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Residential lighting load profile modelling

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ABSTRACT

Occupant dynamic presence and characteristics associated with lighting loads/usage in residential buildings are not replicated in most practices currently adopted in modelling lighting profile. This study involves the use of adaptive neural fuzzy inference system (ANFIS) for lighting load profile prediction. Natural light, occupancy (active) and income level are the characterization (variables) factors considered in this investigation. The accuracy of the developed prediction models in relation to various income earners groups were analyzed using statistical measures; correlation output of the ANFIS approach and the impact of the characteristics on the lighting profile development in relation to trend analysis were also employed. Results obtained after validation of the developed models using investigative data, metering data and regression model showed a better correlation and root mean square error (RMSE) in comparison with actual values. The intelligence approach showed a better correlation of fit and good learning predictive accuracy in terms of behavioural and environmental variableness; and presents its output according to the complex nature of lighting usage in relation to the variables. The efficacy of the method was also validated.

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1. Introduction

Optimal estimation of energy usage in residential buildings is an important contributor in energy conservation and environmental emission reduction. One of the measures for conservation, reduction and management of electricity is lighting. It is an essential part of human daily activities especially in households. Some current simulation tools based actions of residential occupants on assumptions thereby providing a poor instrument to evaluate and predict demand initiatives outcomes; while some others are mostly based on conventional mathematical tools which are not well suited for ill-defined or uncertain (behavioural) system. The complexities of the impact occupants have on lighting loads in residential households are not reflected in most practices. As a result, good lighting demand or energy prediction accuracy is rarely found.

Literature discussions have shown that human behaviour and environmental climate could significantly impact on lighting usage in residential dwellings within a period e.g. monthly or yearly basis [1–4]. Factors such as occupant presence and effect on lighting usage, comfort level and income of individuals, location of residences and areas in terms of daylight effect, demographics characteristics etc. can be introduced to contribute and improve the modelling, estimation or prediction of lighting load techniques within the residential sector. Techniques available for prediction or estimation of energy usage or lighting load include analytical methods, empirical methods and modelling methods [1–11]. Most of these methods do not rely on occupant behaviour from survey data/long-term observations. While presence of people and interactions of people are handled in an entirely deterministic way in some simulation programmes and models.

An approach that may impact greatly on lighting load prediction accuracy is metering at consumer points. However, such an exercise is expected to be very expensive and time consuming. Apart from that, some lighting fixtures are not always separated at the distribution board level, hence making it difficult to detach the lighting load from the household total energy consumption at different time of use (TOU) periods. Metering at substation level gives an idea of the demand of an area; or point to the impact of any energy efficiency programme carried out (using historical data within the shortest time after implementation). This is contentious due to other activities that may have taken place during such periods; consequently making it complicated for utilities and government to quantify the impact of lighting project initiatives on the grid and its people. The complexity, non-linearity etc. associated with lighting usage has created a need for more research interest.

Based on issues raised, it is therefore imperative to investigate a technique where such variables can be introduced and

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accounted for in predictions of lighting load profile pattern, i.e. an approach that is capable of such characterization as non-linearity, variableness, uncertainty and the ability to learn from historical data. Adaptive network-based fuzzy inference system (ANFIS) is one such approach. Various studies and investigation carried out using ANFIS has shown its good predictability capabilities. Such investigations include water resource development, planning and management in an area using available variables (rainfall, temperature, stage height and relative humility) [12]; prediction of surface roughness in turning operation [13]; river flow estimation based on the use of different combinations of antecedent flows gauging station of Aydin Bridge in the construction of appropriate input structure [14]. Another work carried out using ANFIS in combination with radial basis function (RBF) neural network was in the real-time price environment for the electricity market [15]. Using the mean absolute percentage errors and other statistical results obtained in the study, ANFIS model had a better forecasting performance in comparison with regression model, support vector machines with genetic algorithms, artificial neural network (ANN) model, recurrent support vector machines with genetic algorithms (RSVMG) model and the hybrid ellipsoidal fuzzy systems for time series forecasting (HEFST) model. Other works include using decision tree for predicting energy demand of building [16]. The model has the ability to classify and predict categorical variables apart from being computationally friendly to non-mathematical users. The authors were with the opinion that regression models are normally complicated equations, not understandable and interpretable for common users without mathematical background; thereby making it a difficult predictive tool [16]. The use of ANFIS to forecast regional electricity loads in Taiwan and demonstration of its proficient has also been investigated [17]. The study analysis based on statistical and mean bias errors showed than ANFIS model had better forecasting performance than the regression model, ANN, etc.

