A Hybrid Adaptive Rule based System for Smart Home Energy Prediction

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ABSTRACT

The increase in energy prices combined with the environmental impact of energy production has made energy efficiency a key component towards the development of smart homes. An efficient energy management strategy for smart homes results in minimized electricity consumption leading to cost savings. Towards this goal, we investigate the impact of environmental factors on home energy consumption. Home energy demand is observed to be affected by environmental factors such as temperature, wind speed and humidity which are inherently uncertain. Analyzing the impact of these factors on electricity consumption is challenging due to the unpredictability of weather conditions and non-linear relationship between environmental factors and electricity demand. For demand estimation based on these time varying factors, a hybrid intelligent system is developed that integrates the adaptability of neural networks and reasoning of fuzzy systems to predict daily electricity demand. A smart home dataset is utilized to build an unsupervised artificial neural network known as the Self-Organizing Map (SOM). We further develop a fuzzy rule based system from the SOM to predict home energy demand. Evaluation of the system shows a strong correlation between home energy demand and environmental factors and that the system predicts home energy consumption with higher accuracy.

Keywords

Artificial Neural Network , Fuzzy Logic, Adaptability, Artifical Intelligence, Self-Organizing Map, Machine Learning, Demand Prediction.

1. INTRODUCTION

The rise in energy demand proportional to increased urbanization has emphasized the need for comprehensive measures to promote sustainability and improve energy efficiency. Incorporating the principles of sustainability and energy efficiency in building design is expected to cut down operational costs along with the reduction in greenhouse gas emissions [23]. In cities, buildings account for a significant share of the total energy consumption [17], emphasizing the need for smarter building energy management policies.

The growing human needs for comfort, convenience and reliability are expected to shift traditional building designs towards the development of smart dwelling environments referred commonly as 'smart homes'. The smart home of the future is expected to minimize energy consumption by intelligent control of heating, lighting, air-conditioning and household appliances [1]. Smart homes are projected to integrate sustainable and energy conscious policies in addition to traditional design concepts such as comfort, safety and cost-effectiveness [7].

The problem of demand prediction as a function of environmental factors is challenging due to the transitional nature of environmental parameters like temperature, humidity and wind speed. The relationship between constituent variables in this problem are not fully understood and therefore cannot be described by a precise mathematical model. Traditional statistical modeling approaches are generally not suited for such problems involving varying environmental conditions.

The biologically inspired computational paradigm of artificial neural network (ANN) has various advantages over traditional methods for solving problems involving time varying conditions [9]. ANNs are attractive due their properties such as the ability to model nonlinear phenomena, tolerance to noisy or incomplete data, robustness to deal with dynamic real world situations and adaptability to changing conditions. The fundamental characteristic of an ANN is its ability to learn and behave based on the states of its inputs. An ANN trained to operate in a specific surrounding can be retrained based on changing environmental states. ANN adapts to the changes in the environment by adjusting the synaptic weights of the constituent neurons.

Fuzzy logic [14] is a soft computing approach that imitates human reasoning to arrive at solutions for computationally hard problems. This technique has been used to solve problems in diverse domains such as automatic control, modeling, forecasting and classification. Fuzzy systems are limited in the aspect that they cannot adapt to situations where the input conditions change. ANNs appear to be an appealing technique to facilitate adaptability to fuzzy systems. While fuzzy systems approximate human reasoning based on the inputs, ANNs can be used to provide features such as error tolerance and adaptation. The confluence of the two methodologies can be used to develop hybrid adaptive intelligent systems capable of solving real world problems more efficiently.

In this work, we utilize a smart home data set to analyze the impact of environmental factors on home energy consumption for developing efficient energy management policies for smart homes. Home energy demand is observed to be significantly affected by environmental factors. Understanding energy consumption patterns is vital for resource optimization. We use a class of artificial neural networks (ANN) called the Self-Organizing Maps (SOM) [15] to analyze the energy consumption patterns and their relationship with environmental factors. The input space of SOM consists of a set of environmental factors (temperature, humidity and wind speed) along with the home electricity demand. The SOM implements an orderly transformation of the multidimensional input space to a lower dimensional grid so that it can be visualized to detect energy consumption patterns. The SOM is then utilized to extract relationships between electricity use and environmental factors. Further, we develop a adaptable rule-based demand estimation system from the SOM using fuzzy logic to predict the daily home electricity demand. In our proposed model, the neural network architecture supports the fuzzy system by integrating learning capabilities and adaptability features to the electricity demand estimation system.

