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Prediction of Power Consumption Utilization in a Cloud Computing Data Centre using Kalman Filter parameters with Genetic Algorithm

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ABSTRACT

Data Centre (DC) has become a critical computing infrastructure that is essential to modern society by providing services such as cloud computing, Internet of Things (IoT) and big data. However, the cost of maintaining DC continues to rise as the demand for information technology services increase and this situation is further exacerbated in a country like Nigeria where there is highly unstable power supply from the national grid. The optimization of energy consumption in cloud computing DC using Genetic Algorithm (GA) to minimize the consumption of energy thereby extending network lifespan was one of the techniques used for optimization of power consumption. But the optimization was carried out with the assumption that all the parts of the modular server that are not carrying traffic is on idle mode and not completely off which consumes extra power compare to when it is completely off. Therefore, this work proposed optimization of power consumption utilization in a cloud computing DC using Kalman Filter (KF) with GA. Historical consumption trend and network traffic is analyzed to reduce the amount spent on power with assumption that servers in the DC operate as modular units which can be powered separately as required, in contrast to keeping entire servers always powered. Data from five different servers were collected from MTN Abuja DC in Nigeria. The servers were named BSC 13, BSC 14, BSC 15, RNC 05 and RNC 06. These consist of data recorded for two year - 5th January to 30th December 2019 as well as 5th January to 31st December 2020. The GA optimizer is used to obtain the best possible values for the Kalman Filter (KF) parameters. Then, the KF model is used to predict the future power consumption value on hourly basis for each day of the week. The proposed model gives low power consumption with accurate prediction when compared with the existing models.

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1. INTRODUCTION

Cloud Computing (CC) describes the pattern that manages and provides Information Communication Technology (ICT) resources to different users. It is a model that enables businesses and developers to access hardware resources as well as infrastructure anytime it is required [1, 2]. The environment of cloud computing comprises of various essential components such as Data Center (DC), Tasks and Virtual Machine [3, 4]. DC is a place or an area where CC core materials are located and interconnected based on their functionality. It can be described as a critical computing infrastructure that has become essential to modern society by providing services such as cloud computing, Internet of Things (IoT) and big data. It also provides information technology backbone for computing technology with large numbers of servers that process enormous tasks for complex scientific problems, businesses and facilitate users to achieve their goals [5, 6, 7, 8]. In today's world, DC is an essential part of the smart world, being the core centre of information processing and data storage for all telecommunication industries. As the demand for data-related services continues to rise around the world, so does the dependence on data centres increase. However, DC consumes high energy resulting in high cost of maintaining data cetre. Therefore, the continuous increase in the load demand, increase the cost of maintaining DC [9]. In United State (US), the data obtained in the year 2014 revealed that data centres consume an estimated 70 billion kWh annually, which is equivalent to \$8.764b and 1.8% of total U.S. electricity consumed that year [10, 11]. Also, in Nigeria, total amount of \$4b is believed to be spent annually in the last three years by four big players (MTN, 9Mobile, Glo and Airtel) in the telecommunication industry and also expected to grow further in the coming years because of an increase in data demand [12]. Therefore, reduction in energy cost by a small percentage will result in a huge amount of savings in the operation cost of data centres [13, 14]. This has more effect in a country like Nigeria, where there is inadequacy in utility grid power systems supply to support the emerging trend. It is therefore important to give attention to the amount of money spent on powering data centres because of its impact on the profit margin of investors in the telecommunication industry [15]. Most existing work on data centre cost reduction majorly focused on job distribution among different computing equipment based on their thermal profiles and workload

