Adaptive Neuro-fuzzy Inference System (ANFIS) for a multi-campus institution energy consumption forecast in South Africa

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Abstract

University campus as a service industry consumes considerable amount of energy, most especially those with multiple campuses. This study develops four ANFIS models for four campuses of an institution located in South Africa using five climatic data as inputs against energy consumption. The clustering method is fundamental to the feasibility and tractability of ANFIS model. The study explores two clustering techniques- fuzzy c-means (FCM) and grid partition (GP) for data clustering. Their forecast accuracy and computational efficiency were compared. FCM gave a better-forecast accuracy and higher computational efficiency in terms of the CPU time compared to the GP technique. The FCM clustering technique was recommended for use in ANFIS model, where similar time series data is used, due to its accuracy and lesser computational time.

Keywords
Adaptive neuro-fuzzy inference system; Clustering; Multi-campus energy consumption forecast; South Africa.

1. Introduction

Despite the increase in alternative energy sources, global energy demand in buildings continues to rise on a yearly basis. This is attributed to the increase in the plug load devices in homes as well as the increase in the number of homes with access to electricity [1]. A parallel occurrence prevails in the university campuses, where the quest for tertiary education increases on a yearly basis. Global statistics from 2000 to 2014 shows student enrolment increased by more than double, from 100 million to 207 million [2]. This in turn, increases the number of institutions or buildings to satisfy the rising population of students. There exists a complex dynamics of energy consumption in multi-campus institutions where students access same resources in all campuses compared to single-campus institutions. An intelligent forecast is therefore essential for strategic planning and effective budgeting.

The literature is replete with several forecasting techniques for energy forecast in buildings. This includes the forecast for administrative buildings, student residences to the institution as a whole. Amber *et al.* [3] considered energy consumption in the administrative buildings of a typical UK tertiary institution. Energy consumption in the administrative buildings was discovered to amount to 26% of the campus annual energy consumption. With a six years data for ambient temperature, relative humidity, solar radiation, weekday index and wind speed, Genetic Programming (GP) and multiple regression (ML) models were developed to forecast daily energy consumption. The GP approach recorded a better performance with a total absolute error of 6% compared to the ML approach with a total absolute error of 7% [3]. Cooling load equipment is one of the major energy-consuming equipment in buildings. To predict the energy consumption of this equipment, Deb *et al.* [4] considered three institutional buildings in Singapore. The study used Artificial Neural Network (ANN) and ANFIS model, consisting of a three-input time series data (air temperature, humidity and solar radiation) and the energy consumed as output for the system forecast. The performance of both models was laudable with no significant difference between their forecasts. Many of these studies are directed to a section of the institution, a holistic energy consumption for multi-campus institutions have, however, received less attention.

Adaptive neuro-fuzzy inference system first proposed by Jang in 1993 combines back propagation neural network and fuzzy inference system [5], [6]. The technique, which consists of a five-layer network: fuzzy layer, product layer, normalized layer, de-fuzzy layer and total output layer follows the Takagi Sugeno fuzzy inference system; a type-II fuzzy system [7]. Optimization of parameters in the first and fourth layer is performed by the back propagation component of the network [4]. ANFIS model has found its application in many fields; in financial analysis [7], hydrological studies [8] and also in energy systems [9]. Applications of ANFIS to institutional energy forecast in the literature have often been for a component of the whole system or few buildings oriented. A holistic study of energy consumption of the institution is less explored. While few studies considered energy consumption in campuses from the holistic point of view, with clusters of university buildings [10]–[12], multi-campus institution energy forecast has however, received less attention. A multi-campus institution offers a form of complexity most especially when students migration from one campus to another to access same resources is more frequent as is the case in this study. The typical multi-campus institution located in Gauteng Province in South Africa was considered.

The rest of this paper is structured as follows: section 2 presents the methodology adopted for the work. The result of the techniques used are presented in section 3 while section 4 concludes the work.

2. Methodology

2.1 Data description

A multi-campus institution, with four campuses, located in Gauteng Province of South Africa was used as a case study. Energy consumption data (in Kilowatt-hour) for the four campuses were collected from 2015 to 2017. The energy data comprises a monthly aggregate of energy consumption in all the buildings in each campus. Similarly, climatic data (average wind speed, minimum and maximum temperature, dew point and relative humidity) within the same horizon from weather stations central to the geographical location of all the campuses were also collected from the South African Weather Service and used as model inputs.

