficient	75	Triangular
Very inefficient	100	Triangular

Each linguistic term was represented using triangular membership functions over a normalized range of 0 to 100, providing overlapping zones that enable smooth defuzzification. The increased granularity in the output domain allows the fuzzy inference system (FIS) to provide more refined and differentiated feedback, particularly useful for comparative efficiency analysis, benchmarking, and strategic prioritization in energy management planning. The distribution and structure of these membership functions are illustrated as shown in Figure 6, which presents the comprehensive fuzzy set definition applied to the output variable within the MATLAB FIS environment.

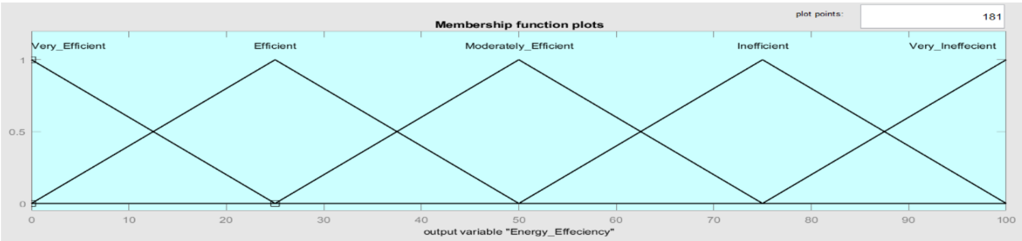

Figure 6. Membership function plot for the output variable "energy_efficiency"

This figure depicts the triangular membership functions associated with the output variable "Energy_Efficiency" in the fuzzy inference system. The output domain spans from 0 to 100 and is divided into five linguistic categories: Very Inefficient, Inefficient, Moderately Efficient, Efficient, and Very Efficient. Each category overlaps with adjacent terms, ensuring smooth transitions and allowing for partial memberships. This configuration enables the system to evaluate building energy performance on a continuous and interpretable scale, supporting nuanced decision-making in energy efficiency assessment.

This structure provides a foundation for robust rule-based inference and facilitates defuzzification through centroid-based methods, ultimately yielding a quantifiable assessment of energy efficiency that accommodates uncertainty and heterogeneity in energy use patterns across buildings.

Fuzzy Rule Base Construction

A core component of the fuzzy inference system is the rule base, which defines the logical relationships between input variables and the corresponding output classifications. The fuzzy rule base is formulated using expert-driven linguistic rules of the form *IF–THEN*, integrating multiple input variables to infer the level of energy efficiency. In this study, six key end-use electricity consumption variables were considered as inputs: Appliances & Others, Lighting, Cooling, Cooking & Water Heating, Distributed Heating, and Central Heating. Each variable is fuzzified into three linguistic categories—Low, Medium, and High—based on normalized annual energy consumption values.

To systematically handle the combinatorial possibilities of these inputs, a comprehensive fuzzy rule base was constructed using the Rule Editor in MATLAB, as shown in Figure 7.

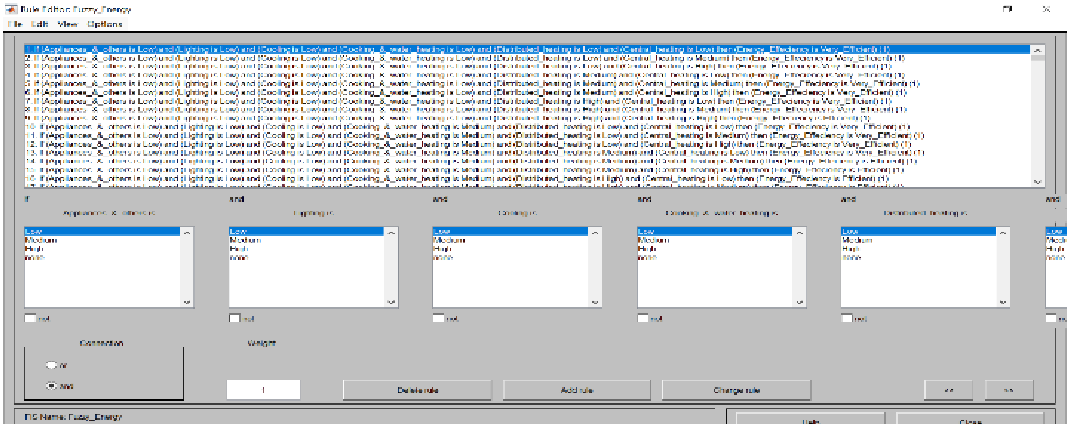

Figure 7. Rule base configuration for energy efficiency classification in MATLAB fuzzy inference system

The figure shows the Rule Editor interface in MATLAB used to define the fuzzy inference system for classifying energy efficiency. Each row represents a unique rule that combines the fuzzy values of six energy end-use variables. For example, a rule might state: *If (Appliances & Others is Low) and (Lighting is Low) and (Cooling is Low) … then (Energy_Efficiency is Very_Efficient)*. Rules are evaluated using logical AND connections, and the output variable is mapped to one of five efficiency classes. This rule base serves as the core mechanism for reasoning within the fuzzy model, linking real-world energy profiles to evaluative outcomes.

