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Hybrid adaptive neuro-fuzzy inference system (ANFIS) for a multi-campus university energy consumption forecast

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ABSTRACT

This study compares the performance of standalone adaptive neuro-fuzzy inference system (ANFIS) and its hybrid with particle swarm optimisation (PSO) in predicting the energy consumption from climatic factors for a multi-campus institution in South Africa. Monthly weather condition datasets (average wind speed, average maximum temperature, average minimum temperature, average dew point and average relative humidity) for 36 months were mapped with the corresponding monthly energy consumption for each campus as the model inputs and output respectively. The ANFIS and ANFIS-PSO models were trained and tested with 70% and 30% of the dataset respectively. The root mean square error (RMSE), mean absolute deviation (MAD), mean absolute percentage error (MAPE) and the computational time were used to evaluate the model for the four campuses. The ANFIS standalone model developed for campus C outperforms other standalone models for campus A, B and D with the following performance indices: RMSE = 1.27, MAD = 1.01, MAPE = 13.34, computational time = 14.61 *secs*. On the contrary, the ANFIS-PSO model developed for campus D outperforms both the standalone and the hybrid models for campus A, B and C with the following values of performance indices except for computational time: RMSE = 0.147, MAD = 0.125, MAPE = 2.89, computational time = 95.60 *secs*. This study concludes that tuning ANFIS parameters with PSO offers a better prediction accuracy, which is reliable for strategic energy planning, though at a higher computational time.

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KEYWORDS
Adaptive neuro-fuzzy inference system; particle swarm optimisation; energy forecast; multi-campus energy consumption

Nomenclature

Acronyms	Meaning
i	Each particle in the swarm
j	ANFIS node
k	Data point
l	ANFIS layer
N	Population size
X_i^d	Position Component of particle i at dth dimension
V_i^d	Velocity component of particle i at dth dimension
P_i	Best position of the ith particle
P_g	Global best position
a_1, a_2	Particle acceleration coefficient
w	Particle inertia weight
$rand1_i^d, rand2_i^d$	Randomly generated numbers between 0 and 1.
c	Cluster
v_c	Centre of cluster c
m	Weighting exponent
A	Positive definite weight matrix
N	Number of observations
$I_{1\ldots5}$	Model input
C	Total number of clusters
O_j^1	Output of layer 1 in node j
$\mu_{A_j}(I_1)$	Fuzzy membership function of input I_1 at node A_j.
$\mu_{B_j}(I_2)$	Fuzzy membership function of input I_2 at node B_j.
w_j	Firing strength at jth node.
$\overline{w_j}$	Normalised firing strength at jth node.
p_j, q_j, r_j	Consequent parameter set at jth node.
y_k	Observed value
$\widehat{y_k}$	Predicted value
$\bar{y}$	Sample mean
z_j	Consequent at jth node.

1. Introduction

Data-driven decision-making process is fast gaining roots in the field of energy systems. This has enabled informed decision-making at the strategic management level of both service and manufacturing industries. One of these data-driven processes, which has tremendously influenced industrial systems is forecasting. The university campus, associated with high energy consumption due to its numerous plug-load devices and buildings requires intelligent energy management systems to minimise cost expended on energy. With increasing technological development in equipment for multi-disciplinary research, there is anticipated increase in plug-load devices (Hafer 2017), which

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translates into an increase in energy consumption (Moorefield, Frazer, and Bendt 2011). Similarly, the enrolment rate of students of higher institutions increases on a yearly basis. This in turn necessitates an increase in both residential buildings as well as lecture theatres to accommodate the increasing population. A ripple effect is anticipated on the expenses on energy consumption in every fiscal year. The situation becomes more complex in universities with multiple campuses like the case considered in this study.

The energy consumption in residential and commercial buildings, which educational institutions belong, varies with geographical location, season andtype of activities. From the hemispherical perspective, countries located around the northern hemisphere are hotter (with annual average surface temperature of 14.6°C) (Jones et al. 1999) than those in the southern hemisphere (with annual average surface temperature of 13.4°C) (Jones et al. 1999; Kang et al. 2015) due to several reasons, one of which is the gradual heating of ocean transports across the great circle. Consequentially, the energy consumption in the southern hemisphere is much higher than the northern hemisphere counterpart (Oree, Khoodaruth, and Teemul 2016). Sudden Stratospheric Warming (SSW) – a sudden warming in the stratosphere associated with the winter period, which often occurs in the northern hemisphere seldom occurs in the southern hemisphere (Smith-Johnsen et al. 2018). Most studies on energy consumption forecast and modeling have been carried out on buildings around the western and northern hemispheres (Khosravani et al. 2016; Li and Su 2010; Tahmassebi and Gandomi 2018), which leaves the southern hemisphere less explored. Among the few studies in the energy consumption forecast in the southern hemisphere is the study by Mohamed and Bodger (Mohamed and Bodger 2005). The study investigated the effect of selected demographic (population) and economic variables (gross domestic product, average price of electricity) on annual energy consumption in New Zealand. The study employed multiple linear regression, whose result showed a correlation between all the independent variables and the electricity consumption in the country.