2. RELATED WORK

Various approaches have been proposed in the past for solving the problem of demand estimation, the majority of which belong to the class of time-series analysis. The time-series analysis techniques predominantly consist of approaches based on statistical modeling[18] and artificial neural networks (ANN). Statistical modeling techniques [8] include exponential smoothing, linear regression analysis, autoregressive methods like ARMA and ARIMA models, chaos time series models and Kalman filtering-based methods.

N. A. A. Jalil et al. [13] used exponential smoothing techniques for load forecasting from time series data. They compared several such smoothing techniques to identify the most effective solution for demand estimation. J.Hinman et al. [10] used regression analysis for short-term load estimation for a electric utility. S.-J. Huang et al. [12] improved on the existing ARMA model by incorporating non-gaussian processes to increase the accuracy of demand prediction. J. Contreras et al. [4] successfully used ARIMA model to estimate future electricity prices of customers. Their approach involved using time series analysis to arrive at accurate price forecasts. H.Mori et al. [16] successfully demonstrated the validity of chaos times analysis for short-term load forecasting. M. Falvo et.al [5] estimated short term loads based on a time series model using Kalman filtering techniques.

Statistical methods may fall short of performance due to the improper modeling of the non-linear factors like environmental variables affecting the energy demand. In addition, the models developed for such problems are not adaptable to changing operating conditions. This has led to growing interest in ANN based techniques for demand estimation. ANN-based methods do not require the exact model of the relevant physical process as neural networks are able to learn and model the non-linear relationship between demand and environmental factors based on historical samples. Various neural network techniques have been used to incorporate the non-linearity between underlying factors in demand estimation.

H.S. Hippert et al. [11] examined a list of works that use ANNs for short-term load forecasting. S.V. Verdu et al. [21] classified the customers of an electrical utility in a given geographical area using self-organizing maps. Based on their approach, they identified customers by the behavior patterns in their electricity usage. O. A. Carpinteiro et al. [3] successfully applied a neural network architecture composed of two self-organizing maps to solve the problem short-term load forecasting. M. Sperandio et al. [20] developed Markov models for short term load forecasting using self-organizing maps. M. Farhadi et al. [6] utilized a combination of ANN and fuzzy system for daily load forecasting.

Traditionally, SOM based approaches for electricity demand forecasting, customer classification and load profiling were developed for applications corresponding to larger geographic regions such as cities or countries [19]. Our approach differs from the existing works in that we utilize our hybrid approach involving fuzzy logic and SOM for the development of efficient energy management policies for smart homes. This paper proposes a hybrid technique based on Self-Organizing Maps combining the potential of fuzzy logic and neural networks. We develop a rule based system from SOM and analyze the dependence of external factors on energy consumption. The proposed system estimates the daily electricity demand taking into account the impact of environment variables on home energy usage. The SOM developed in our method projects hidden structures in the multidimensional input data set on a 2-D map which is utilized for data analysis. We leverage SOM to reveal the extent of the impact of environmental factors on daily home energy demand.

3. BACKGROUND

3.1 Self-Organizing Map

The self-organizing map is a machine learning technique based on artificial neural networks (ANN). SOM uses unsupervised learning to cluster higher dimensional data inputs to a 2-D map based on similarity while preserving the topological relations of the data. As illustrated in Figure 1, the SOM is composed of two layers, a 1-D input layer, and a 2-D output layer.Each input layer node is connected to neurons in the output layer via 'weights' which is updated during the training process. The weight update rule for a SOM unit m_i is computed as

$$m_i(t+1) = m_i(t) + h_c(t)[x(t) - m_i(t)] \tag{1}$$

where t= the current time step, $x(t)$= the input vector and $h_c(t)$ is the neighbourhood function computed as

$$h_c(t) = l(t)e^{(-|r_k - r_i|^2)} \tag{2}$$

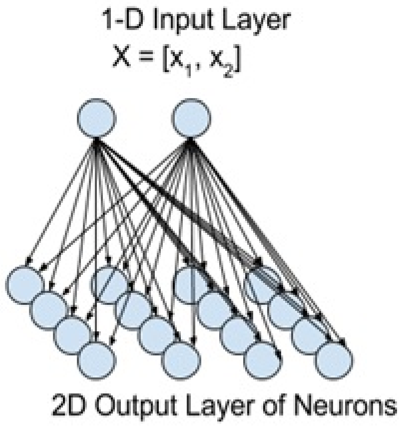

Figure 1: A SOM having two inputs and 16 neurons.

where $|r_k - r_i|$ = the distance between units i and k at the output layer and $l(t)$ is the learning rate computed as

$$l(t) = l_0 e^{-t/\lambda} \tag{3}$$

where l_0 = initial value of learning rate, λ = the time constant.