The main purpose of this study is to investigate and demonstrate the applicability of ANFIS for lighting load profile modelling. The outline of the investigation consists of ANFIS main network structure, model process design strategy, investigation analysis, ANFIS predictor model, validation: correlation analysis and trend analysis. Lastly, model technique applicability and efficacy is evaluated.

2. Method of investigation

2.1. Investigation approach: adaptive neural fuzzy inference system

As a result of human behaviour complexity, non-linearity of lamp usage as well as climatic conditions, the proposed investigation methodology is known as adaptive neuro fuzzy inference system. Neural network and fuzzy logic combine together make up ANFIS. ANFIS attributes include the ability to learn, organize network structure and adapt the parameters of the fuzzy system to solve engineering problems [12,14]. ANFIS can simply be defined as a set of fuzzy 'if–then' rules with appropriate membership functions (MF) to generate stipulated input–output pairs in the solution of uncertain and ill-defined systems. The process of fuzzy inference involves membership functions, fuzzy logic operators, and if–then rules. Backward propagation algorithm and hybrid-learning algorithm methods are use for determination of the membership functions, learning provision of ANFIS and construction of rules. ANFIS can be describe as a five layer structured architecture, with all five layers having a function in the development of the model. In general ANFIS system has input layer, output layer, and hidden layers that represent membership function and fuzzy rules. A typical three rule systems is shown as follows:

Rule 1: if x is A_1, y is B_1 and z is C_1, then $f_1 = p_1x + q_1y + k_1z + r_1$
Rule 2: if x is A_2, y is B_2 and z is C_2, then $f_2 = p_2x + q_2y + k_2z + r_2$
Rule 3: if x is A_3, y is B_3 and z is C_3, then $f_3 = p_3x + q_3y + k_3z + r_3$
General rule being $f_i = p_ix + q_iy + k_iz + r_i$

where x, y and z represents inputs which are fuzzy sets A_i, B_i, and C_i representing natural lighting, occupancy and income. p, q, k and z are the design parameters that will be determined during the training process. For instance the input nodes i.e. first layer (i.e. Q_i^1) has the following inputs with a node function output.

$$Q_i^1 = \mu_{A_i}(x) \text{ for } i = 1, 2, 3; \quad Q_i^1 = \mu_{B_i}(y) \text{ for } i = 4, 5, 6;$$
$$Q_i^1 = \mu_{C_{i-3}}(z) \text{ for } i = 7, 8, 9 \tag{1}$$

x is the input to node i, and A_i is the linguistic label (high, middle, and low) associated with this node function. μ_{A_i}, μ_{B_i} and μ_{C_i} are the appropriate membership functions of $A_iB_iC_i$ fuzzy sets. Nodes in this layer represent the MF associated with each linguistic term of input variables. A trapezoidal membership curve was chosen for this investigation due to human behavioural inclination (occupancy and natural lighting patterns – switch ON/OFF event) and historical lighting load metering profiles. The trapezoidal membership is a function of a vector x, and depends on four parameters a, b, c, and d, as given by (2). a and d parameters locate the "feet" or base of the trapezoidal shape and b and c the parameters locate the "shoulder".

$$f(x;\ a_i, b_i, c_i, d_i) = \max\left(\min\left(\frac{x - a_i}{b_i - a_i}, 1, \frac{d_i - x}{d_i - c_i}\right), 0\right) \tag{2}$$

The output nodes (fifth layer (Q_i^5) compute the overall output as the summation of all incoming signals. The defuzzification process is used to transform each fuzzy rule which results into a crisp output as shown below. N represents the number of rules, i.e. 27 for three variables in this investigation.

$$Q_i^5 = f(\text{out}) = \frac{\sum_{i=1}^{N} w_i \times f_i}{\sum_i^N w_i}$$
$$Q_i^5 = f(\text{out}) = \frac{\sum_{i=1}^{27} \mu_{A_i}(x) \times \mu_{B_i}(y) \times \mu_{C_i}(z) \times f_i}{\sum_{i=1}^{27} w_i} \tag{3}$$

The other layers include: second layer outputs the firing strength w_i, third layer calculates the ratio of ith rule's firing strength to the sum of all rule's firing strengths while the fourth layer computes the ratio of the firing strength and consequent parameters.

2.2. Model process design strategy

The process design strategy shown in Fig. 1 was applied in the model development strategy. This involves interactive importing and exploration of files, query of databases, filtrations and categorization of data feeds and generation of Matlab code or Excel Solver (visual code); use of Matlab/Excel sheet or interactive data language. While the model development approach involves exploration in terms of relationship to develop a model that captures the non-linear and complexities associated with household lighting usage using these variables. For the fuzzy light usage output design, three input variables namely natural light level, effective occupancy (active/awake occupancy) and income of a household are applied.

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