2.2 ANFIS Model description

The ANFIS model integrates Artificial Neural Network (ANN) and Fuzzy Inference System (FIS) such that optimal distribution of membership function is obtained by an input-to-output mapping [5]. In this study, two clustering techniques were used: Grid Partitioning (GP) and Fuzzy c-Means Clustering (FCM). The ANFIS framework maps the five inputs (average wind speed, maximum and minimum temperature, dew point, relative humidity) to the energy consumption (the output) across three parameterized Gaussian membership functions. A M-file script was written in MATLAB R2015a for the computation.

2.2.1 Fuzzy c-means clustering

The FCM minimizes generalized least square error function $J_m(U,v)$ in eqn. (1), such that each data point x_i in N observations belong to a cluster j according to a degree of membership U_{ij}.

$$J_m(U,v) = \sum_{i=1}^{N}\sum_{j=1}^{C} U_{ij}^{m} \left\|x_i - v_j\right\|_A^2, \qquad 1 \le m \le \infty \tag{1}$$

where v_j = the centre of cluster j
C = number of clusters | $2 \le C < n$
m = weighting exponent
A = positive definite $(n \times n)$ weight matrix

$\|\quad\| = n -$dimensional Euclidean space wherein sample data belong.

A total number of 20 epochs was specified for the fuzzy model and a total of 10 rules was generated using FCM clustering.

2.2.2 Grid Partition

The grid partitioning (GP) technique splits a given data space into rectangular subspaces known as grids, dependent on the number of membership functions and type, [13]. The technique performs enumeration of all feasible combinations of membership functions of the five climatic inputs. Grid partitioning technique is associated with dimensionality problem as the rule base increases exponentially within the system, which often leads to an 'out of memory' situation during model compiling. The number of rules generated largely depends on the number of input variables as well as the number of membership functions. In this study, the grid partitioning technique generated rules.

3. Results

3.1 Data Analysis

Presented in Table I is the statistics of the energy consumption in each campus as well as the season of occurrence of the minimum and maximum.

Table I: Energy consumption statistics per campus

Campus	Mean (KWh)	Maximum (KWh)	Season of Maximum Consumption	Minimum (KWh)	Season of Minimum Consumption
Campus A	71,501.95	103,064.90	Winter	29,423.56	Summer
Campus B	15,913.89	31,345.86	Winter	1,955.40	Summer
Campus C	14,405.51	23,495.22	Winter	2,775.98	Summer
Campus D	23,334.64	34,780.94	Winter	10,179.26	Summer

Campus A has the highest average energy consumption (71,501.95KWh) while the campus D has the least (14,405.51KWh). The highest consumption of electricity in all the campuses occur during the winter season while the least occur in the summer period. This can be attributed to the decrease in temperature, increase in relative humidity during the winter season, which is the reverse during summer periods. Campus A is the main campus with high number of plug load equipment as well as the highest number of students hostel and lecture halls compared to other campuses, which have fewer of these facilities and students.

3.2 ANFIS result

The model was trained with 70% of the data used for both clustering techniques and the other 30% used for model validation. The algorithm was computed on a workstation with configuration 64 bits, 32GB RAM Intel (R) Core (TM) i7 5960X. Mean Absolute Deviation (MAD), Root Mean Square (RMSE), and Mean Absolute Percentage Error (MAPE) were calculated for forecasts from the two models and the observed energy consumption as shown in Table 2 to 5. The GP clustering yielded a higher mean absolute percentage error of 28.78, 70.74, 28.07 and 26.52 % for campuses A, B, C and D respectively compared to the FCM clustering technique which yielded 20.39, 53.71, 22.11 and 16.89 % for the same order of campuses. This shows the degree to which the forecast is off. FCM clustering technique asides its computational efficiency as obtained from the CPU time, offers more accuracy for all the campuses.

