International Journal of Computer Information Systems and Industrial Management Applications
ISSN 2150-7988 Volume 18(14s) 2026 pp. 574-589
https://doi.org/10.70917/ijcisim-2026-4268
Article

# Adaptive Interval Type 2 Neuro Fuzzy Model for Occupant Comfort Prediction and Energy-Efficient Smart Home Control

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**Abstract:** This paper investigates an adaptive type 2 neuro fuzzy control approach for energy efficient smart home IoT systems. The proposed method integrates a neural network based comfort prediction model, an adaptive type 2 fuzzy(T2F) inference mechanism to generate intelligent control actions for HVAC, lighting, and ventilation systems. Environmental parameters including temperature, humidity, illumination, and occupancy are continuously monitored through IoT sensors and utilized for real time decision making. The adaptive T2F system effectively handles uncertainty and imprecision. Experimental evaluation on smart home environmental data demonstrates improved comfort maintenance, enhanced adaptability, and reduced energy consumption compared with conventional threshold based, classical fuzzy, and neuro fuzzy control approaches. The developed controller can be applied to smart home automation systems because its rule base remains interpretable while adapting to changing environmental conditions, making it applicable to energy management systems.
**Keywords:** Interval Type 2 Fuzzy Logic; Artificial Neural Network; Internet of Things; Smart Home; Energy Management; Occupant Comfort Prediction.

## 1. Introduction

Recent developments in IoT technology have enabled smart home systems to monitor environmental conditions, communicate with connected devices, and automate household operations. Through the integration of smart sensors, wireless communication technologies, cloud computing, and intelligent analytics, smart homes can enhance energy efficiency, occupant comfort, security, and sustainability. The convergence of IoT and artificial intelligence has contributed to the development if intelligent residential systems capable of real time decision making and adaptive automation. Recent studies have reported that machine learning and IoT technologies in improving energy efficiency in smart buildings and residential environments [16].

Energy management remains one of the primary objectives of modern smart home systems due to increasing energy demand, environmental concerns, and the need for sustainable resource utilization. Several researchers have proposed intelligent energy management frameworks for residential applications. Alowaidi [2] developed a fuzzy-based energy management algorithm for renewable-energy-enabled smart homes, while Kanso *et al.* [9] proposed an automated energy management framework for residential environments. Karuna *et al.* [10] introduced a real-time prediction and optimization strategy for IoT-enabled smart homes, whereas Khan *et al.* [11] investigated machine-learning-based approaches for sustainable energy management. Alotaibi *et al.* [1] further integrated IoT technologies with machine learning to coordinate energy generation, storage, and appliance utilization. In addition, intelligent non-intrusive load monitoring techniques have been developed to improve residential energy management and appliance-level energy analysis [12].

The increasing availability of sensor-generated data has encouraged the adoption of advanced machine learning techniques for smart-home intelligence. Drir and Kebour [4] employed ensemble learning methods for forecasting energy demand and efficiency in residential environments. Similarly, Padmini Devi *et al.* [13] proposed a hybrid fuzzy clustering and deep neural network framework for efficient data collection and processing in wireless sensor networks. These studies demonstrate the effectiveness of data driven intelligence in improving prediction accuracy and system performance. However, many machine learning approaches operate as black box models that provide limited transparency and interpretability, thereby restricting user trust and explain ability in automated control systems.

To address uncertainty and imprecision in environmental measurements, fuzzy logic has been widely adopted in smart home and IoT applications. Fuzzy systems enable human like reasoning through linguistic rules and interpretable decision making mechanisms. Existing studies have successfully applied fuzzy logic to energy management [2], intelligent smart home management and safety [3], fire prevention systems [5], fault tolerant IoT-enabled wireless sensor networks [17], photovoltaic fault detection framework [14], and intelligent recommendation systems in IoT environments [19]. These applications demonstrate the effectiveness of fuzzy reasoning for manage uncertainty and supporting decision making in complex environments.

Conventional Type 1 fuzzy systems use fixed membership functions and predefined rule structures, which can limit their ability to represent uncertainties caused by changing environmental conditions and occupant preferences. T2F logic addresses this limitation by introducing a footprint of uncertainty (FOU), allowing uncertainty in the membership functions to be represented more effectively. Ghosh *et al.* [6] demonstrated the effectiveness of Type 2 fuzzy systems for non-intrusive load monitoring and smart home control applications. Hassan *et al.* [8] and Long *et al.* [20] developed Interval Type-2 Fuzzy systems for IoT-based decision-making and HVAC energy management, respectively. Their results show that T2F controllers can better accommodate uncertainty in operating conditions while maintaining reliable control performance.

Artificial intelligence has enabled the integration of neural networks and fuzzy reasoning for intelligent environmental control. Neural networks effectively learn nonlinear relationships from sensor data, while fuzzy systems provide interpretable decision-making under uncertainty, making their integration suitable for smart-home energy management.

Recent studies have also emphasized privacy, safety, security, and explainability in smart-home systems through privacy-preserving frameworks, IoT-based fire detection, and explainable decision-making techniques. Despite these advances, existing approaches remain limited. Machine-learning models often lack interpretability, conventional fuzzy controllers have limited adaptability, and reinforcement learning methods suffer from instability and poor explainability. Furthermore, most existing systems address individual objectives rather than providing a unified solution for comfort regulation, uncertainty handling, interpretability, and real-time energy optimization.

To address these limitations, this paper presents an Adaptive Type-2 Neuro-Fuzzy Control Framework for Energy-Efficient Smart Home IoT Systems by combining neural network-based comfort prediction with adaptive Type-2 fuzzy reasoning. The frame-work processes IoT sensor data to generate control actions for HVAC, lighting, and ventilation, with the goal of improving energy efficiency, occupant comfort, and decision transparency.