Energy consumption forecast predicates an energy-efficient policy as well as optimisation of usage. Several studies have been carried out in forecasting energy consumption in tertiary institutions. For example, Deb et al., (Deb et al. 2015) investigated the use of adaptive neuro-fuzzy inference system (ANFIS) and Artificial Neural Network (ANN) in forecasting energy consumed by cooling load devices in three institutional buildings in Singapore. Three inputs (air temperature, humidity and solar radiation) were used against energy consumption. While subtractive clustering was used for data clustering in ANFIS, back-propagation neural network trained with Bayesian regularisation was used for the ANN model. Both models gave good predictions, however, ANN model gave a better result with an average R-squared value of 0.974. Similar to this is the study by Amber et al.,(Amber, Aslam, and Hussain 2015) which used two models; the Multiple Regression (MR) and Genetic Programming (GP) to forecast energy consumption in South Bank University using five independent variables- ambient temperature, relative humidity, solar radiation, wind speed and weekday index. GP model outperformed the MR model with a total absolute error of 6% compared to 7% recorded for MR model.

A good number of institutional energy forecast in the literature considers a single campus institution with multi-campus institutions receiving less attention. It could be argued that each campus can be considered as a single entity, however, the campuses considered in this study possess a centralised system of administration. The energy cost is bored by the central system and not by individual campuses. Also, student migration between campuses makes attributing energy consumption in a campus to students on that campus fuzzy. Several forecasting techniques have been used in energy consumption forecast (Amber, Aslam, and Hussain 2015; Barak and Sadegh 2016; Boran 2014; Tahmassebi and Gandomi 2018) and it has been established that using heuristic algorithms in training ANFIS model gives better predictive results, with GA, particle swarm optimisation (PSO) and Artificial Bee Colony (ABC) heuristics ranking top three in ANFIS training (Karaboga and Kaya 2018). However, studies on the effectiveness and efficiency of PSO-ANFIS model on multi-campus energy consumption forecast and most especially in the southern hemispherical part of the world is sparse in the literature. Close to this study is the use of standalone ANFIS and its hybrid with PSO, Genetic Algorithm (GA) and Differential Evolution (DE) for monthly prediction of solar radiation using meteorological parameters (sunshine, minimum and maximum air temperature, rainfall and clearness index) (Halabi, Mekhilef, and Hossain 2018). Hybrid ANFIS models in the study demonstrated a high reliability in solar radiation forecast than the standalone ANFIS model.

The increasing revolution in the field of artificial intelligence has opened a new chapter for hybrid algorithms towards model parameter optimisation for enhanced model effectiveness and efficiency. ANFIS model is preferred to other intelligent learning algorithms like ANN, Support Vector Machine (SVM), *k*-nearest neighbour (*k*-NN) and so on due to its robustness in its performance, online adaptability and its self-adjusting ability to obtain minimum global error on non-linear problems (Adedeji et al. 2019; Shihabudheen and Pillai 2018). To further enhance these capabilities, a hybrid of ANFIS with evolutionary algorithms to effectively integrate the relational structure and learning capability of the ANN, the dynamic nature of the fuzzy logic in decision making (Karaboga and Kaya 2018) and the parameter-tuning capability of evolutionary techniques towards model performance improvement is fast gaining traction. PSO-ANFIS model is one of the hybrid models which offers improved model accuracies in several areas where it has been applied and reduced computational time compared to some other hybrid ANFIS models like, ANFIS-GA and ANFIS-DE even though this factor also depends on the computing power of the computing device. For example, Hossain et al. (2018) experimented hybridised ANFIS with GA, DE and PSO for long-term prediction of wind power density. The authors compared the effectiveness of the three hybrid models and concluded that the PSO and GA hybrids of ANFIS model outperformed the DE hybrid. However, a comparison between their computational times was not reported. Similarly, (Olatunji et al. 2019a) investigated the effectiveness and efficiency of ANFIS-PSO in predicting enthalpy of combustion municipal solid waste based on its elemental compositions. Statistical performance measures were used for model evaluations and a mean absolute percentage error (MAPE) of 22.6202, mean absolute deviation (MAD) of 2.562, root mean square error of 3.4443 and log accuracy ratio of 0.0337 were obtained at the model testing phase. Also, the model computational time of 36.96 *secs* was computed on similar computing device as used in this study. This further commends the quick converging prowess of PSO-based ANFIS model. The same authors further investigated the effectiveness of ANFIS-PSO in predicting elemental compositions from the proximate values of biomass using a large dataset (Olatunji et al. 2019b). For all the elemental compositions predicted, ANFIS-PSO outperformed standalone ANFIS model with an average computational time of 36.8 *secs,* which further emphasises the model's quick convergence and predictive accuracy. Training ANFIS models with evolutionary algorithms improves the model's adaptive layer parameters towards obtaining a global minimum error, rapid convergence and improved model accuracy at a lower throughput (Adedeji et al. 2019). This informed the selection of the ANFIS-PSO model for this study.

Energy consumption in buildings exhibits dynamic pattern, which gives relevance to PSO-ANFIS in energy consumption forecast. Forecasting energy consumption in educational buildings is not novel in the literature, however, forecasting for a multi-campus university whose campuses have different weather conditions and different electricity consumption pattern (with central energy cost centre) using an ANFIS model optimised with an evolutionary algorithm stands as the novelty of this study. This study therefore (i) predicts the energy consumption of a multi-campus institution from meteorological data of the campuses using ANFIS and PSO-ANFIS models. (ii) compares the performance of the two models using statistical performance metrics in all the campuses. The rest of this article presents the methodology adopted (Section 2), the results (Section 3), which entails a comparison of the PSO-ANFIS with standalone ANFIS model and Section 4 concludes the work.

Table 1. Calendar dates in the southern hemisphere.