This graphical interface enables the specification of multiple rule sets by combining the linguistic terms of input variables. Logical operators (AND/OR) and rule weights can also be configured to control the influence of each rule within the inference process. Each rule maps a specific combination of input states to one of five fuzzy output categories: Very Inefficient, Inefficient, Moderately Efficient, Efficient, and Very Efficient.

Such rules enable the fuzzy inference system to generalize across diverse consumption profiles and provide interpretable, rule-based classifications of energy performance. The full rule set forms the knowledge base of the system and serves as the foundation for applying the Mamdani fuzzy inference method and subsequent defuzzification.

These rules represent expert-informed reasoning on how various load combinations contribute to building-level efficiency, allowing the fuzzy inference engine to produce an output classification score.

Fuzzy Classification Output and Defuzzification

In accordance with the Mamdani fuzzy inference approach, the final step in the model involves defuzzification, a process that translates the aggregated fuzzy output into a single crisp value. This value provides a quantitative assessment of a building's energy efficiency level. The defuzzification method employed in this study is the Centroid of Area (COA) technique, which determines the center of gravity of the output membership functions resulting from the rule evaluation. This method offers a balanced and interpretable measure of system behavior across multiple overlapping rules and membership degrees. The resulting scalar value lies on a normalized scale (e.g., 0–100) and is subsequently mapped to qualitative linguistic labels (e.g., *Very Inefficient*, *Inefficient*, *Moderately Efficient*, *Efficient*, *Very Efficient*), thereby enhancing interpretability and policy relevance, as shown in Figure 8.

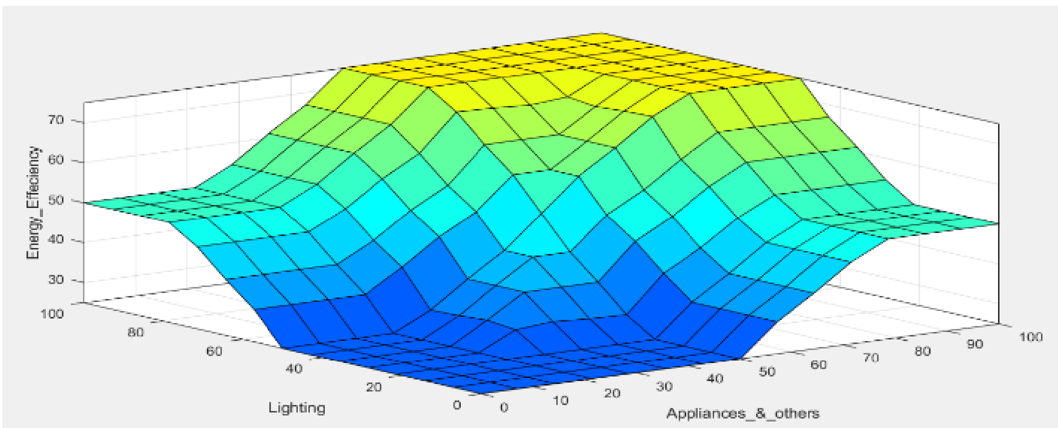

Figure 8. The 3D surface plot of the output variable energy efficiency

This figure illustrates the fuzzy inference process and output defuzzification for a specific test case, as implemented in MATLAB's Rule Viewer interface. The six input variables—Appliances & Others (29), Lighting (14), Cooling (12), Cooking & Water Heating (7), Distributed Heating (14), and Central Heating (12)—are mapped to their corresponding fuzzy sets through the fuzzification process. The yellow bars indicate the degree of membership of each input value within the defined fuzzy terms (e.g., Low, Medium, High). Based on these fuzzified inputs, the system activates a subset of the rule base, with each rule contributing to the aggregation of output membership functions.

The final output, shown in the rightmost column, is the defuzzified energy efficiency score of 8.22, derived using the centroid method. This value corresponds to a position near the peak of the *Very Efficient* fuzzy set, suggesting that the building configuration under evaluation exhibits a high degree of operational energy performance. The Rule Viewer provides an interpretable visual representation of how input variables interact through the fuzzy rule base to yield a specific classification outcome, thereby validating the model's transparency and applicability for energy efficiency analysis in public and commercial buildings.