The two commonly used approaches for SOM representation are the unified distance matrix (U-Matrix) and the component planes. The U-matrix representation describes the Euclidean distance between neurons to identify clusters. Component planes display the values of input variables (components) in each output SOM weight vector as separate maps, enabling them to be used for discovering dependencies in the input data. In this work,we use component planes for SOM representation.

3.2 Fuzzy Logic

Fuzzy logic is a multi-valued logical system that recognizes all possible values between Boolean logic evaluations of TRUE (logic 1) or FALSE (logic 0). It models human-like reasoning in decision making by offering a computational framework for addressing imprecise linguistic notions such as 'very small', 'small', 'large' etc. A fuzzy rule is a conditional statement of the form

IF x is P THEN y is Q

where x and y are linguistic variables; P and Q are linguistic values defined on a fuzzy set. Fuzzy rule-based systems deal with imprecision or ambiguity in knowledge representation by defining fuzzy sets and fuzzy numbers expressed in linguistic terms (e.g. 'small', 'very small', 'medium' etc.). Fuzzy rule-based systems utilize a set of linguistic IF-THEN constructions called fuzzy rules to model non-linear relationships between inputs.

4. MODEL DEVELOPMENT

The flowchart of model development is described in Figure 2. Towards developing the rule-based system, we train the SOM with a prior measurements of input variables. The training process generates 4 component planes corresponding to each input variable. With the SOM trained, we identify clusters in the component plane corresponding to the electricity demand. To identify clusters effectively, we use a clustering evaluation algorithm along with K-means clustering to cluster the 'electricity demand' component plane. Once the clusters are identified, the process of rule extraction is initiated. We calculate the cluster averages for individual component planes based on clusters identified from the 'electricity demand' component plane. We define relationships between input variables by comparing the cluster averages and building fuzzy rules. The set of developed fuzzy rules is used to construct the rule based system.

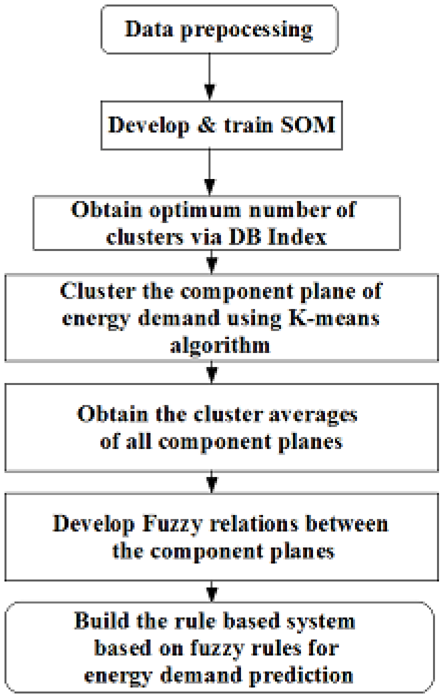

Figure 2: Model development Flowchart

4.1 Smart Home Data set

We utilize the data sets provided by the University of Massachusetts, Amherst [2] for system development. The data is collected from two homes instrumented with sensors to record weather and electricity usage information. In our case, we use the data collected during the months of May, June and July.

4.2 SOM Training

We use the SOM toolbox package [22] in MATLAB computational environment for developing the SOM. We train the SOM with hourly measurements of home energy demand (kWh) and environmental factors such as temperature (°C), wind speed (m/s) and relative humidity (%) from a home recorded during the month of May.

4.3 SOM Analysis

Figure 3 illustrates the SOM component planes for all the input variables. We use the batch training algorithm for SOM development. A SOM with 36 neurons in a 6 X 6 hexagonal arrangement was constructed. In the SOM, 720 hourly measurements of data for one month were projected onto the 6 X 6 grid. In Figure 3, the lighter shades in the component plane (blue, cyan, yellow) correspond to inputs of lesser magnitude compared to darker shades (red, orange).