Table II: Model performance evaluation for Campus A

Method	MAD	RMSE	MAPE	Computational Time (seconds)
GP	2169561.79	5697920.55	28.78	15.64
FCM	1921544.26	5485068.99	20.39	1.09

Table III. Model performance evaluation for Campus B

Method	MAD	RMSE	MAPE	Computational Time (seconds)
GP	287561.44	395020.56	70.74	16.64
FCM	254490.74	356525.26	53.71	1.06

Table IV. Model performance evaluation for Campus C

Method	MAD	RMSE	MAPE	Computational Time (seconds)
GP	764768.81	1723799.88	28.07	14.61
FCM	699774.98	1665245.48	22.11	1.03

Table V. Model performance evaluation for Campus D

Method	MAD	RMSE	MAPE	Computational Time (seconds)
GP	123230.34	154583.63	26.52	14.80
FCM	66491.92	85738.96	16.89	1.02

The ANFIS structure in Figure 1 with climatic inputs feeding into the input membership function layer (layer 1). The second layer of the structure calculates the firing strength of each of the nodes using a product operation while the third normalizes the firing strengths from all firing nodes. The fourth layer of the structure controls the consequent parameters of the fuzzy system while the fifth layer consists of a single node, which computes the output of all coming signal via a summation operation.

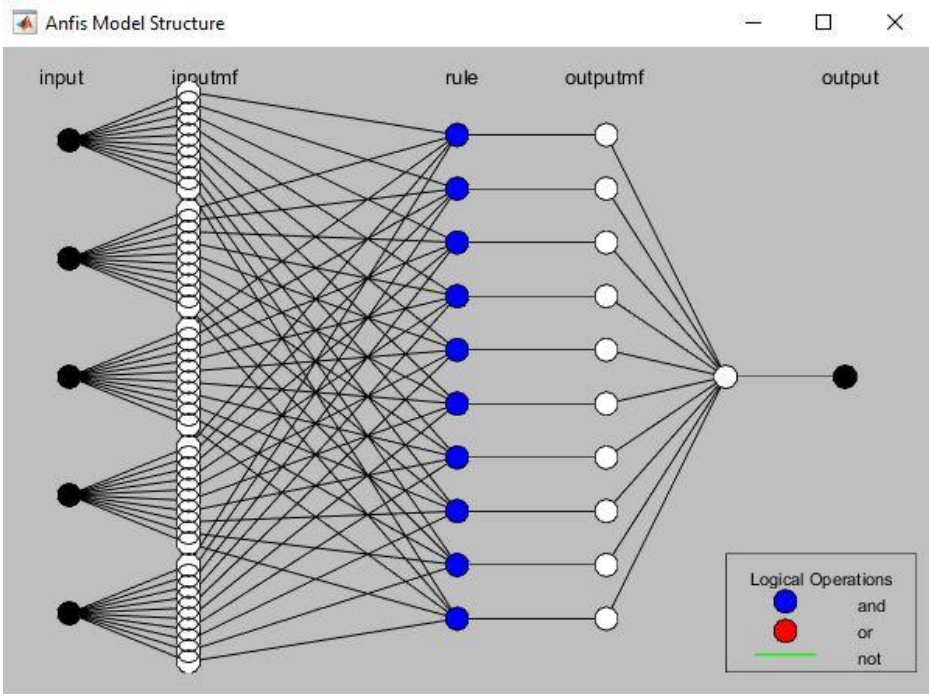

Figure 1. ANFIS structure with five inputs and one output

Figures 2 to 5 shows the plot of energy consumption forecast for FCM and GP clustering technique compared with the observed energy consumption for the next eleven (11) months in the series. From Figure 2, the observed energy consumption varies across the months. However, a significant variation is observed in the second month. This is due to a decrease in the environmental temperature and during this period, which could have necessitated more energy consumption for space heating, and other weather dependent activities in the campus.
Despite a variation in the observed energy consumption and that predicted by FCM technique for campus A as shown in Figure 2, there exists a close trend between the two values. Similar, trend exists between the observed energy consumption and that predicted from the GP technique, however, asides its higher computational time as recorded in Table 2, the degree of accuracy of the prediction falls below that predicted by the FCM technique. FCM as a clustering technique performs better for energy forecast for campus A than GP technique.