Southern hemisphere	Calendar dates
Autumn	1 March to 31 May
Winter	1 June to 31 August
Spring	1 September to 30 November
Summer	1 December to 28/29 February

Source: (SA Weather Service 2015)

2. Methodology

2.1. Data description

The University of Johannesburg was used as a case study. The university is a multi-campus institution located in Gauteng Province of South Africa. Each campus is located at different geospatial locaations. Weather station used was correlated with the geographical locations of the campuses using Google Earth Pro. Climatic data (average wind speed, average maximum and minimum temperature, average dew point, average relative humidity) from 2015 to 2017 on monthly basis (36 months) were collected from the South African Weather Service. The choice of these parameters stems from their high correlation with energy consumption in residential and non-residential buildings (Idahosa, Marwa, and Akotey 2017; Wang, Liu, and Brown 2017), most especially in the southern hemisphere. These climatic data were used as inputs against one output (energy consumption) for each campus as shown in Figure 1.

Monthly energy consumption data (in megawatt-hour) for all the campuses within the same time horizon was used. The energy consumption data were collected from the energy management department of the university, which spans the four campuses. Their mode of data collection is through a data logger, which keeps a historical record of energy consumption in real time. Highest and lowest energy consumptions in each campus and the seasons when these occurred were identified. Weather classification of the southern hemisphere by the South African Weather Service, based on climatological and

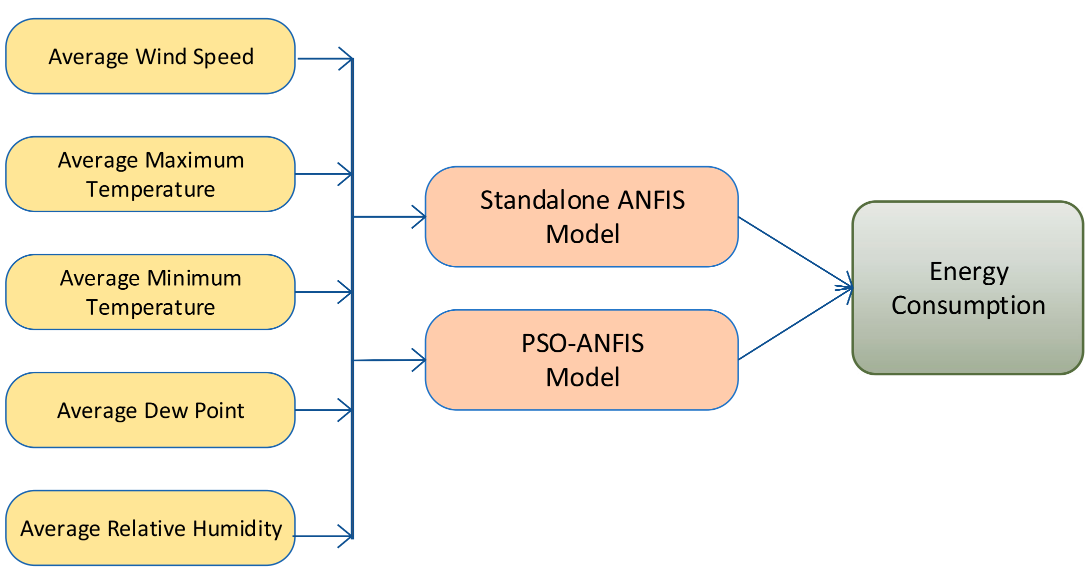

Figure 1. Model architecture comprising the standalone and PSO-ANFIS models.

sociological grounds as presented in Table 1 was used to determine seasons with high, and low energy consumption.

2.2. Model description

2.2.1. PSO optimisation

The PSO optimisation technique forms one of the common population-based stochastic algorithms inspired by social and biological behaviour (Lynn, Ali, and Nagaratnam 2018). It is one of the few optimisation search algorithms notable for its simplicity and quick convergence after a stochastic search within a high-dimensional search space. The PSO optimisation algorithm consists essentially of swarm of particles with each particle representing a potential solution and the properties of each particle being the parameters to be optimised (Engelbrecht, Cleghorn, and Engelbrecht 2019). With a random position of particles within the solution space, each particle possesses a random velocity value. The particle velocity (step size) controls the optimisation process. It presents the experiential knowledge gathered by the particle and the socially exchanged information regarding viable areas within the solution feasibility region. Thus, the flight of each particle is controlled by its personal flying experience and the experience of its flying companions. These two experiences represent the two model parameters called the cognitive and the social acceleration coefficients respectively. Every particle in the solution space temporarily stores its best position so far within the search space. In the course of each iteration, each particle's velocity is adjusted relative to its previous best position and the best position obtained from any particle within its region (Lynn, Ali, and Nagaratnam 2018). The position and velocity of the particle are updated using population topology functions as defined in (Shi and Eberhart 1998) as

$$V_i^d = [w \times V_i^d] + [a_1 \times rand1_i^d (P_i^d - X_i^d)] + [a_2 \times rand2_i^d [P_g^d - X_i^d]] \quad (1)$$

$$X_i^d = X_i^d - V_i^d \quad (2)$$

such that each particle i in N population possesses X_i^d position component and V_i^d velocity component at dth dimension. P_i represents the best position of the ith particle and P_g the global best position. The acceleration coefficients are defined by a_1 and a_2, w is the linearly decreasing inertia weight. The a_1 and a_2 are positive cognitive and social acceleration coefficients respectively of which stability of the algorithm is ensured when $a_1 + a_2 \leq 4$ (Kennedy 1998). The $rand1_i^d$ and $rand2_i^d$ components of the equation are randomly generated numbers within the range of 0 and 1.