1. An adaptive Interval Type 2 neuro fuzzy framework for intelligent smart home control under uncertain environmental conditions.
2. An artificial neural network model for occupant comfort prediction using temperature, humidity, illumination, and occupancy data.
3. Integration of comfort prediction and Interval T2F reasoning for interpretable and uncertainty aware control decision making.
4. A Comfort Control Index (CCI) for adaptive HVAC, lighting, and ventilation management.
5. This model evaluated using the Occupancy Detection Dataset demonstrating im-proved comfort maintenance and reduced energy consumption.
6. An IoT enabled architecture suitable for real time smart home automation applications.

Unlike existing smart home energy management approaches that separately employ ANN or Interval T2F systems, the proposed framework integrates both techniques into a unified IoT-enabled architecture for occupant comfort prediction and adaptive control. The framework combines ANN-based comfort estimation with an interval T2F controller to generate interpretable control actions for HVAC, lighting, and ventilation systems. Furthermore, a CCI is introduced as an intermediate decision variable that bridges prediction and control, enabling uncertainty aware reasoning, improved interpretability, and energy efficient smart home operation under dynamic environmental conditions.

The remainder of this paper is organized as follows. Section 2 presents the system model and mathematical problems formulation. Section 3 introduces the proposed adaptive type 2 neuro fuzzy methodology. Section 4 presents the overall IoT enabled smart home architecture and implementation framework. Section 5 reports the experimental setup and performance metrics. Section 5 simulation results, comparative performance and comparative performance analysis, and discussion. Section 6 concludes the paper and outlines future research directions. Finally, Section 7 concludes the paper.

## 2. System Model and Problem Formulation

### *2.1 Smart Home Environment*

The considered smart home environment consists of an IoT enabled residential space equipped with multiple environmental sensors, communication modules, intelligent processing units, and controllable appliances. The primary objective of the system us to maintain occupant comfort while minimizing energy consumption through adaptive control actions.

Environmental conditions are continuously monitored using IoT sensors measuring temperature, humidity, illumination, and occupancy. The collected sensor data are transmitted to a centralized processing unit where comfort prediction and intelligent control decisions are performed. Let the environmental state vector at time instant *t* be represented as

$$\boldsymbol{X}(\boldsymbol{t}) = [\boldsymbol{T}(\boldsymbol{t}), \boldsymbol{H}(\boldsymbol{t}), \boldsymbol{L}(\boldsymbol{t}), \boldsymbol{O}(\boldsymbol{t})]^{\boldsymbol{T}} \qquad (1)$$

where, $T(t)$ denotes indoor temperature ( ∘ C), $H(t)$ denotes relative humidity (%), $L(t)$ denotes illumination level (Lux), $O(t)$ denotes occupancy status. Based on the observed environmental conditions, the intelligent controller generates control actions for HVAC, lighting, and ventilation systems to maintain desired comfort levels while reducing unnecessary energy usage.

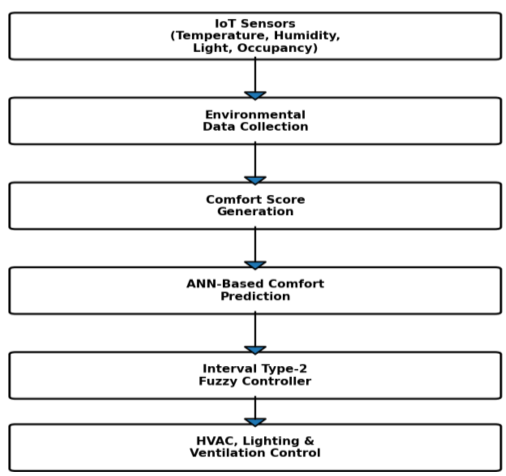


**Figure 1:** Overall architecture of the adaptive Interval Type 2 neuro-fuzzy smart home control framework.

The overall control objective can be expressed as max $C(t)$ subject to min $E(t)$ where $C(t)$ represents occupant comfort and $E(t)$ represents energy consumption. Therefore, the smart-home control problem can be viewed as a multi-objective optimization task that seeks a balance between comfort maintenance and energy efficiency.

### *2.2 Occupancy Detection Dataset*

To evaluate the presented method, experiments were conducted using the publicly available Occupancy Detection Dataset obtained from the UCI Machine Learning Repository. The dataset consists of environmental measurements collected from an office room with wireless sensors and occupancy monitoring devices. Sensor readings were obtained under different occupancy conditions to crepresent typical indoor environmental changes. The dataset recorded variables are attributes: Temperature (°C), Relative Humidity (%), Light Intensity (Lux), Carbon Dioxide Concentration(ppm), Humidity Ratio, Occupancy Status (0 or 1).

The dataset was originally developed for occupancy detection; however, its the environmental variables are also suitable for estimating occupant comfort and supporting intelligent energy management decisions. Temperature, humidity, light intensity, and occupancy were selected as input variables due to their direct influence on indoor environmental comfort.

| Feature | Minimum | Maximum | Mean | Std. Dev. |
|---|---|---|---|---|
| **oC** | 19.000 | 24.408 | 20.906 | 1.055 |
| % | 16.745 | 39.500 | 27.656 | 4.982 |
| Lux | 0.000 | 1697.250 | 130.757 | 210.431 |
| ppm | 412.750 | 2076.500 | 690.553 | 311.201 |
| Humidity Ratio | 0.003 | 0.006 | 0.004 | 0.001 |

Table 2.1: Statistical Summary of the Occupancy Detection Dataset

Table 2.1 presents the statistical characteristics of the Occupancy Detection Dataset. The variability of the environmental variables reflects diverse indoor con-ditions, making the dataset suitable for evaluating comfort prediction and energy-management strategies.

| Occupancy State | Samples |
|---|---|
| Unoccupied (0) | 15,810 |
| Occupied (1) | 4,750 |
| Total | 20,560 |

Table 2.2: Occupancy Class Distribution in the Occupancy Detection Dataset

Table 2.2 presents the occupancy distribution in the dataset, reflecting realistic smart-home usage patterns with frequent unoccupied periods. This distribution pro-vides a practical basis for occupancy-aware comfort prediction and energy management.