In [16] Kalman filter process for optimization of energy consumption in Wireless Sensor Networks (WSNs) was proposed to minimize the consumption of energy thereby extend network lifespan. The results obtained showed that the technique gave better performance with high energy efficiency without any negative effect on the latency. However, the technique lacks accurate prediction of power consumption which is necessary to forecast the power consumption of the data centre. Managing the consumption of energy in a distributed data centre using a Genetic Algorithm (GA) to reduce the huge amount of energy consumes by the data centre and to reduce the amount of carbon dioxide released was proposed in [17]. The authors stated that the reduction of high energy consumption in a data centre is achieved by implementing a green cloud computing system by optimizing the utilization of energy. The results obtained revealed that the proposed energy distributed GA based algorithm gave better performance when compared to other metaheuristic algorithms. However, the optimization was carried out with the assumption that all the parts of the modular server that are not carrying traffic is on idle mode and not completely off. This also consumes extra power compare to when it is completely off.

Also, in [18], optimization of energy consumption in a cloud Internet of Things (CIoT) was carried out to solve the problem of energy efficiency and delay sensitivity which happened to be the major issues in a CIoT. The results obtained revealed that the proposed technique gave better performance when compared with ETCORA with reduced energy consumption of request task. However, the optimization was carried out with the assumption that all the parts of the modular server that are not carrying traffic is not completely off but rather on idle mode. Furthermore, in [19] an energy efficiency based on a Genetic Algorithm (GA) for consolidation of container for reduction of energy consumption in a large-scale cloud computing data centre system was carried out. The optimization was carried out with the assumption that all the parts of the modular server that are not carrying traffic is not completely off but rather on an idle mode which consumes extra power when compared to when it is completely off. In summary, the existing works suffers from assumption that all the modular that are not carrying traffic will be on idle mode. This generates additional heat and requires a cooling system that consumes extra power compare to when it is completely off. Hence, this paper proposed an optimum way of powering DC at a minimum cost without compromising the system protection and stability. The contributions of this paper are as follows:

a. a novel algorithm that utilizes probability of traffic arrival for the prediction of hourly power consumption has been proposed. This algorithm provides, in addition to predicted power consumption, the estimated maximum number of servers needed to be active for a given hour. This approach helps to improve the Power Usage Effectiveness (PUE) performance of the data centre.
b. a more accurate prediction model named PCoKFGA was also proposed. This model is a combination of Kalman filter (KF) estimator and genetic algorithm (GA) with the aim of achieving negligible prediction error. The remaining part of this paper is organised as follows; section 2 presents the details of the proposed technique, while the simulation results as well as performance comparison was presented in section 3. The conclusion was presented in section 4.

2. PROPOSED POWER CONSUMPTION UTILIZATION OPTIMIZATION TECHNIQUE

Data were collected and assessment of historical data from the DC under study was also carried out. Data of two years (January to December of 2019 and 2020) were collected from five servers in the DC. The equipment used for data collection includes a power analyzer, multi-meters and thermometer. The power was captured using an analyzer and double-checked on an interval basis with multimeter readings and HMI display.

This is to ensure that, the calibration on the analyzer is okay. Traffic out were obtained from the equipment memory on an hourly basis. The temperature was captured by the thermometer installed in the switch and the equipment display. Data from five different servers were collected from a DC in Nigeria. The servers were named BSC 13, BSC 14, BSC 15, RNC 05 and RNC 06. These consist of data recorded for two year - 5th January to 30th December 2019 as well as 5th January to 31st December 2020. The reasons why five DC were selected is to ensure that enough samples are taken for analysis. Both RNC and BSCs are critical nodes in telecommunication, designed to handle traffics. Also, different RNC handles different traffic and is expected to have different data.

The DC data were recorded on an hourly basis for each day (24 hours make a day), and a total of 8568 and 8592 samples were recorded for the year 2019 and 2020, respectively. After carried out assessments on the available data, the data were pre-processed for consistency and the final data used, for each year under study, consists of 8400 samples which represent 50 weeks of which 1 week is made up of 7 days (Sunday to Saturday). The final data were divided and categorized into two as contained in Table 1. Dataset 1 represents the DC data for the first 30 weeks (used for creating a prediction model); while Dataset 2 represents the DC data for the remaining 20 weeks (used for testing a prediction model) in line with the work in [20]. The months of January to March belong to the dry season while June to August belongs to the rainy season. These seasons also represent sub-Saharan Africa. Six attributes were contained in the data for each server, and the attributes are, hour of day (h), total current consumed (A), total power consumed (kW), ambient temperature (ºC) and traffic (Erl). Figure 1 shows the schematic of the data centre and how the equipment was powered.