2.2.2. ANFIS model

The ANFIS model integrates ANN and Fuzzy Inference System (FIS) such that optimal distribution of membership function is obtained from input-to-output mapping (Jang 1993). A typical ANFIS network is a five-layer structure consisting of the fuzzy layer, the product layer, the normalised layer, the de-fuzzy layer and the total output layer (Adedeji, Madushele, and Akinlabi 2018; Jang 1993; Rosadi, Subanar, and Suhartono 2013) as shown in Figure 2. ANFIS model with Takagi-Sugeno fuzzy inference system mapped the five climatic variables as inputs to the energy consumption (the output) across three parameterised Gaussian membership functions used in this study. ANFIS model requires a clustering technique of which Fuzzy c-Means (FCM) was used.

The first layer consists of fuzzy membership functions with output functions for each node represented by Equations (3) and (4):

$$O_j^1 = \mu_{A_j}(I_1), \quad j = 1, 2 \quad (3)$$

$$O_j^1 = \mu_{B_j}(I_2), \quad j = 1, 2 \quad (4)$$

The second layer computes the firing strength of a rule using multiplicative operator as:

$$O_j^2 = w_j = \mu_{A_j}(I_1).\mu_{B_j}(I_2), \quad j = 1, 2 \quad (5)$$

Normalisation of the firing strength at the jth node of the structure using the ratio between the firing strength in the jth node and the sum of all firing strengths from all the rules Equation (6) is performed in the third layer. Nodes in this layer are non-adaptive.

$$O_j^3 = \overline{w_j} = \frac{w_j}{w_1 + w_2} \quad j = 1, 2 \quad (6)$$

A nodal function exists in the fourth layer, which calculates the effect of jth rule towards the output of the model using

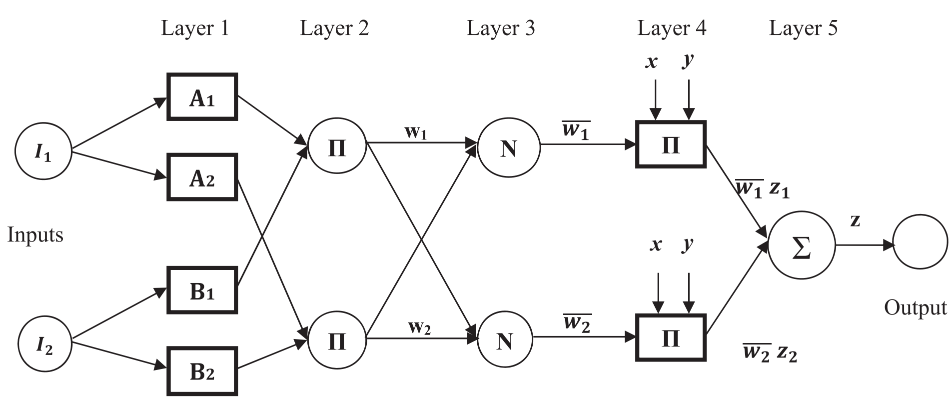

Figure 2. ANFIS model architecture.

Equation (7):

$$O_j^4 = \overline{w_l}(p_j I_1 + q_j I_2 + r_j) = \overline{w_l} z_j \quad (7)$$

where p_j, q_j, r_j is a parameter set of the node and $\overline{w_i}$ is the normalised firing strength of the third (3) layer.

The fifth layer has a single non-adaptive node, which calculates the overall output of the ANFIS model using a summing function (Suparta and Alhasa 2016) expressed by Equation (8):

$$O_j^5 = \sum_j \overline{w_i} z_j = \frac{\sum_j w_j z_j}{\sum_j w_j} \quad (8)$$

Fuzzy rules. From Figure 2, the first order Takagi-Sugeno fuzzy model has fuzzy rules with the structure:

Rule 1: If I_1 is A_1 AND I_2 is B_1 then $f_1 = p_1 I_1 + q_1 I_2 + r_1$.

Rule 2: If I_1 is A_2 AND I_2 is B_2 then $f_2 = p_2 I_1 + q_2 I_2 + r_2$.

In this work, the above rules where adapted with input $I_i (i = 1 \ldots 5)$, output O_1 and cluster $C_j (j = 1 \ldots 10)$ with equal weights using fuzzy c-means clustering technique. The rules then follow:

Rule 1: If I_1 is in I_1C_1 AND I_2 is in I_2C_1 and I_3 is in I_3C_1 and I_4 is in I_4C_1 and I_5 is in I_5C_1 then O_1 is in O_1C_1.

Rule 2: If I_1 is in I_1C_2 AND I_2 is in I_2C_2 and I_3 is in I_3C_2 and I_4 is in I_4C_2 and I_5 is in I_5C_2 then O_1 is in O_1C_2.

Rule 3: If I_1 is in I_1C_3 AND I_2 is in I_2C_3 and I_3 is in I_3C_3 and I_4 is in I_4C_3 and I_5 is in I_5C_3 then O_1 is in O_1C_3.

Rule *N*: If I_1 is in I_1C_N AND I_2 is in I_2C_N and I_3 is in I_3C_N and I_4 is in I_4C_N and I_5 is in I_5C_N then O_1 is in O_1C_N.

The rule structure applies to all the campuses. Shown in Figure 3 is the resulting ANFIS structure for a campus, which applies to the remaining three campuses.

2.2.3. PSO-ANFIS hybrid model

ANFIS with FCM clustering was trained using PSO algorithm. The FCM minimises generalised least square error function $J_m(U, v)$ in Equation (9), such that each data point x_k in N observations belong to a cluster c according to a degree of membership μ_{kc}.

$$J_m(U, v) = \sum_{k=1}^{N} \sum_{c=1}^{C} \mu_{kj}^m \|x_k - v_c\|_A^2, \quad 1 \leq m \leq \infty$$

$$for\ C = number\ of\ clusters | 2 \leq C < n \quad (9)$$

where m is the weighting exponent, A is a positive definite $(n \times n)$ weight matrix, || || is an $n -$ dimensional Euclidean space wherein sample data belong and v_c is the centre of cluster c. The procedure for the hybrid model is described as follvnows:

Step 1: Structure the inputs and output to the model.