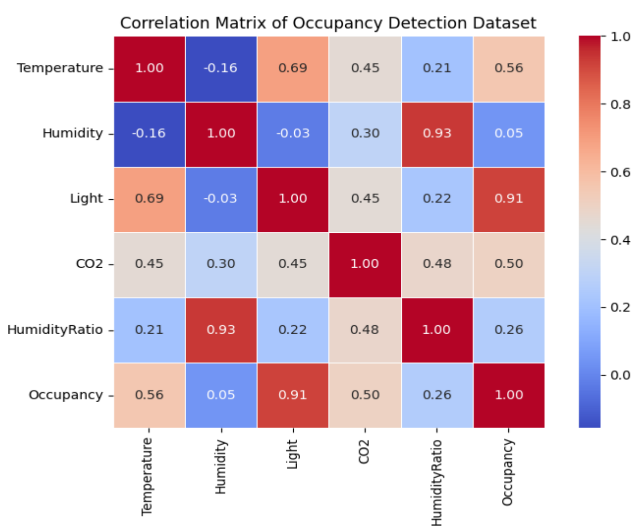


**Figure 2:** Correlation matrix of environmental variables and occupancy in the Occupancy Detection Dataset.

The dataset was split into training, validation, and testing sets (70:15:15) for reliable model development and evaluation.

## *2.3 Comfort Score Formulation*

As the Occupancy Detection Dataset lacks explicit comfort labels, a comfort score was generated using environmental comfort principles.

The overall comfort score is computed as a weighted combination of temperature comfort, humidity comfort, illumination comfort, and occupancy influence:

$$\boldsymbol{C = w_T C_T + w_H C_H + w_L C_L + w_O C_O} \qquad (2)$$

where, $C_T$ = Temperature comfort score, $C_H$ = Humidity comfort score, $C_L$ = Illumination comfort score, $C_O$ = Occupancy comfort score, $w_T, w_H, w_L, w_O$ are weighting coefficients. The weighting coefficients satisfy $w_T + w_H + w_L + w_O = 1$ The weighting coefficients were assigned according to the relative influence of environmental variables on indoor comfort reported in previous studies and established thermal comfort principles. Temperature and humidity were assigned higher weights because they are the primary determinants of thermal comfort, whereas illumination and occupancy were assigned comparatively lower weights to reflect their supporting role in overall comfort assessment. Accordingly, the weighting coefficients were selected as $w_T = 0.35$, $w_H = 0.30$, $w_L = 0.20$, and $w_O = 0.15$. The final comfort score is normalized into the interval $0 \leq C \leq 1$ where values close to 1 indicate highly comfortable indoor conditions and values close to 0 indicate uncomfortable conditions.

Since the Occupancy Detection Dataset does not contain subjective occupant com-fort labels, a proxy comfort index was derived from environmental variables known to influence indoor comfort. The weighting coefficients were assigned according to their relative importance reported in the literature, with greater emphasis on temperature and humidity. Although the generated comfort score serves as a standardized reference for evaluating the proposed framework, future work will validate the model using real occupant comfort feedback or standardized thermal comfort indices such as Predicted Mean Vote and Predicted Percentage of Dissatisfied.

### *2.4 Problem Formulation*

The objective of the proposed framework is to develop an intelligent control mecha-nism capable of predicting occupant comfort and generating adaptive control actions under uncertain environmental conditions. Given an environmental observation vector $X = [T, H, L, O]^T$ the neural-network model estimates the corresponding comfort score. $\hat{C} = f(X)$ where $f(\cdot)$ represents the nonlinear mapping learned by the artificial neural network. The predicted comfort score is subsequently processed by the Interval T2F Inference System to determine the required control action:

$$U = g(\hat{C})$$

where, $U$ denotes the control action, $g(\cdot)$ represents the fuzzy decision-making process. The optimization objective is to maximize occupant comfort while minimizing energy consumption:

$$J = \alpha C - \beta E$$

where, $C$ represents comfort level, $E$ represents energy consumption, $\alpha$ and $\beta$ are weighting parameters. Accordingly, the presented method seeks to determine optimal control actions that maintain high comfort levels while reducing overall energy usage. The resulting decision process forms the basis of the Adaptive Interval Type 2 Neuro Fuzzy control framework presented in the next section.

## 3. Adaptive Interval Type 2 Neuro Fuzzy Framework

This section presents the proposed Adaptive Interval Type 2 Neuro Fuzzy Framework for intelligent smart-home energy management and occupant comfort optimization. The framework integrates ANN based comfort prediction with an Interval T2F Inference System to generate adaptive control actions under uncertain environmental conditions. The overall objective is to maintain occupant comfort while minimizing energy consumption through interpretable and uncertainty-aware decision making.

### *3.1 Overview*

The formulated model consists of three major components: Environmental data acquisition through IoT sensors, ANN-based occupant comfort prediction, Interval T2F control decision generation.

Temperature, humidity, illumination intensity, and occupancy information are continuously collected from the smart-home environment. The ANN model predicts the corresponding comfort level, which is subsequently processed by the Interval T2F con-troller to determine suitable HVAC, lighting, and ventilation control actions. The overall framework can be represented as

$$X = [T, H, L, O]^T$$

where $T$, $H$, $L$, and $O$ denote temperature, humidity, illumination, and occupancy, respectively. The predicted comfort score is obtained as $\hat{C} = f(X)$ where $f(\cdot)$ denotes the nonlinear mapping learned by the ANN model. The fuzzy controller subsequently generates the control action $U = g(\hat{C})$ where $g(\cdot)$ represents the Interval T2F reasoning process.