To validate the model across multiple input scenarios, a set of test cases with varied input combinations are shown in Table 3. Each row in the table represents a unique configuration of energy consumption values for six major end-use categories. The final column shows the defuzzified energy efficiency scores derived from each configuration. These results confirm that the fuzzy model responds consistently to changes in input consumption profiles, and produces nuanced efficiency assessments aligned with the expected performance classifications.

Table 3. Defuzzified Energy Efficiency Scores for Sample Building Input Configurations

Appliances & others	Lighting	Cooling	Cooking & water heating	Distributed heating	Central heating	Defuzzification Result
25	14	10	10	26	15	8.02
26	14	10	10	25	14	8.02
28	15	11	10	22	14	8.14
32	15	13	9	18	14	8.57
33	15	13	9	17	13	8.71
29	14	12	7	14	12	8.22

To further elucidate the relationship between end-use electricity consumption profiles and the resulting energy efficiency classifications, a comparative analysis was conducted across multiple input configurations. This visualization serves not only as a tool for validating the robustness of the fuzzy inference system but also as a medium for interpreting the influence of each consumption parameter on the overall performance index. By aligning each input scenario with its corresponding defuzzified output, this graphical representation enables a more nuanced understanding of how efficiency classifications are derived in practice, enhancing model transparency and interpretability.

The annual segmentation of building energy efficiency results over six years, derived using the proposed fuzzy logic framework, is presented as shown in Table 3, where each row captures a distinct configuration of electricity consumption across six major end-use categories alongside the corresponding defuzzified efficiency scores obtained via the centroid method, thereby providing a clear, structured, and analytically robust representation of the relationship between consumption patterns and energy efficiency performance.

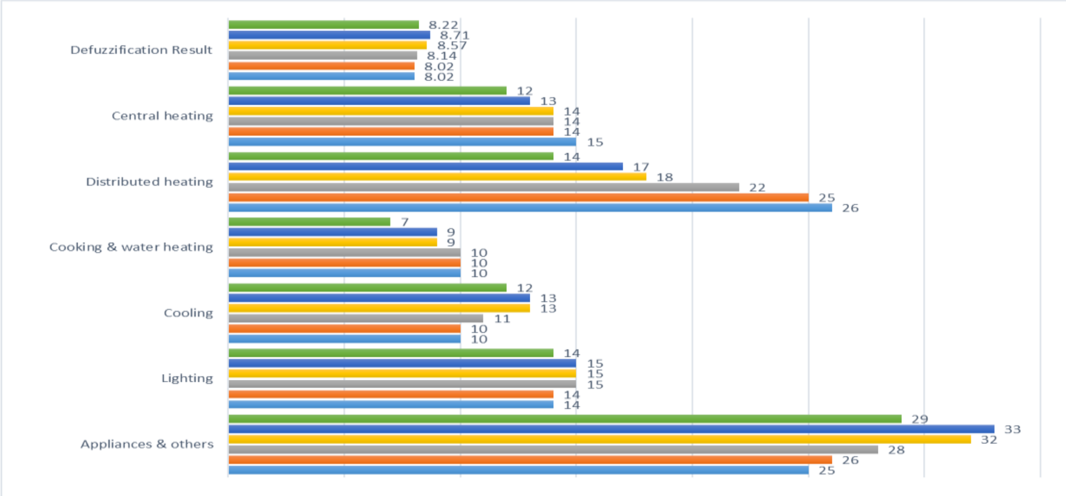

Figure 9. Comparative analysis of energy end-use inputs and corresponding defuzzified energy efficiency scores

As shown in Figure 9, the modeling output is visualized to facilitate direct comparison between input parameter values and the corresponding defuzzified outcomes. The figure presents a comparative horizontal bar chart illustrating energy consumption across six end-use categories Appliances & Others, Lighting, Cooling, Cooking & Water Heating, Distributed Heating, and Central Heating under multiple building scenarios. Each scenario corresponds to the configurations detailed in Table 3 and is associated with a defuzzified energy efficiency score, normalized on a 0–10 scale, ranging from 8.02 to 8.71, derived using the Mamdani fuzzy inference system and the Centroid of Area (COA) method.