Step 2: Generate initial fuzzy inference system (FIS) structure.

Step 3: Generate initial swarm as follows:

(i) Generate random population size (Particles), P of length *Var_Size* each and positions $p_{k,l} \in (P_{min}, P_{max})$ such that $k = 1, 2, 3, \ldots, Pop_{Size}; l = 1, 2, 3, \ldots, Var\_Size$

(ii) Initialise the velocity of each particle ($Inital\_Vel = 0$).

(iii) Initialise the best cost at *Gbest* ($Inital\_BestCost = \infty$).

Step 4: Create next generation of particle with updated position, velocity and inertia weight according to the Equations (1), (2) and (10), respectively (Semero, Zheng, and Zhang 2018).

$$\omega = \omega_{damp} \times \omega \quad (10)$$

where ω is the weight inertia, and ω_{damp} is the inertia weight damping ratio.

Step 5: Assign optimised particle parameters to the ANFIS structure.

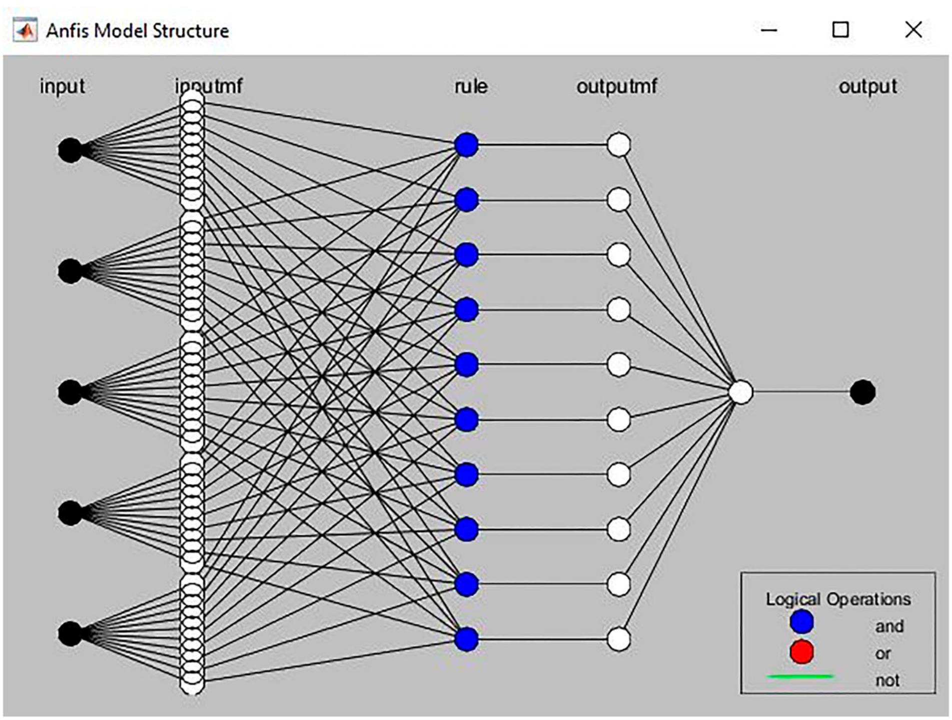

Figure 3. Structure of ANFIS used in this study.

Step 6: Evaluate the cost of each particle using a conditional statement, updating the *Pbest* and *Gbest* values, such that:

$$
\begin{aligned}
& If Cost_i|_{it} < Cbest_p \\
& \quad P_i|_{it} = Pbest \\
& \quad\quad C_i|_{it} = Cbest_p \\
& \quad If Cbest_p < Cbest_G \\
& \quad Cbest_p = Cbest_G \\
& \quad\quad Pbest = Gbest \\
& \quad end \\
& end
\end{aligned}
$$

Step 7: Check if stopping criterion of maximum iteration is satisfied. If not satisfied, the algorithm returns to step 4, else proceed to step 8.

Step 8: Perform a short-term forecast of electricity consumption for the four campuses.

Step 9: Perform statistical performance evaluation on the forecast.

Step 10: Plot a comparison between actual electricity consumption and the predicted within the same time horizon.

Step 11: Terminate the programme.

An initial population of 25 and initial weight damping ratio of 0.99 was used for all campuses. The cognitive and social acceleration parameters were both chosen to be equal ($c_1 = c_2 = 2$) based on the recommendation of Kennedy (1998) and previous studies. A maximum iteration of 1000 was used such that the convergence at values, which minimises the training error objective function was made a stopping criteria. The model flow chart is as shown in Figure 4. The ANFIS model was trained using the PSO algorithm until the convergence, minimum training error or maximum number of iterations is reached.

The computation was performed in MATLAB (R2015a). The two models were trained using 70% of the data while 30% was used for model validation. The hybrid model was compared with the ordinary ANFIS model for each campus and the result presented in Section 3.