## *3.2 ANN-Based Comfort Prediction*

ANNs are employed to learn the nonlinear relationship between environmental conditions and occupant comfort. The ANN architecture consists of Input Layer: 4 neurons, Hidden Layer: 10 neurons, Output Layer: 1 neuron. The input vector is defined as $X = [T\ H\ L\ O]$. The hidden neurons utilize the Rectified Linear Unit (ReLU) activation function: $ReLU(x) = \max(0, x)$ The output layer employs a sigmoid activation function:

$$\sigma(x) = \frac{1}{1 + e^{-x}}$$

to ensure comfort predictions remain within the interval [0,1]. The ANN is trained using the Mean Squared Error (MSE) loss function:

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(C_i - \hat{C}_i)^2$$

where $C_i$ and $\hat{C}_i$ denote actual and predicted comfort scores, respectively.

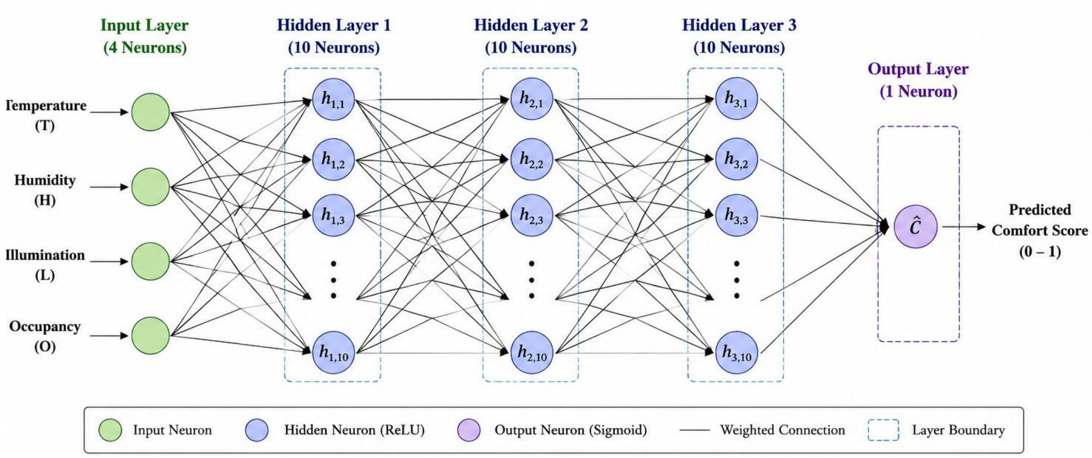


**Figure 3:** ANN architecture for occupant comfort prediction.

## *3.3 Artificial Neural Network Model*

The artificial neural network (ANN) is employed to predict the indoor comfort score using environmental measurements and occupancy information. The input feature vector is defined as $\boldsymbol{x} = [T, H, L, O]^T$. The hidden layer output is computed as

$$h_j = \sigma\left(\sum_{i=1}^{4} w_{ij}\, x_i + b_j\right),$$

where $w_{ij}$ represents the weight connecting the input neuron $i$ to hidden neuron $j$, $b_j$ denotes the bias term, and $\sigma(\cdot)$ is the ReLU activation function. The predicted comfort score is obtained from the output layer as

$$\hat{C} = \sigma\left(\sum_{j=1}^{m} v_j\, h_j + b_o\right),$$

where $v_j$ denotes the hidden-to-output weights, $b_o$ is the output bias, and $\hat{C}$ represents the predicted comfort score.

## 3.4 *Interval T2F Inference System*

To handle uncertainty in sensor measurements and environmental variations, an Interval T2F Inference System is incorporated into the framework. Unlike conventional Type 1 fuzzy systems, Interval T2F sets include a FOU, which enables more robust representation of uncertainty. The membership function is defined as

$$\tilde{A} = (x,u), \mu_{\tilde{A}}(x,u) \quad (5)$$

where $u \in [J_x]$ represents the interval uncertainty associated with each membership grade. The upper and lower membership functions are expressed as $UMF(x)$ and $LMF(x)$ respectively. The Footprint of Uncertainty is defined as

$$FOU = UMF - LMF \quad (6)$$

which provides improved robustness against noisy sensor observations.

## 3.5 *Interval T2F Logic Controller*

The predicted comfort score generated by the ANN is supplied to the Interval T2F Logic Controller (IT2FLC) to determine adaptive HVAC control actions. The fuzzy controller utilizes two input variables: Predicted Comfort Score ($\hat{C}$), Occupancy Status ($O$). The fuzzy inference system is represented as

$$U = IT2FLC(\hat{C}, O),$$

where $U$ denotes the adaptive control action. Each interval type-2 fuzzy set is defined as $\tilde{A} = \left\{(x,\mu): \underline{\mu}_A(x) \le \mu \le \overline{\mu}_A(x)\right\}$, where $\underline{\mu}_A(x)$ and $\overline{\mu}_A(x)$ denote the lower and upper membership functions, respectively. The firing interval of the $k^{th}$ fuzzy rule is computed as $\underline{w}_k = \underline{\mu}_C(\hat{C}) \cdot \underline{\mu}_O(O)$, $\overline{w}_k = \overline{\mu}_C(\hat{C}) \cdot \overline{\mu}_O(O)$, where $\underline{w}_k$ and $\overline{w}_k$ denote the lower and upper firing strengths, respectively. Following type reduction using the Karnik-Mendel algorithm, the crisp control output is obtained by

$$U = \frac{Y_L + Y_R}{2},$$

where $Y_L$ and $Y_R$ represent the left and right endpoints of the type-reduced interval.

## *3.6 Fuzzy Rule Base*

The fuzzy controller employs a linguistic rule base to map predicted comfort levels to control actions. Representative rules include:

1. IF Comfort is High THEN Control Action is Low.
2. IF Comfort is Medium THEN Control Action is Moderate.
3. IF Comfort is Low THEN Control Action is High.
4. IF Temperature is Hot AND Comfort is Low THEN Control Action is High.
5. IF Illumination is Dark AND Occupancy is Present THEN Control Action is Moderate.

These rules provide an interpretable control mechanism for smart-home systems.