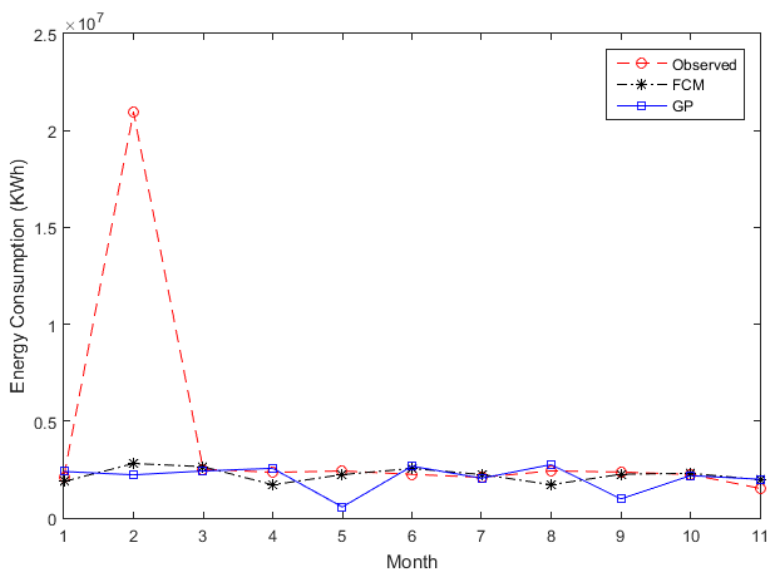

Figure 2. Forecast comparison between the observed, the FCM and the GP predicted energy consumptions for Campus A

From Figure 3, energy consumption in campus B shows significant fluctuations across the test months, with the highest consumption recorded in the first month. The forecast in Figure 3 shows a similar trend between the observed energy consumption and the predicted for FCM and GP techniques, however, FCM outperforms the GP in terms of closeness to the observed energy consumption. The prediction from GP model was off by 70.74% which shows less of model reliability while the FCM was off by 53.71% from the mean absolute percentage error in Table III. Both techniques for campus B do not prove a better prediction, however, FCM has a lesser root mean square error as well as a lesser computational time. The two models do not present a good forecast for campus B and so requires further optimization of model parameters.

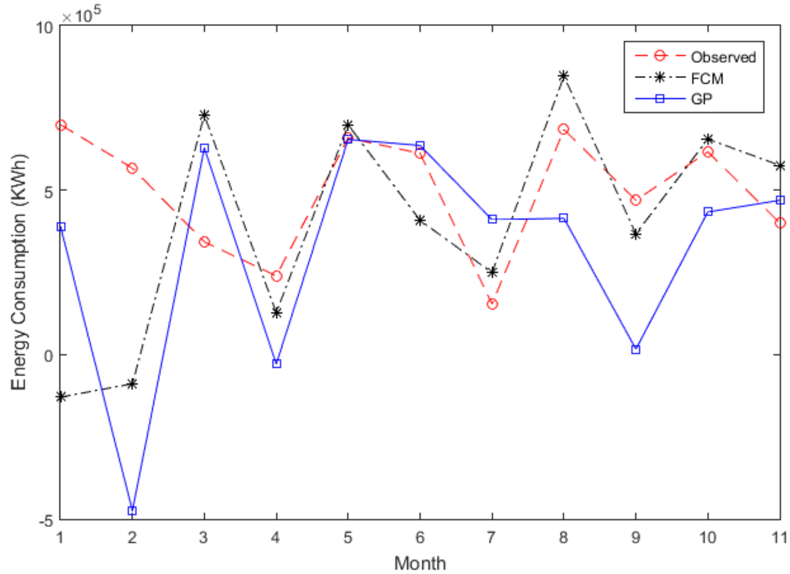

Figure 3. Forecast comparison between the observed, the FCM and the GP predicted energy consumptions for Campus B

There exists no significant fluctuation in the test energy consumption for campus C except for the first and the seventh month in the series. From the forecast plot for campus C, there exists a close relationship between the observed energy consumption and the predicted from FCM and GP techniques as shown in Figure 4. However, the FCM technique gives a closer prediction with the prediction off by 22.11% as obtained from the mean absolute percentage error (Table IV). The GP technique on the other hand has the forecast off by 28.07%. Asides the two outliers from the observed energy consumption in the 1st and 7th month, forecast for the FCM technique is closer to the observed energy consumption than the GP.