Table 1. DC's data categorization

Category	**Period**	**Samples**
Dataset 1	Week 1 to Week 30	5040
Dataset 2	Week 31 to Week 50	3360

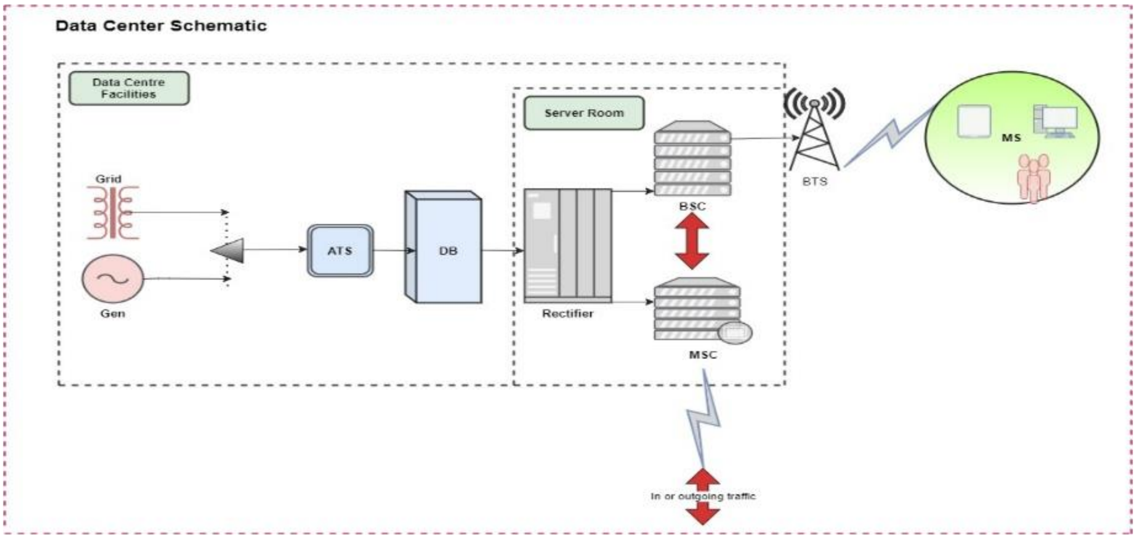

Figure 1. Data centre schematic

2.1. Power Consumption of Selected Data Centre

The power consumption is the most important attribute of the DC due to its ability to determines the energy efficiency of the DC. Some approaches were proposed in this study to minimize the power consumption of the DC. Table 2 contains the power consumptions for Dataset 1. It was observed that in the year 2019, the DC incurred a maximum of 16.6088 kW and a minimum of 7.9257 kW. For the year 2020, as contained in Table 3, the DC incurred a maximum of 17.0761 kW and a minimum of 8.1107 kW. These reveal that the DC does not require up to the total rated power capacity of 26.4 kW supplied to it. The maximum power utilized by the DC was approximately 17 kW as against 26.4 kW supplied to it; hence, this limits the Power Usage Effectiveness (PUE).