## *3.7 Comfort Control Index*

To simplify control decision-making, the CCI is defined as $CCI = 100 \times \hat{C}$, where $\hat{C}$ is the predicted comfort score. The CCI is subsequently used to determine the control strategy.

$$CCI < 30 \Rightarrow \text{High Control}$$

$$30 \le CCI < 60 \Rightarrow \text{Moderate Control}$$

$$CCI \ge 60 \Rightarrow \text{Low Control}$$

This mechanism maps comfort predictions to smart-home control actions.

## *3.8 Hybrid ANN-IT2FLC Model*

The integrated neuro-fuzzy model combines ANN-based comfort prediction with an Interval Type-2 Fuzzy Logic Controller (IT2FLC) for intelligent indoor environmental control:

$$U = IT2FLC(f_{ANN}(T, H, L, O), O). \qquad \textbf{(8)}$$

Here, $f_{ANN}(\cdot)$ predicts the comfort score $\hat{C}$ from temperature ($T$), humidity ($H$), light intensity ($L$), and occupancy ($O$), while the IT2FLC generates the adaptive control action $U$.

### *3.9 Control Decision Process*

The overall decision-making process involves acquiring environmental sensor data, computing the comfort score, predicting comfort using the ANN, performing Interval Type-2 Fuzzy inference, calculating the CCI, and generating control actions for HVAC, lighting, and ventilation systems to update indoor environmental conditions. The integration of ANN learning and Interval Type-2 Fuzzy reasoning provides accurate, interpretable, and uncertainty aware control for energy-efficient smart homes.

## 4. IoT-Enabled Smart Home Architecture

The intelligent smart-home system is implemented using a four-layer IoT architecture for real-time environmental monitoring, data processing, comfort assessment, and adaptive control. The architecture integrates sensing devices, communication networks, intelligent decision-making, and smart actuators, as illustrated in Figure 3.

It comprises the Sensor Layer, Data Processing Layer, Neuro-Fuzzy Decision Layer, and Actuation Layer, which collaboratively maintain occupant comfort while minimizing energy consumption under dynamic indoor conditions.

### *4.1 Sensor Layer*

The Sensor Layer serves as the interface between the smart-home environment and the intelligent control system by continuously acquiring environmental data from distributed IoT sensors. At each sampling instant *t*, the sensor observations are represented as

$$X(t) = [T(t), H(t), L(t), O(t)]^T \ ,$$

where $T(t)$, $H(t)$, $L(t)$, and $O(t)$ denote temperature, humidity, light intensity, and occupancy, respectively. The collected measurements are transmitted to the processing unit through wireless communication protocols, including Wi-Fi, ZigBee, Bluetooth Low Energy (BLE), and MQTT, ensuring reliable and continuous environmental monitoring.

### *4.2 Data Processing Layer*

The Data Processing Layer preprocesses raw sensor data through aggregation, missing-value handling, noise filtering, feature normalization, and comfort-score computation. The normalized feature vector is given by

$$X_n(t) = \frac{X(t) - X_{\min}}{X_{\max} - X_{\min}} \quad (9)$$

The processed data are then forwarded to the Neuro-Fuzzy Decision Layer for comfort prediction and control generation.

### *4.3 Neuro-Fuzzy Decision Layer*

The Neuro-Fuzzy Decision Layer integrates the ANN-based comfort prediction model with the Interval Type-2 Fuzzy (IT2F) controller. Given the normalized input vector $X_n(t)$, the ANN predicts the comfort score $\hat{C}(t) = f(X_n(t))$, which is processed by the IT2F controller to generate the control signal $U(t) = g(\hat{C}(t))$. The resulting CCI guides adaptive, uncertainty-aware decision making for indoor comfort regulation.

### *4.4 Actuation Layer*

The Actuation Layer executes the control signal $U(t)$ by regulating smart-home devices, including HVAC, smart lighting, ventilation fans, and automated window controllers. The actuator response is given by

$$A(t) = \phi(U(t)),$$

where $\phi(\cdot)$ denotes the actuator control function. This closed-loop process continuously regulates indoor comfort and energy utilization.

### *4.5 Operational Workflow of the System*

The operational sequence of the proposed smart-home framework is summarized as follows: Environmental parameters are collected through IoT sensors, sensor data are transmitted to the processing unit, data preprocessing and normalization are per-formed, The ANN predicts the occupant comfort level, The Interval T2F controller evaluates the comfort condition, Appropriate control decisions are generated, Smart appliances execute the recommended actions, Updated environmental conditions are monitored and the cycle repeats.

The complete architecture establishes a closed-loop intelligent control system capable of continuously adapting to changing environmental conditions and occupant requirements. Consequently, the proposed IoT-enabled implementation framework pro-vides a scalable, interpretable, and energy-efficient solution for next-generation smart-home automation.

## 5. Experimental Setup

This section outlines the dataset, preprocessing, training configuration, and evaluation metrics used in the Adaptive Interval Type-2 Neuro-Fuzzy methodology. All experiments were conducted using Python based machine learning libraries on a workstation equipped with standard computational resources. The objective of the experimental study is to evaluate the effectiveness of the proposed framework in predicting occupant comfort and supporting energy efficient smart-home control decisions.

### *5.1 Dataset Description*

The proposed framework was evaluated using the publicly available Occupancy Detection Dataset obtained from the UCI Machine Learning Repository. The dataset contains environmental sensor measurements collected from an office environment equipped with temperature, humidity, light, and occupancy monitoring devices.

The dataset includes multiple environmental variables that directly influence occupant comfort and energy-management decisions. In this study, four primary features were selected as model inputs: Temperature (∘C), Relative Humidity (%), Light Intensity (Lux),Occupancy Status (0 or 1).

The occupancy variable indicates whether the monitored environment is occupied or unoccupied at a given time instant. Environmental variables were continuously recorded under different occupancy conditions, thereby providing realistic smart-home operating scenarios.