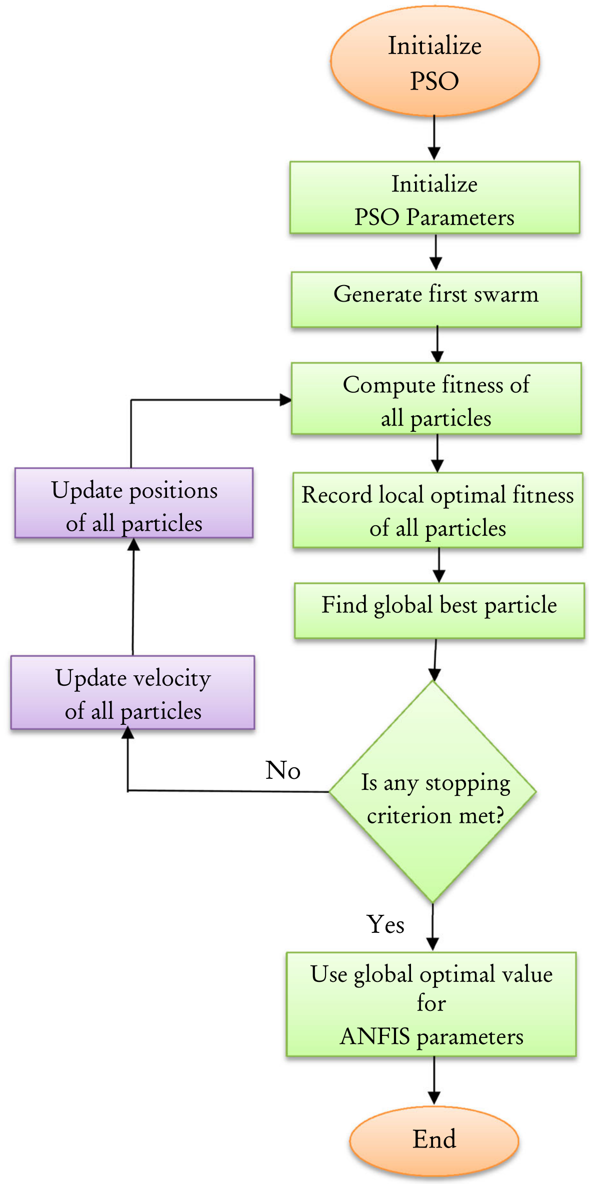

Figure 4. ANFIS-PSO flow chart.

3. Results

3.1. Data analysis

Shown in Figure 5 is the proportion by mean of the energy consumption on campus basis. Campus A has the highest average energy consumption (71.50 MWh) consuming 57% of the institution's energy. Campus D with average energy consumption of 14.41 MWh consumes less energy compared to campus A and it takes 19% of the total energy consumed by the institution. Campus B and C accounts for 13% and 11% of the institution energy consumption, respectively. Shown in Figure 6 is the maximum and minimum energy consumption for each campus. While the maximum energy consumption occurred in the winter season, the minimum energy consumption occurred in the summer season in all four campuses.

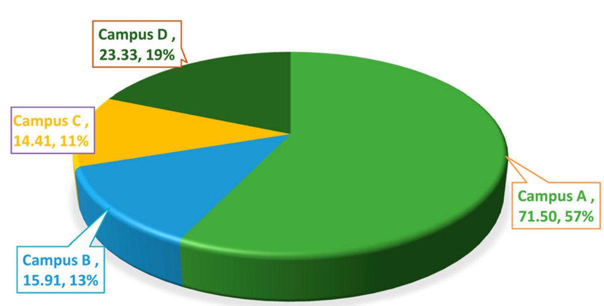

Figure 5. Mean proportion of energy consumption per campus (in MWh).

From Figure 6, average energy consumption in campus A accounts for more than twice of those consumed by each of the other campuses. This high consumption in campus A is due to its high number of plug-load equipment, high number of student hostels as well as lecture halls compared to other campuses. More so, campus A is the administrative headquarters of the institution and so has more buildings than the other campuses.

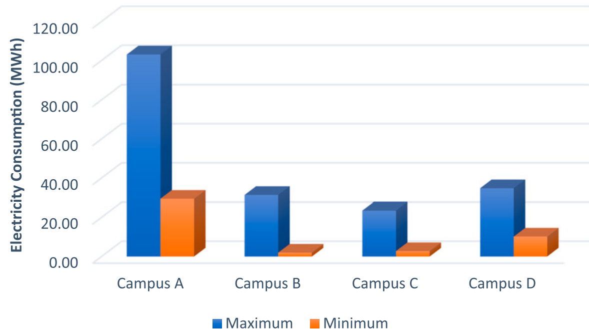

Figure 6. Minimum and maximum energy consumption per campus.

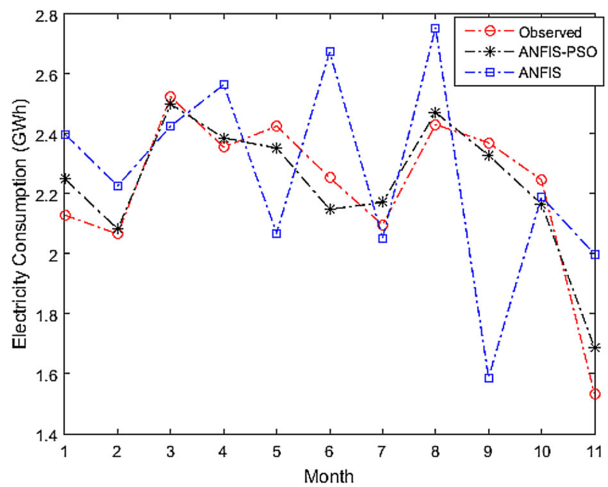

Figure 7. Prediction of energy consumption- Campus A.