Table 2. Power consumptions for Dataset 1 of 2019

Server	No. of Samples	Minimum (kW)	Maximum (kW)	Average (kW)	Standard deviation
BSC 13	5040	1.8200	3.1304	2.5631	0.1199
BSC 14	5040	2.5844	4.5396	3.7581	0.1061
BSC 15	5040	0.9265	3.0545	2.2331	0.2306
RNC 05	5040	1.6120	2.8787	2.3841	0.2159
RNC 06	5040	0.9828	3.0056	2.3924	0.2077

Table 3. Power consumptions for Dataset 1 of 2020

Server	No. of Samples	Minimum (kW)	Maximum (kW)	Average (kW)	Standard deviation
BSC 13	5040	1.7836	3.0678	2.6385	0.1043
BSC 14	5040	2.6619	4.6758	3.8394	0.1164
BSC 15	5040	0.9636	3.2054	2.2838	0.2387
RNC 05	5040	1.6708	2.9858	2.4547	0.2230
RNC 06	5040	1.0308	3.1413	2.4568	0.2077

2.2. Traffic of Selected Data Centre

The traffic is another important attribute of the DC. It is used to determine the number of servers to turn on or off at a given time. Table 4 contains the total load for Dataset 1. It was observed that in the year 2019, the DC handled a maximum of 21090 Erl and a minimum of 64.808 Erl. For the year 2020, as contained in Table 5, the DC handled a total maximum of 22275 Erl and a minimum of 32.1 Erl. If the system has prior knowledge of the traffic load pattern, the amount of power needed by the DC to handle the load can be predicted.

Table 4. Traffic load for Dataset 1 of 2019

Server	No. of Samples	Minimum (Erl)	Maximum (Erl)	Average (Erl)	Standard deviation
BSC 13	5040	14.2060	6762.8	2433.3	1741.6
BSC 14	5040	25.5810	5967.0	2544.5	1885.3
BSC 15	5040	18.1810	6130.7	2287.5	1607.9
RNC 05	5040	4.2500	1129.1	478.65	312.53
RNC 06	5040	2.5900	1100.0	464.76	306.63

Traffic characteristics or demands of most areas/locations do not change weekly unless otherwise; for instance, if there is sudden demand in traffic because of occasional events or activities in a location as shown in Figure 2.

Table 5. Traffic load for Dataset 1 of 2020

Server	No. of Samples	Minimum (Erl)	Maximum (Erl)	Average (Erl)	Standard deviation (Erl)
BSC 13	5040	8.4	6919.7	1430.5	1769.9
BSC 14	5040	0.0	6146.0	2517.1	1866.5
BSC 15	5040	18.4	6660.7	2396.1	1673.5
RNC 05	5040	3.2	1252.9	507.5	332.7
RNC 06	5040	2.1	1296.0	429.4	289.6

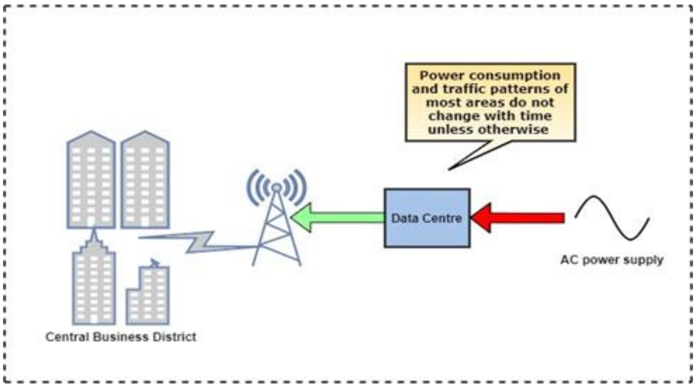

Figure 2. Data centre schematic

2.3. Power Consumption Optimization using KF with GA

The proposed LPCP system measures the total traffic inflow for the current hour (h), and then forwards the value $A_r(h)$ to a logger. The logger then supplies the previous hour's traffic size $A_r(h-1)$ to be multiplied with the value of k representing the current day of week to estimate the power usage, P_{usage}, for the server. The estimated P_{usage} was then forwarded to the power supply controller, which computes the total power to be consumed by the server in the current hour $P_S(h)$. The process was carried out every 5 minutes to the next hour of the day. The LPCPS model is a simple linear power consumption prediction model which can be useful for online prediction. The model saves significant amount of power for the DC. The proposed LPCPS model requires traffic size as input for it to be able to predict the required amount of power to be used by the server. Likewise, the ARMA prediction model can only produce coarse prediction. Hence, a more robust strategy is required to further improve the power consumption prediction accuracy and invariably, the energy efficiency of a server and in consequence an entire DC. In view of this, a power consumption optimization technique using KF with GA is proposed in this study. This technique is named PCoKFGA. The structure for the PCoKFGA technique is shown in Figure 3. The GA optimizer is used to obtain best possible values for the KF parameters. Then, the KF model is used to predict the future power consumption value on hourly basis for each day of the week.