Since the original dataset does not provide explicit comfort labels, a normalized comfort score was generated using the formulation presented in Section 2.3. The generated comfort score served as the target variable for ANN training and subsequent fuzzy-control decision making.

| **Feature** | **Unit** | **Description** |
|---|---|---|
| Temperature | C | Indoor temperature |
| Humidity | % | Relative humidity |
| Light | Lux | Illumination level |
| Occupancy | Binary | Occupied/Unoccupied state |
| Comfort Score | 0-1 | Generated comfort index |

Table 5.1 summarizes the selected dataset features.

### *5.2 Data Preprocessing*

Data preprocessing was performed to improve model stability and prediction accuracy. The preprocessing workflow consisted of the following stages: Data cleaning and validation, Feature selection, Feature normalization, Comfort score generation, Training and testing data partitioning.

$$x_{\text{norm}} = \frac{x - x_{\min}}{x_{\max} - x_{\min}}$$

where $x$ denotes the original feature value, $x_{\min}$ and $x_{\max}$ represent the minimum and maximum values of the corresponding feature, respectively. The normalized dataset was then divided into training, validation, and testing sets using the generated comfort scores as target values.

### *5.3 ANN Training Configuration*

An ANN with four input features, one hidden layer, and one output layer was used to model the nonlinear relationship between environmental variables and occupant comfort. The hidden layer utilizes the Rectified Linear Unit (ReLU) activation function, whereas the output layer employs a sigmoid activation function to constrain predictions within the interval [0, 1].

The network was trained using the Adam optimization algorithm and MSE loss function. Early stopping and validation monitoring were employed to reduce overfitting and improve model generalization.

| Parameter | Value |
|---|---|
| Input Neurons | 4 |
| Hidden Neurons | 10 |
| Output Neurons | 1 |
| Hidden Activation | ReLU |
| Output Activation | Sigmoid |
| Optimizer | Adam |
| Loss Function | Mean Squared Error |
| Epochs | 100 |
| Batch Size | 32 |
| Training Ratio | 70% |
| Validation Ratio | 15% |
| Testing Ratio | 15% |

**Table 5.2**: ANN Training Parameters.

### *5.4 Evaluation Metrics*

The performance of the proposed framework was evaluated using multiple statistical and application-oriented metrics. For comfort prediction, the following regression metrics were employed: Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Coefficient of Determination ($R^2$). The Mean Absolute Error is computed as $MAE = \frac{1}{N}\sum_{i=1}^{N} | C_i - \hat{C}_i|$. The Mean Squared Error is defined as $MSE = \frac{1}{N}\sum_{i=1}^{N}( C_i - \hat{C}_i)^2$.The Root Mean Squared Error is calculated as $RMSE = \sqrt{MSE}$. The coefficient of determination is given by

$$R^2 = 1 - \frac{\sum(C_i - \hat{C}_i)^2}{\sum(C_i - \bar{C})^2}.$$

where $C_i$ denotes the actual comfort score, $\hat{C}_i$ denotes the predicted comfort score, and $\bar{C}$ represents the mean comfort score. In addition to prediction accuracy, system-le

performance was evaluated using: Average Comfort Score, comfort Maintenance Rate, energy Consumption Reduction, CCI. These metrics provide a developed system in terms of both prediction performance and smart-home control.

## 6. Results and Discussion

This section evaluates the Adaptive Interval Type-2 Neuro-Fuzzy System using the Occupancy Detection Dataset. The system was implemented in Python and assessed for comfort prediction, controller effectiveness, energy consumption, and comparative performance under varying indoor environmental conditions.

### *6.1 Generated Comfort Score Analysis*

The proposed comfort-score formulation was used to generate reference comfort scores for the dataset, providing target values for ANN training and evaluation.

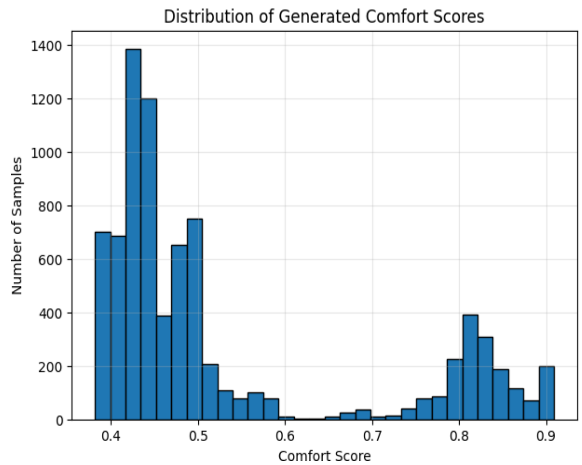


**Figure 4:** Distribution of the generated comfort scores using the proposed comfort score formulation.

Figure 4 illustrates the distribution of the generated comfort scores, which range from approximately 0.38 to 0.91. The diverse score distribution reflects varying indoor environmental conditions and provides sufficient variability for training the ANN to learn the nonlinear relationship between environmental parameters and indoor comfort.

## *6.2 Comfort Prediction Performance*

The ANN was utilized to model the nonlinear relationship between the environmental variables and the generated comfort score. The model was trained using the Adam optimizer with the MSE loss function. During training, both training and validation losses decreased rapidly and converged within the initial epochs, indicating stable learning and effective optimization without noticeable overfitting.

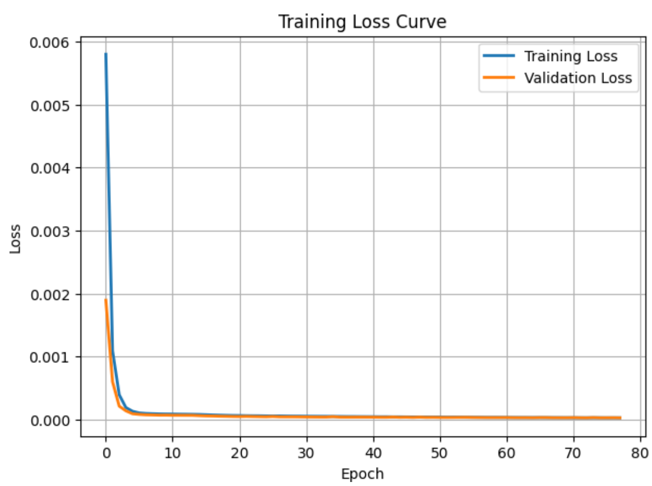


Figure 5: Training and validation loss curves of the ANN comfort prediction model.