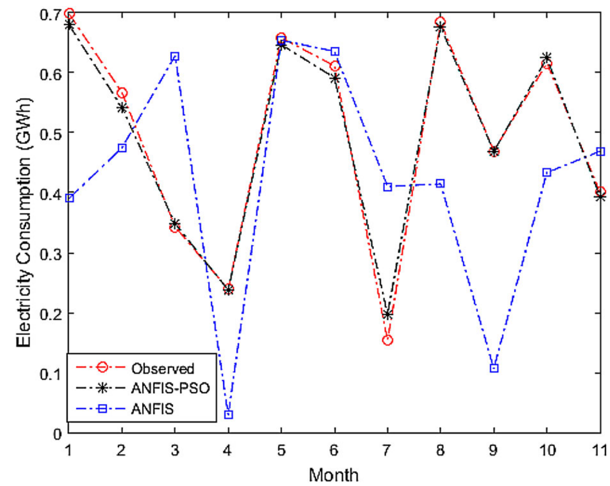

Figure 8. Prediction of energy consumption- Campus B.

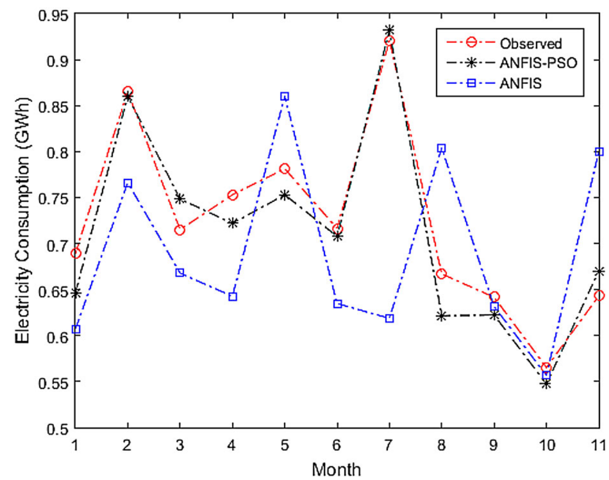

Figure 9. Prediction of energy consumption- Campus C.

3.2. Simulation results

Energy consumption data and corresponding weather data for 11 months in the series, which signifies 30% of the data were used for model validation. Shown in Figures 7–10 is the result for the model validation for campus A, B, C and D. There exists a close relationship between the observed energy consumption and the PSO-ANFIS predicted results for all the campuses. ANFIS model gave similar results, however, there exist larger deviations between energy consumption obtained from ANFIS standalone model and the observed energy consumption. The results obtained for PSO-ANFIS models show a minimal deviation from the observed values. The effectiveness of both models in relation to computational time performance evaluation of both the training and testing data were also recorded as well as the model computational time.

Shown in Figures 7–10 are comparison plots between the observed electricity consumption, the predictions from the standalone ANFIS and the ANFIS-PSO models for campus A, B, C and D, respectively. There exists variability in the electricity consumption from one month to another in all the four campuses as there is no month with the same electricity consumption both from the observed and the model-predicted results for all the four campuses. Standalone ANFIS technique for prediction has offered good results in many studies, however, in this study, the hybrid ANFIS (ANFIS-PSO) predicted electricity consumption for all the four campuses better than the standalone ANFIS model, which agrees with some findings in the literature on predictive application of the model (Chen 2013; Olatunji et al. 2019b). Campus A consumes more electricity compared to the other three campuses and the standalone ANFIS model predicts with a higher deviation from the observed electricity consumption. However, the ANFIS-PSO model predicts electricity consumption more accurately compared to the standalone ANFIS model with the same test dataset as shown in Figure 7. Increased accuracy in the predictions obtained from the ANFIS-PSO models compared to the standalone ANFIS model was observed in the forecasts for Campus B, C and D as shown in Figures 8–10, respectively. However, this increased prediction accuracy attracted an increase in computational time as presented in Table 2–5. This is due to the optimisation process performed by the PSO algorithm such that membership function parameters are tuned to achieve optimality. The PSO optimisation model searches for the best solution

Table 2. Model comparison- Campus A.

Model	RMSE	MAD	MAPE	Computational time (seconds)
ANFIS	3.56	2.90	13.44	15.64
PSO-ANFIS	0.810	0.694	3.37	94.60

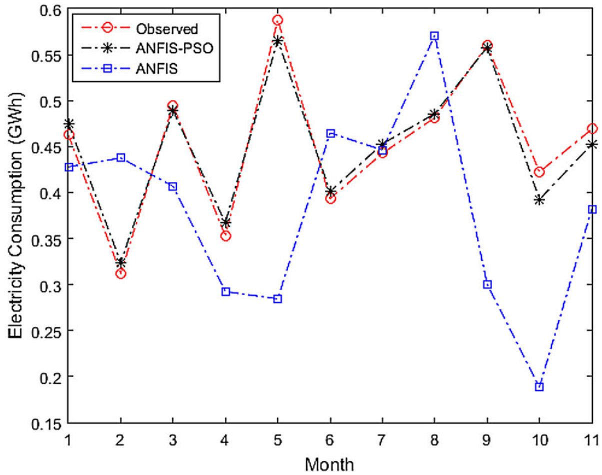

Figure 10. Prediction of energy consumption- Campus D.

Table 3. Model comparison- Campus B.

Model	RMSE	MAD	MAPE	Computational time (seconds)
ANFIS	2.21	1.88	51.59	16.29
PSO-ANFIS	0.183	0.137	4.31	51.15

Table 4. Model comparison- Campus C.

Model	RMSE	MAD	MAPE	Computational time (seconds)
ANFIS	1.27	1.01	13.34	14.61
PSO-ANFIS	0.276	0.245	3.52	64.16

Table 5. Model comparison- Campus D.