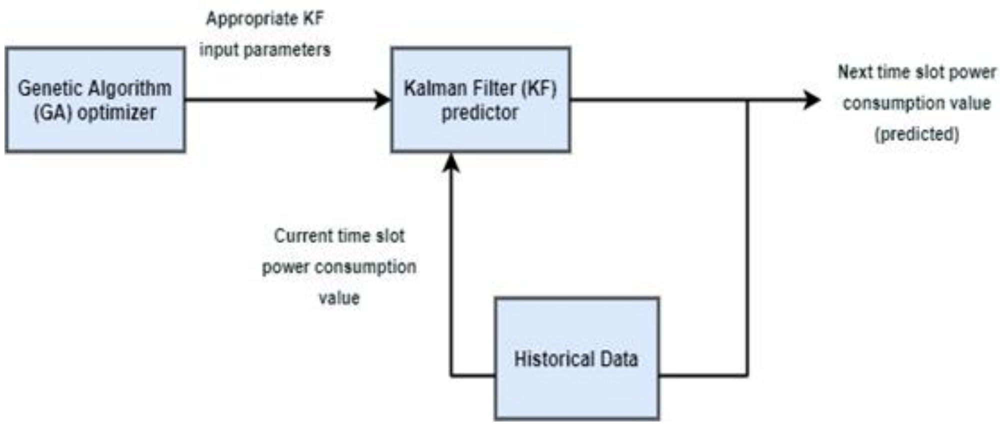

Figure 3. The PCoKFGA technique for power consumption prediction

2.4. Kalman Filter-Based Power Consumption Estimation Model

A server's power consumption at a given time t, P_{S_t}, is expressed as:

$$P_{S_t} = P_{S_{t-1}} + a_t \tag{1}$$

where $P_{S_{t-1}}$ is the power consumption as time $t-1$ and a_t is the variation of power consumption at time t. The parameters P_{S_t} and a_t are referred to as process state and process noise, respectively, in KF terminology. The measured power consumption at time t, Z_t , can be expressed as:

$$Z_t = P_{S_t} + b_t \tag{2}$$

where b_t is the measurement noise. The prediction of power consumption for the next time slot $t+1$ is obtained from the current time slot t as:

$$\tilde{P}_{S_{t+1}} = A\hat{P}_{S_t} \tag{3}$$

where $\tilde{P}_{S_t}$ is a priori estimate of P_{S_t}
$\hat{P}_{S_t}$ is a posteriori estimate of P_{S_t}
A is the transition matrix

The state covariance matrix is given as:

$$\tilde{C}_{t+1} = A\hat{C}_t A^T + Q_t \tag{4}$$

where C is the state noise covariance matrix

Q is the process noise covariance matrix
The next stage is the measurement update which begins as:

$$K_t = \tilde{C}_t H^T S_t^{-1} \quad (5)$$

with

$$S_t = H\tilde{C}_t H^T + R_t \quad (6)$$

where K is Kalman gain matrix.
H is design matrix
S is the residual covariance
R is the measurement noise covariance matrix

The process state is corrected as:

$$\hat{P}_{S_t} = \tilde{P}_{S_t} + K_t\left(Z_t - H\tilde{P}_{S_t}\right) \quad (7)$$

and

$$\hat{C}_t = (1 - K_t H)\tilde{C}_t \quad (8)$$

where Z is the measurement vectors.