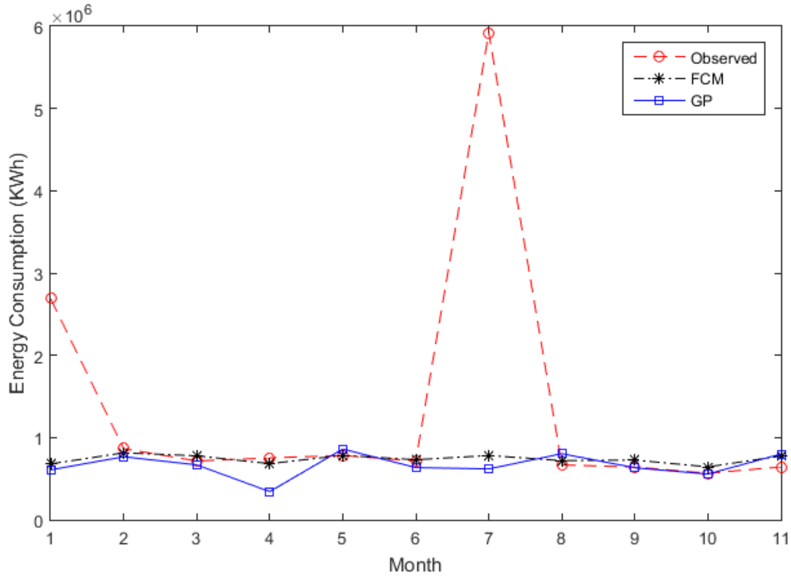

Figure 4. Forecast comparison between the observed, the FCM and the GP predicted energy consumptions for Campus C

Shown in Figure 5 is the energy consumption comparison plot for campus D between the observed and the two clustering techniques. The observed energy consumption for model validation shows a fluctuation. However, there exists a similarity in trends along the series with the FCM predicted energy consumption, as compared to the forecast obtained from GP technique. The FCM technique was off in the forecast by 16.89% compared with 26.53% recorded by the GP technique as obtained from mean absolute percentage error from Table V.

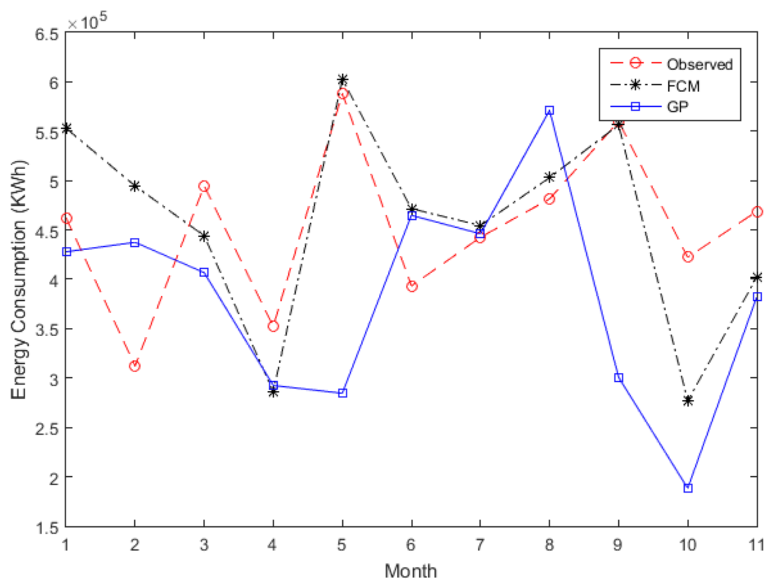

Figure 5. Forecast comparison between the observed, the FCM and the GP predicted energy consumptions for Campus D

4. Conclusion

Energy consumption in a multi-campus tertiary institution could be complex, most especially when common resources are accessed with frequent migration from one campus to another. This is the condition of the campus used as case study in this paper. The effectiveness and efficiency of two clustering techniques: Fuzzy C-Means clustering (FCM) and Grid Partitioning (GP) were investigated. FCM technique offers less computational complexity and so gave a higher forecast accuracy at lesser computational time for all campuses compared to GP technique. The GP technique on the other hand offers a large rule base, which in turn results in model complexity and more computational time. Campus D records the best forecast for both clustering techniques with MAPE= 26.52% (GP) and 16.89% (FCM). This translates to 73.48% and 83.11% forecast accuracy respectively.

The type of data clustering technique selected in ANFIS modeling plays an important role in the accuracy and computational complexity. For further studies the use of hybrid ANFIS model, with evolutionary algorithm is recommended in the field of energy consumption forecast for ANFIS parameter tuning. Similarly, multiple trainings until a lower forecast error within the domain of the observed values and high convergence at the global minimum domain is obtained should be ensured. This would enable network parameters in the first and fourth layer of the ANFIS structure attain global optimal values for network tuning.

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Biographies

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