The visualization reveals consistent and interpretable patterns that affirm the internal coherence of the fuzzy logic model. Scenarios with reduced energy consumption in Appliances & Others and Distributed Heating consistently result in higher energy efficiency scores, while configurations with increased values in these categories yield marginally lower scores. Notably, the scenario with the highest score (8.71) is characterized by a significant reduction in distributed heating and moderate levels in other end-use categories. These trends are in direct alignment with empirical data, which show a steady increase in energy consumption in Appliances & Others and Lighting, both of which significantly influence defuzzified efficiency outcomes. In contrast, Distributed Heating exhibits a declining trend over the observed period, highlighting its potential as a target for energy-saving interventions. Cooking & Water Heating consumption remains relatively stable, whereas Central Heating displays a modest upward trend.

The alignment between historical data trends and fuzzy-based scenario outcomes substantiates the reliability and validity of the fuzzy rule base and membership function design. The defuzzified outputs provide a comprehensive and aggregated representation of energy efficiency performance, enabling comparative assessment across varying building configurations. Furthermore, the fuzzy classification system's capacity to translate multidimensional technical outputs into coherent, policy-relevant insights underscores its applicability in evidence-based energy planning. This approach not only enhances diagnostic accuracy in building performance evaluations but also supports the formulation of strategic interventions aimed at promoting energy efficiency in public and commercial building sectors.

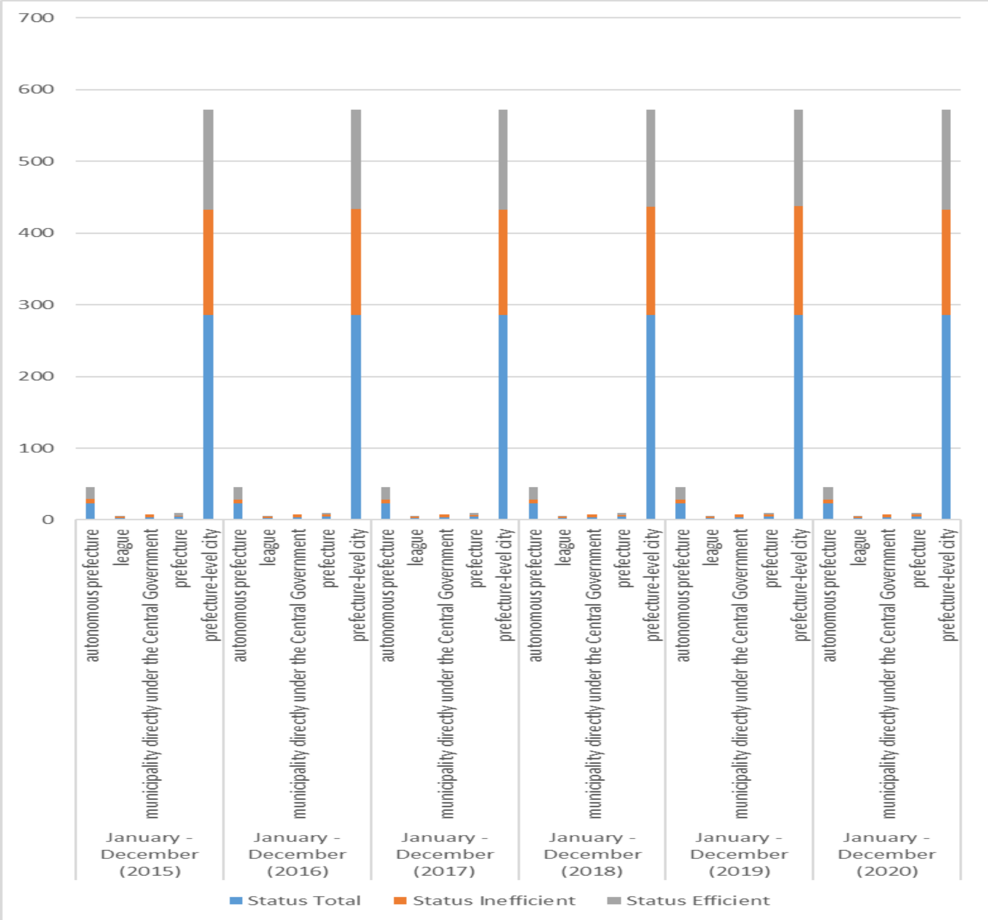

Figure 10. Spatial and Temporal Distribution of Energy Inefficiency Across Administrative Regions (2015–2020)

As shown in Figure 10, a spatially disaggregated depiction of energy inefficiency patterns is presented, highlighting persistent regional disparities in energy performance over the period 2015–2020. Notably, municipalities directly under the Central Government consistently recorded the highest levels of inefficiency among all administrative categories. Over the six-year observation period (2015–2020), these municipalities reported a sustained 100% inefficiency rate, with no instances of buildings falling within the efficient classification range an alarming indicator of systemic inefficiencies in energy governance at the central urban level. Temporal disaggregation further reveals that 2019 represents the peak in recorded inefficiencies, with prefecture-level cities experiencing a marked increase in inefficient building prevalence, rising from 51% in the 2015–2017 period to 53% in 2019.