The design matrix, H, is a 2x4 matrix such that $h_{ij} \in \{0,1\}$, and the set of H can be given as:

$$H = \begin{pmatrix} h_{11} & h_{12} & h_{13} & h_{14} \\ h_{21} & h_{22} & h_{23} & h_{24} \end{pmatrix} \quad (9)$$

Similarly, the transition matrix, A, is a 4x4 matrix such that $a_{ij} \in \{0,1\}$, and the set of A can be given as:

$$A = \begin{pmatrix} a_{11} & a_{12} & a_{13} & a_{14} \\ a_{21} & a_{22} & a_{23} & a_{24} \\ a_{31} & a_{32} & a_{33} & a_{34} \\ a_{41} & a_{42} & a_{43} & a_{44} \end{pmatrix} \quad (10)$$

Furthermore, the measurement noise, R, is a Gaussian random variable with possible value as $0 < R \leq 1$. It is worth noting that the elements of R have the same value.

2.5. Optimizing the KF Model Parameters using GA

The values of the KF parameters: H, A and R have significant effect on the estimation or prediction accuracy of the KF model; hence, appropriate values must be chosen for the parameters. This is achieved by the help of GA. The GA is an optimization tool applicable to non-linear problems. The GA consists of five processes namely; Initialization, Objective function, Selection, Crossover and Mutation.

i. **Initialization process:** This process involves the initialization of the population. Each (chromosome) in the GA population is a possible solution set of the KF parameters H, A and R. Each element of H and A takes a bit 0 or 1, while each element of R takes a random value that is greater than 0 but less than or equal to 1. The matrices H and A are converted into vector form, and a single value for R is placed in between the vectors of H and A. The vector is concatenated to produce a chromosome of length 25 genes.
ii. **Objective function process:** The objective function for the PCoKFGA technique is formulated as:

$$\begin{aligned} &Minimize\ \frac{\sum_{t=1}^{N}\left(P_{S_t} - \hat{P}_{S_t}\right)^2}{N} \quad (11) \\ &subject\ to: h_{ij} \in \{0,1\} \\ &\qquad a_{ij} \in \{0,1\} \\ &\qquad 0 < r \leq 1 \end{aligned}$$

where P_{S_t} is the actual power consumption value at t-th time
$\hat{P}_{S_t}$ is the predicted power consumption value t-th time
N is the number of times or samples)
h_{ij}, a_{ij} and r are the elements of KF parameters H, A and R, respectively
The objective function is to minimize the Mean Squared Error (MSE) between the actual and predicted values. The objective function is evaluated on each chromosome in the GA population, and the chromosome that gives the lowest MSE is the fittest in the population.

iii. **Selection process:** The process involves the selection of fit chromosomes for reproduction. The chromosomes are sorted by their fitness values and the fit chromosomes are selected to replace the weak parent chromosomes in the population.
iv. **Crossover process:** In this process, some of the genes between two parent chromosomes are exchanged to produce offspring (a child chromosome). The genes to crossover are randomly selected with a specified crossover probability. Only the selected parent chromosomes from the selection stage are used to reproduce two new offspring for the next generation. The mating of two parent chromosomes produces two new chromosomes with a different set of genes.
v. **Mutation process:** This process performs little changes to some genes of a chromosome. A boundary is chosen within the chromosome and some genes can be mutated with a specified probability of mutation. This helps to ensure that all the chromosomes in the population do not have the same genes in a given generation.

The first stage is to input the specified GA parameters' values as contained in Table 6. Then, the initial population of chromosomes is generated using the chromosome coding method. The initial population is evaluated using the objective function to get the fitness values of the chromosomes. The calculated fitness values are used to select chromosomes for the next generation. This is followed by performing crossover between two chromosomes using the crossover probability to reproduce two offspring to replace the parent chromosomes. The next stage after crossover is a mutation of some randomly selected genes within some chromosomes using the mutation probability. The mutation process is followed by an evaluation of the objective function. The procedure is repeated until the final generation is reached. Then, in the final generation, the fittest chromosome, which is the set of the best possible values for the KF parameters, is outputted.