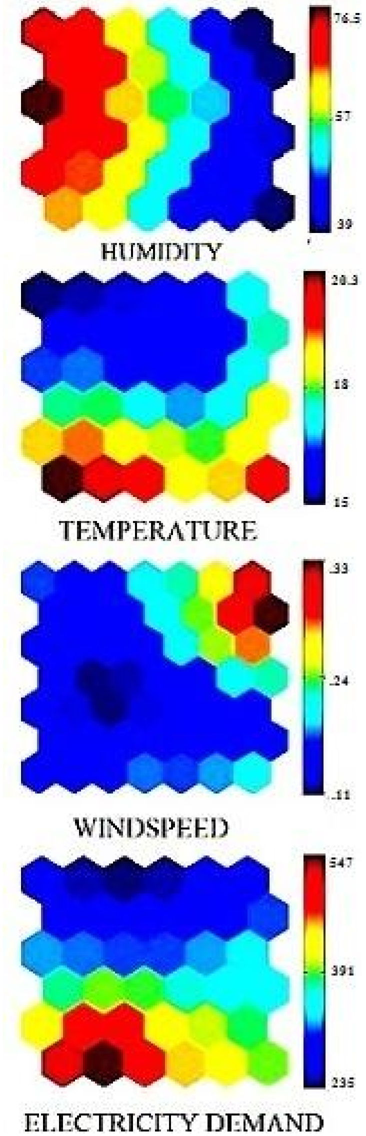

Figure 3: Component planes of input data.

It is observed that towards the lower left corner of the energy component plane, which corresponds to higher energy demand there is high temperature, high humidity and medium wind speed in the respective component planes near the same region. Similarly, towards the top left corner, where energy demands are lower, we observe low temperature, medium humidity and low wind speed in the respective component planes near the same region.

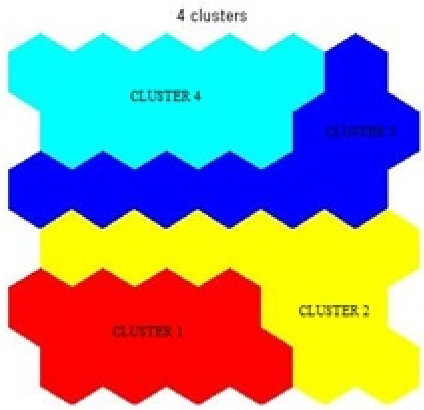

Figure 4: Clustered Energy component plane

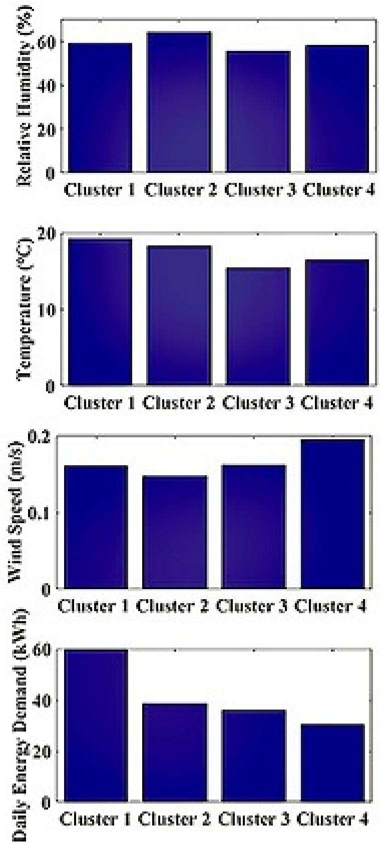

Figure 5: Cluster averages of component planes

In this manner, using the SOM, we explore inherent relationships between energy demand and environmental factors. For the purpose of rule extraction, we cluster the component plane corresponding to energy demand using K-means clustering algorithm. The optimal 'K' value for clustering the energy component plane was calculated using the Davies-Bouldin (DB) clustering evaluation algorithm (optimal K=4). The clustered energy component plane is given in Figure 4. For fuzzy rule development, we use individual cluster averages for representing each cluster. Cluster average is calculated as the arithmetic mean of SOM cluster values. Cluster averages of component planes are expressed as bar graphs in Figure 5.

4.4 Rule Based System Development

To model and predict the energy demand, we map the 4 clusters described in ''electricity demand' component plane (Figure 4) into the input component planes for temperature, humidity and wind speed (Figure 3). Cluster averages of the component planes are calculated and expressed in the four classes of linguistic terms 'Highest', 'High', 'Low', 'Lowest' depending on the decreasing order of their values (Table 1). We develop the rules to model and predict energy demand by building relationships between cluster averages (Table 1) through fuzzy IF-THEN rules. The fuzzy rules are developed with the help of membership functions of the input variables (Figure 6). We further use the extracted fuzzy rules to construct a rule-based system for the prediction of energy demand. The rule-based system is described in Table 2.