This multifaceted analysis framework enables the identification of entrenched inefficiency patterns, both at the building and regional governance levels. Moreover, the integration of spatial, temporal, and categorical dimensions allows for a more comprehensive understanding of energy use dynamics, thus providing an evidence-based foundation for the formulation of geographically targeted and temporally responsive energy efficiency policies. These insights are particularly critical for high-density urban centers governed directly by the central authority, where strategic interventions are urgently needed to address persistent inefficiencies and align with broader national sustainability objectives.

DISCUSSION

The use of fuzzy logic modeling, incorporating triangular membership functions and rule-based reasoning, allows this study to address a critical limitation of many previous works: the inability to robustly represent the uncertainty and ambiguity inherent in real-world building energy behavior. By introducing linguistic variables (e.g., Low, Medium, High) and capturing gradual transitions across consumption levels, the fuzzy inference system (FIS) demonstrates an enhanced capacity for handling imprecision, thus making it more applicable for heterogeneous building datasets, particularly in urban contexts with diverse usage profiles.

Importantly, the large-scale validation involving 11,736 building records affirms the model's scalability and transferability. The persistent inefficiency observed in municipalities directly under central government jurisdiction suggests a structural governance issue rather than merely a technical or behavioral shortfall.

From a broader perspective, the study contributes to the literature on intelligent energy systems by demonstrating how soft computing techniques, such as fuzzy logic, can support evidence-based energy planning and real-time performance diagnostics. The insights derived from scenario-based and spatial-temporal analyses are directly relevant for policymakers, facility managers, and energy service providers seeking to prioritize retrofitting interventions, optimize load distribution, or enhance demand-side management strategies.

Nevertheless, several limitations warrant attention. First, the model does not explicitly incorporate climatic, behavioral, or socioeconomic variables, which are known to influence building energy dynamics. Second, while the fuzzy classification system is robust, it currently assumes equal weight for all input variables, which may oversimplify the influence of certain end-use categories on overall efficiency performance.

To address these limitations and extend the utility of this framework, future research should consider the integration of multi-dimensional contextual variables, including climatic zones, occupancy schedules, building typologies, and control strategies. Furthermore, hybrid approaches that combine fuzzy logic with machine learning (e.g., ANFIS, fuzzy-CNNs) could enhance predictive accuracy and adaptability. Longitudinal tracking of post-retrofit performance could also provide valuable feedback loops to refine the rule base and membership function definitions.

CONCLUSION

This study presents an integrative framework for evaluating electricity consumption and energy efficiency in public and commercial buildings through the application of fuzzy logic-based classification. By utilizing a disaggregated dataset spanning six years (2015–2020) from the *City-level Building Operational End-use Carbon Emissions in China*, the analysis reveals key temporal trends in end-use electricity consumption, most notably the consistent rise in demand within the "Appliances & Others" category and a concurrent decline in "Distributed Heating." These empirical patterns reflect evolving operational behaviors and possible technological transitions, providing a critical basis for targeted efficiency interventions.

The developed fuzzy inference system—structured using triangular membership functions and normalized input variables—offers a robust mechanism for handling imprecise, nonlinear, and heterogeneous energy data. By classifying building-level consumption into linguistic categories of energy efficiency (Very Inefficient to Very Efficient), the model accommodates uncertainty and gradation, enhancing interpretability and decision relevance. The use of quartile-based partitioning further ensures that the membership functions are empirically grounded and reflective of actual consumption distributions.

Model validation through scenario analysis, defuzzification via centroid methods, and large-scale evaluation encompassing 11,736 building entries confirm the model's reliability, scalability, and applicability across varying operational contexts. The spatial-temporal analysis further exposes persistent inefficiency patterns, particularly in centrally governed municipalities, where no efficient classifications were observed throughout the study period. This spatial disparity underscores the necessity for differentiated and location-sensitive policy interventions.

The integration of fuzzy logic into energy performance evaluation offers a viable and scalable approach for supporting demand-side management, efficiency benchmarking, and sustainable urban energy planning. Future work should focus on incorporating real-time consumption data, occupant behavior modeling, and integration with dynamic simulation environments to further enhance predictive accuracy and policy relevance. The findings substantiate the utility of soft-computing methodologies in advancing data-driven, interpretable, and actionable strategies for building energy optimization in complex urban systems.

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