Table 6. GA simulation parameters

Parameter	Value
Population size	100
Number of generations	50
Chromosome length	25
Mutation probability	0.02
Crossover probability	0.8
Selection method	Tournament

3. DATA TREND ANALYSIS OF THE DC USING AUTOREGRESSIVE MOVING AVERAGE (ARMA)

Since the DC data are recorded at regular time intervals, that is, 1-hour interval, this study also investigates the use of a univariate time series model to forecast the trend in traffic load as well as total power consumption per time instant of the DC in the study. This study used the MATLAB *Arima* function to create an ARMA (p, q) model (an existing model) to compare its performance to the proposed ones. ARMA equation is given as:

$$.\sum_{i=1}^{p} A_i y_{k-i} \; + \; B_j v_{k-j} \; + \; v_k \tag{12}$$

V_k is m-dimensional vector, that has zero mean,

θ = (p, q) is the predictor order and A

A_1……, A_p, B_1,….. B_q are the m x m coefficient matrices of the MV ARMA model [21].
R,y¼(p,q) is the order of the predictor and A

An ARMA model is created for each of the total power consumption and traffic forecasting of the DC from ARMA model mentioned above. The current sample, of the data, is obtained as:

$$Z_t = \propto + \varepsilon_t + \sum_{j=1}^{p} \beta_j Z_{t-j} + \sum_{j=1}^{q} \gamma_j \varepsilon_{t-j} \tag{13}$$

where $\propto$ is the expectation of Z_t and is assumed to be zero

ε_t is the error term with zero mean and constant variance

Z_{t-j} is the observation j periods from Z_t

p and q are the number of lags for Autoregressive (AR) and Moving Average (MA) respectively β_j and γ_j are parameters of the model

4. LINEAR POWER CONSUMPTION PREDICTION MODEL (LPCPM) FOR DC

A model called Linear Power Consumption Prediction Model (LPCPM) is formulated for the DC. The total power consumed (in kW) by a DC is directly proportional to the total traffic (in Erlang) being processed by the DC. Assuming the traffic loss is negligible, the total power usage by a server, P_{usage}, relates to the size of traffic,

$$A_r\text{, as: } P_{usage} \propto A_r \tag{14}$$

$$P_{usage} = \lceil kA_r \rceil \tag{15}$$

where $\lceil\cdot\rceil$ denotes the ceil operator, k is the constant of proportionality, which is calculated from empirical data obtained from historical records of P_{usage} and A_r from the DC. The value of k was obtained from the ratio of the average values of P_{usage} and A_r over a period as:

$$k = \max\left(k_{in}, \hat{k}_{in}\right) \tag{16}$$

The parameter $\hat{k}_{in}$ is given as:

$$\hat{k}_{in} = E[k_{in}] + tol \tag{17}$$

where $E[\cdot]$ and $\max(a, b)$ denote average value and maximum value between a and b, respectively, and $tol = 10^{-4}$ is a tolerance to ensure that k does not produce a supply power that will be less than required. The parameter k_{in} is given as:

$$k_{in} = \frac{\max\left(E[P_{usage}]\right)}{\max(E[A_r])} \tag{18}$$

where $\max(\cdot)$ denotes the maximum value in a set. Different values for k_{in} is obtained for each day of the week based on the traffic size.