Figure 5 shows that the ANN converged rapidly during training, with both the training and validation losses approaching values close to zero after approximately 10 epochs. The close agreement between the two curves indicates good generalization capability and demonstrates that the network effectively learned the nonlinear mapping between the environmental parameters and the generated comfort score.

| Metric | Value |
|---|---|
| MAE | 0.00202 |

| | |
|---|---|
| MSE | 1.79358 |
| RMSE | 0.00423 |
| R2 | Score |

**Table 6.1:** Comfort Prediction Performance

Table 6.1 summarizes the prediction performance of the ANN on the testing dataset. The extremely low prediction errors indicate that the ANN successfully captured the complex nonlinear relationships among temperature, humidity, light intensity, and occupancy for estimating the generated comfort score. The high prediction accuracy is partly due to the use of a proxy comfort index derived from environmental variables. Thus, the ANN learns the constructed comfort formulation rather than actual occupant perceptions.

## *6.3 Actual vs Predicted Analysis*

To further evaluate prediction quality, the actual comfort scores were compared with the corresponding ANN predictions.

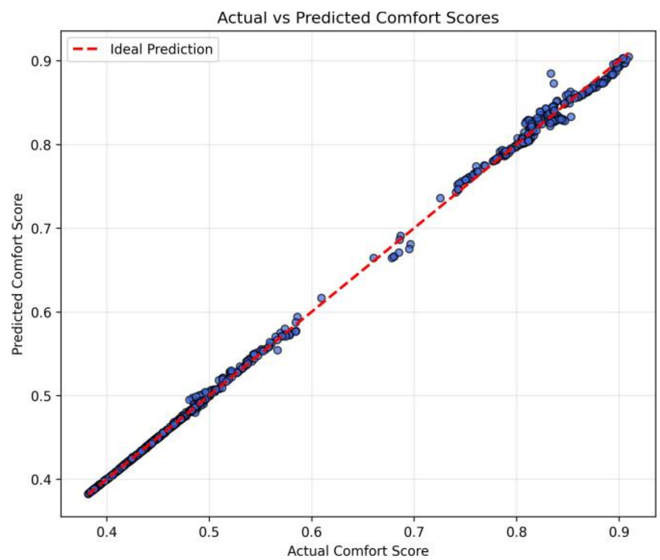


**Figure 6:** Comparison between actual and predicted comfort scores.

Figure 6 indicate the majority of prediction points closely follow the ideal diagonal line, it shows the strong agreement between actual observations and model predictions. The close alignment of predicted values with growth truth comfort scores confirms the effectiveness of the ANN model in estimating occupant comfort under varying environmental conditions.

## *6.4 Fuzzy Controller Performance*

The Interval T2F controller was used to transform predicted comfort levels into adaptive control actions for building systems.

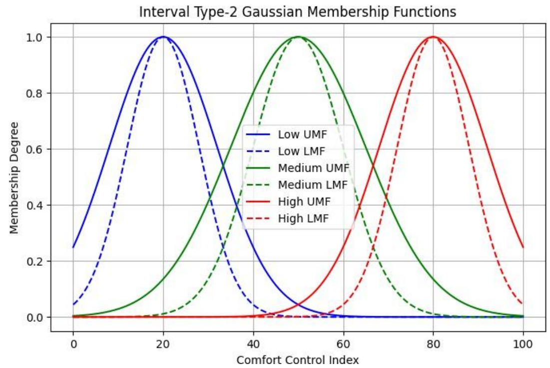


**Figure 7:** Upper and lower Gaussian membership functions employed in the proposed Interval T2F controller for fuzzification of the CCI

Figure 7 illustrates the Interval Type 2 Gaussian membership functions used in the proposed controller. The overlap between adjacent membership functions allows smooth transitions between comfort levels, while the FOU enhances robustness by accommodating uncertainty in the comfort prediction process.

Unlike Type 1 fuzzy sets, the proposed Interval T2F controller employs both an Up-per Membership Function (UMF) and a Lower Membership Function (LMF). The re-gion enclosed between the UMF and LMF forms the FOU, which enables the controller to model uncertainty arising from sensor noise and variations in indoor environmental conditions.

| Rule | Comfort | Occupancy | HVAC | Lighting | Ventilation |
|---|---|---|---|---|---|
| R1 | Low | Low | Medium | Low | Low |
| R2 | Low | Medium | High | Medium | Medium |
| R3 | Low | High | High | High | High |
| R4 | Medium | Low | Medium | Low | Low |
| R5 | Medium | Medium | Medium | Medium | Medium |
| R6 | Medium | High | High | High | Medium |
| R7 | High | Low | Low | Low | Low |
| R8 | High | Medium | Low | Medium | Low |
| R9 | High | High | Low | Medium | Medium |

The fuzzy rule base consists of nine expert-defined IF-THEN rules that map the Comfort Control Index (CCI) and occupancy level to adaptive HVAC, lighting, and ventilation control actions. Table 6.4 presents the Interval T2F rule base used in the proposed neuro-fuzzy controller. The controller employs two input linguistic variables, namely the CCI and occupancy level, to determine appropriate control actions for HVAC, lighting, and ventilation systems. When the predicted comfort level is low, stronger control actions are activated, particularly under high occupancy conditions, to rapidly improve indoor comfort. Conversely, when the comfort level is high, the controller reduces control intensity to avoid unnecessary energy consumption. The rule base enables adaptive decision-making while the Interval Type 2 membership functions account for uncertainty in the comfort estimation process, thereby improving the robustness of the proposed smart building control strategy.