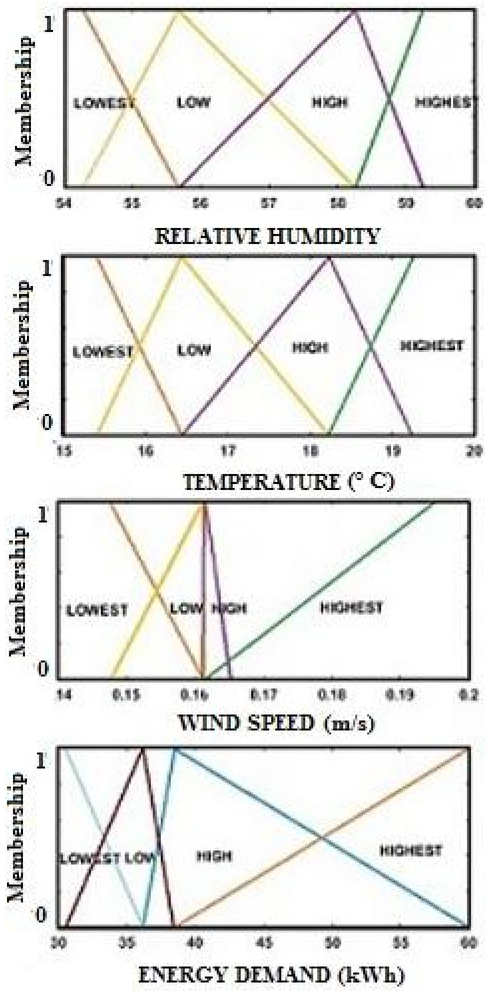

Figure 6: Membership functions of input variables

Table 1: Linguistic Variable Assignment

No.	**Relative Humidity (%)**	**Wind Speed (m/s)**	**Tempe-rature (°C)**	**Daily Energy Demand (kWh)**
1	59.23 (Highest)	.1610 (Low)	19.25 (Highest)	59.975 (Highest)
2	54.27 (Lowest)	.1475 (Lowest)	18.22 (High)	38.466 (High)
3	55.67 (Low)	.1614 (High)	15.40 (Lowest)	36.14 (Low)
4	58.24 (High)	.1950 (Highest)	16.43 (Low)	30.474 (Lowest)

Table 2: Rule Based System

Rule Based System
Rule 1:IF Humidity is near 59.23(Highest) AND Wind speed is near .161(Low) AND Temperature is near 19.25(Highest) THEN Energy demand is 59.975(Highest)
Rule 2:IF Humidity is near 54.27(Lowest) AND Wind speed is near .1475 (Lowest) AND Temperature is near 18.22(High) THEN Energy demand is 38.466(High)
Rule 3:IF Humidity is near 55.67(Low) AND Wind speed is near .1614(High) AND Temperature is near 15.40(Lowest) THEN Energy demand is 36.14(Low)
Rule 4:IF Humidity is near 58.24(High) AND Wind speed is near .1950(Highest) AND Temperature is near 16.43(Low) THEN Energy demand is 30.474(Lowest)

4.5 System Validation

For validating the developed system, we utilized a data set consisting of electricity demand and environmental variables of the home, recorded during the months of June and July. Based on the fuzzy rules developed from the SOM, the proposed system predicted the electricity demand classes with an accuracy of 78.68%. The results of validation are given in Table III. We further developed and evaluated the proposed system for a second home. For the second case, the trained SOM generated four clusters, which was used to develop the corresponding fuzzy rules. The fuzzy rules were similar except for the difference in numerical values for the linguistic variables. The rule based system for the second home estimated demand classes with an accuracy of 73.77%.

Table 3: System Validation

	Home A	Home B
Days of data used for System Validation	61 Days	61 Days
Days of correct Predictions	48 Days	45 Days
Accuracy	78.68 %	73.77 %

4.6 Applications

Systems for accurate electricity demand estimation are essential for the operation of a smart home. Significant reduction in home energy usage could be achieved with the knowledge of energy consumption patterns. Such knowledge could motivate consumers to promote activities leading to cost savings and efficiency improvements. Smart homes can utilize demand estimation systems to make better decisions regarding the purchase, generation, and storage of energy. The system could be utilized to estimate peak load conditions, reduce the occurrence of electrical overload or cut-down electricity costs by regulating home electricity consumption under real-time electricity pricing (RTP) schemes. Under a RTP scheme, customers monitor prices and adjust power consumption accordingly to reduce energy costs.

5. CONCLUSION

Towards the goal of energy efficient smart homes, we presented a hybrid approach combining fuzzy logic and SOM to develop a rule-based system for home energy demand prediction. The SOM developed is a topology preserving transformation from a 4 dimensional input space to 2 dimensions. We used the SOM to analyze and develop a fuzzy rule based system for daily energy demand estimation. The system estimated the daily energy consumption for two homes with an accuracy of 78.68% and 73.77% respectively. The results verified the effectiveness of the proposed approach in discovering the impact of environmental factors on home energy demand. As part of future work, we propose to develop policies to optimize home energy consumption by integrating alternative energy sources.

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