Model	RMSE	MAD	MAPE	Computational time (seconds)
ANFIS	1.55	1.23	26.52	14.80
PSO-ANFIS	0.147	0.125	2.89	95.60

within the solution space. The optimal membership function parameters are then used by the ANFIS model in the ANFIS-PSO model. Campus C consumes the least amount of electricity and the forecast obtained from the ANFIS-PSO is closer to the observed consumption compared to the relativeness between the forecast obtained from ANFIS-PSO and the observed for Campuses A, B and D. This is also revealed in the results of the error analysis performed between the predicted results of both the standalone ANFIS and the ANFIS-PSO which were also reported.

3.3. Model evaluation

Performance evaluation of the two models in terms of the error between the observed values and the predicted values, and the model computational time was performed. A desktop computer workstation with configuration 64 bits, 32GB RAM Intel (R) Core (TM) i7 5960X was used for this study. The root mean square error (RMSE), MAD and MAPE were performed as a measure of model accuracy and deviation of the model from the observed electricity consumption. These error and accuracy metrics were calculated using:

RMSE:

$$RMSE = \sqrt{\frac{\sum_{k=1}^{N} [y_k - \widehat{y_k}]^2}{N}} \tag{11}$$

Mean absolute deviation:

$$MAD = \frac{1}{N}\sum_{k=1}^{N} |y_k - \bar{y}| \tag{12}$$

Mean absolute percentage error (MAPE):

$$MAPE = \frac{1}{N}\sum_{k=1}^{N} \left|\frac{y_k - \widehat{y_k}}{y_k}\right| \times 100\% \tag{13}$$

ANFIS model is a good tool for predictive analysis, most especially in a fuzzy environment. Tables 2–5 present the model evaluation results for each of the campuses. Among the ANFIS standalone models for the four campuses, ANFIS model for campus C has the least RMSE and MAD values of 1.27 and 1.01, respectively. Campus A, however, records the highest RMSE and MAD values of 3.56 and 2.90 respectively. Similarly, the MAPE values obtained from the standalone ANFIS model for campus C (MAPE = 13.34) is the least compared to that obtained from other campuses. From the results obtained for the standalone ANFIS models, the model developed for campus C predicts the best compared to other campuses. However, the computational time for each standalone ANFIS model centres around the mean for all the campuses. Thus, there is no significant difference between the computational time of the standalone ANFIS models across the four campuses.

For the PSO-ANFIS models, by comparison on campus basis, the hybrid model for campus D performs optimally than the others with predicted electricity consumption close to the observed consumption. This hybrid model (campus D) records the least RMSE and MAD of 0.147 and 0.125, respectively, while the model for campus A records the highest RMSE and MAD values of 0.810 and 0.694 respectively. Contrary to the standalone ANFIS model, the PSO-ANFIS model for tuning the adaptive layers of the ANFIS model with PSO is observed to increase the model performance and reduce the statistical error between the predicted and the actual, however with a trade-off in the computational time (Tables 2–5).

Similar studies that used PSO-ANFIS model for predicting energy consumption in buildings reported a significant accuracy however, an increase in computational time. Presented in Table 6 is a comparison between the results of few studies, which used PSO optimised ANFIS for system modeling based on their

Table 6. PSO-ANFIS model with VAF performance measurement.

	Ghasemi, Kalhori, and Bagherpour (2016)	Shahnazar et al. (2017)	Mottahedi, Sereshki, and Ataei (2018)	This study
Area of Application	Mining	Ground Vibration	Underground Excavation	Electricity Consumption
VAF (%)	93.37	98.35	93.42	94.84

variance account for (VAF) as calculated using:

$$Variance\ accounted\ for\ (VAF) = 1 - \left[\frac{var(\widehat{y}_k - y_k}{var\ (y_k)}\right] \times 100 \quad (14)$$

From our study, a VAF of 90.41, 98.99, 93.47 and 96.47% were obtained for PSO-ANFIS models for campus A, B, C and D, respectively. On average, a VAF of 94.84% was recorded by the PSO-ANFIS model. From Table 6, the model in this study performs better than that obtained by Shahnazar et al. (2017) but the models by Ghasemi, Kalhori, and Bagherpour (2016) and Mottahedi, Sereshki, and Ataei (2018) performs marginally better in application than the model in this study. Perhaps, the disparity between these results could be due to the different choice of control parameters of the PSO optimisation model (Engelbrecht, Cleghorn, and Engelbrecht 2019) and the type of data (either skewed or un-skewed).

4. Conclusion

Energy consumption in university campuses is complex, most especially when the university is a multi-campus institution and is residential. The electricity consumption depends on several factors of which climatic factors are significant. This study investigates the effectiveness and efficiency of the standalone ANFIS model and PSO-ANFIS model, where ANFIS adaptive layer is tuned. While the standalone ANFIS model offers good prediction, its hybrid with PSO offers a significant improvement in model accuracy across all the campuses considered. Tuning ANFIS model with PSO ensures quick convergence and adaptive parameter optimisation, thus mapping the inputs to the corresponding output in an intelligent manner. However, this occurs at the expense of the model computational time. In congruence with the literature, PSO-ANFIS models often record high accuracy, however, at a very high computational time (Halabi, Mekhilef, and Hossain 2018; Rezakazemi et al. 2017). This study, being the preliminary part of an ongoing research, the trade-off between PSO-ANFIS accuracy and computational time is open for further research. The use of parallel computing technique in this hybrid ANFIS model is recommended for further studies.

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