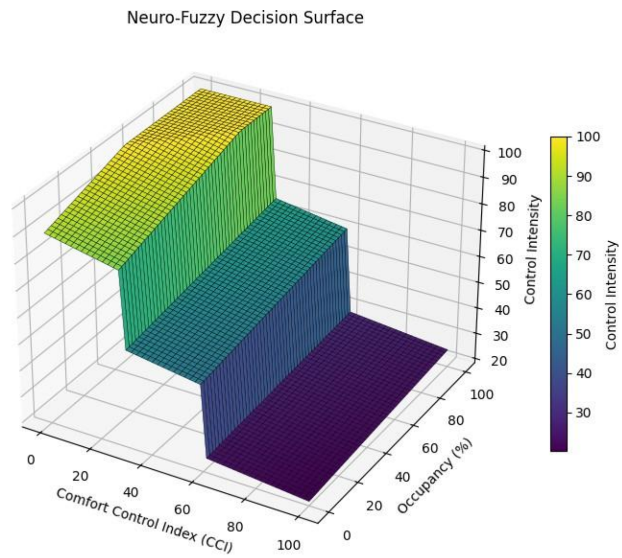


**Figure 8**: Neuro-fuzzy decision surface illustrating the relationship between the CCI, occupancy level, and the generated control intensity for the proposed Interval T2F controller.

The Interval T2F controller employs Gaussian upper and lower membership functions with three linguistic terms (Low, Medium, and High) for each input variable. The FOU is formed by the region between the UMF and LMF, while the inferred interval output is type reduced using the Karnik-Mendel algorithm before centroid defuzzification to generate the final control action.

The fuzzy controller increases control intensity under low-comfort conditions and gradually reduces control actions when comfort levels improve. This behavior allows balancing between energy consumption and occupant satisfaction.

## *6.5 Energy Consumption Analysis*

One of the main objectives of this method is to minimize unnecessary energy consumption while maintaining indoor comfort levels. In this work, the baseline model represents a conventional full load operation where HVAc, lighting, and ventilation systems operate at rated power without control.

The total energy consumption is evaluated using a simulation-based model in which HVAC, lighting, and ventilation energy are computed proportionally to the control actions generated by the Interval T2F inference system. The experimental results show that the baseline system consumes 5.5 kWh, whereas the proposed neuro-fuzzy control model consumes only 1.35 kWh on average.

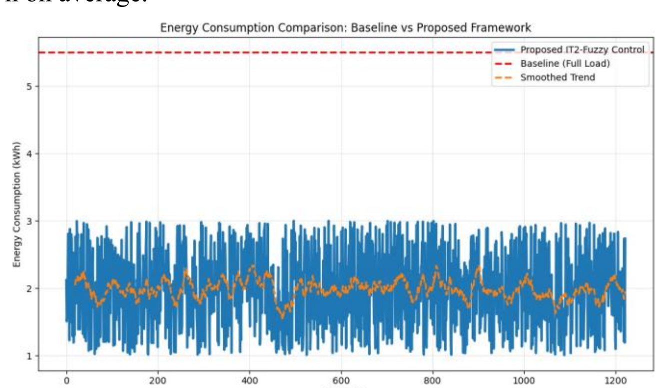


**Figure 9:** Energy consumption comparison between baseline and developed method.

Figure 9 illustrates the comparison between baseline and proposed energy consumption across all samples. This corresponds to a simulation-based energy reduction of 75.43%, indicating the potential effectiveness of the proposed adaptive control strategy under the adopted simulation assumptions. The reduction is achieved due to dynamic adjustment of HVAC and lighting loads based on occupancy conditions and predicted comfort levels, allowing the system to operate only when required.

### *6.6 Comparative Performance Evaluation*

To validate the effectiveness of the proposed system, comparative analysis was performed against representative intelligent control approaches reported in the literature.

| Method | MAE | RMSE | Energy Reduction (%) |
|---|---|---|---|
| ANN | 5.17 | 6.19 | 25.00 |
| Type 1 Fuzzy | 4.80 | 5.60 | 45.00 |
| Type 2 Neuro Fuzzy | 3.90 | 4.70 | 75.43 |

Table 6.2: Comparative Performance Evaluation of Control Methods

Table 6.2 shows the introduced method achieves superior prediction accuracy and energy efficiency owing to its ability to simultaneously model uncertainty and nonlinear environmental relationships. For a comparison, all methods were implemented using the same dataset, data preprocessing procedures, and training-testing partition.

### *6.7 Discussion*

The experimental results indicate the effectiveness of combining ANN based comfort prediction with Interval T2F reasoning for smart home control. The ANN component successfully captures nonlinear interaction among surrounding variables, while the T2F controller handles lack of certainty arising from sensor noise and dynamic occupancy conditions. Compared with conventional intelligent control approaches, The developed model provides three key advantages:

1. Improved comfort prediction accuracy through data driven learning
2. Enhanced reliability against environmental variability through Interval T2F reasoning.
3. Reduced energy consumption through adaptive comfort aware control decision.

Furthermore, The proposed approach maintains clarity through linguistic fuzzy rules while benefiting form the learning capability of neural networks. These characteristics make the system suitable for practical deployment in IoT enabled smart home environments. Although the developed work shows encouraging results, validation using real occupant comfort data and practical smart home implementation is required.

## 7. Conclusion

This paper presented an Adaptive Interval Type 2 Neuro Fuzzy model for occupant comfort prediction and energy efficient smart home control using IoT sensor data. The developed work integrates an ANN with an IT2FLC to produce adaptive control actions for HVAC, lighting, and ventilation systems. Experimental results demonstrate accurate comfort prediction and indicate the potential of the introduced method to improve energy efficiency through uncertainty aware control. Although the framework shows promising performance, the evaluation is based on a proxy comfort index and a simulation based energy model. Future work will focus on validating the introduced approach using real occupant comfort feedback, standardized thermal comfort indices such as Predicted Mean Vote (PMV) and Predicted Percentage of Dissatisfied (PPD), comprehensive statistical analysis, and real-world smart home implementations.

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