5. DEVELOPMENT OF AN ADAPTIVE SERVER UTILIZATION SCHEME(ASUS) FOR DC

In the proposed ASUS, the decision whether additional equipment will be activated is a function of size of traffic arrivals. The traffic arrival to the DC is assumed to follow Poisson distribution, and the probability that n number of packets arrives at the time interval Δt is given as [22]:

$$P(n) = \frac{(\lambda\Delta t)^n \exp\left(-\lambda\Delta t\right)}{n!} \tag{19}$$

where n is the estimated number of packets arrivals which is scaled by 10^{-3} in this study due to the nature of the traffic values, λ is the traffic arrival rate (packets/sec) and Δt is the inter-arrival time. The quantity of power (in kW) required by the DC for a given day of week is given as:

$$P_{DC} = 0.5\ x\ P_{RDC} + P_{RDC} * e \tag{20}$$

where e is the percentage average traffic load for the given day and P_{RDC} is the rated power capacity of the DC while the 0.5 represents 50% of the rate power of the equipment that will be consumed at idle state.

The ASUS aims to minimize power wastage by adaptively activating and deactivating equipment in the DC as the need arises. Thus, the ASUS is modelled as an optimization problem, and the model equation is expressed as:

$$Minimize\ \sum_{q=1}^{Q} P_{DC_q} \left[\frac{(\lambda\Delta t)^n \exp\left(-\lambda\Delta t\right)}{n!}\right] \tag{21}$$

Subject to the following constraints:

$$P_{DC_q} \leq (P_{RDC}/Q), \qquad \forall P_{DC_q}, \quad 1 \leq q \leq Q \tag{22}$$

$$\Delta t \geq 2, \qquad 1 < t \leq 24 \tag{23}$$

$$N_u \leq Q, \tag{24}$$

where

P_{DC_q} denotes the amount of power consumed by equipment q in the DC,
Q denotes the number of equipment in the DC.
N_u is the number of DC equipment activated.

The constraint (22) indicates that the power consumed by equipment q cannot exceed the rated power consumption for an equipment in the DC. Constraint (23) indicates that the inter-arrival time (Δt) must not exceed two hours. Constraint (24) indicates that the number of DC equipment activated cannot be more than the total number of equipment available in the DC. The algorithm below has been developed to solve the ASUS optimization problem.

6. SIMULATION RESULTS AND DISCUSSION

In this work, prediction of power consumption was optimized for more accuracy using the PCoKFGA model developed. Figure 4 shows the PCoKFGA prediction for Sunday 2019 and 2020. For the year 2019, the predicted and actual average DC power consumption for the day was 12.9698 kW and 12.9474 kW, respectively, which gives an absolute error of 0.0017 (0.2%). For the year 2020, the predicted and actual average DC power consumption for the day was 14.6146 kW and 14.5727 kW, respectively, which gives an absolute error of 0.0029 (0.3%). Figure 5 shows the PCoKFGA prediction for Wednesday 2019 and 2020. For the year 2019, the predicted and actual average DC power consumption for the day was 13.0528 kW and 13.0323 kW, respectively, which gives an absolute error of 0.0016 (0.2%). For the year 2020, the predicted and actual average DC power consumption for the day was 14.5496 kW and 14.5140 kW, respectively, which gives an absolute error of 0.0025 (0.25%). The average DC power consumption predictions by the PCoKFGA model revealed that for all the days of the week, the calculated absolute errors between the predicted and actual were less than 0.0029 (0.3%). This implies that the PCoKFGA model is suitable for predicting the average daily and hourly power consumption.

The summary of the computed errors for all models is indicated in Tables 7 and 8.

Table 7. Error measurements of power consumption prediction for the year 2019

	Model	RMSE	MAE	MAPE	Total Error	Average Error	Rank
Linear Models	ARMA (existing)	0.3398	0.2871	0.0216	0.6485	0.2162	2nd
	LPCPS (proposed)	0.7827	0.6615	0.0476	1.4918	0.4973	4th
	TAPC (existing)	3.1300	2.9050	0.1770	6.2118	2.0706	6th
Non-Linear Modes	PCoKFGA (proposed)	0.1935	0.1636	0.0125	0.3696	0.1232	1st
	ASUS (proposed)	0.5954	0.4681	0.0339	1.0974	0.3658	3rd

Table 8. Error measurements of power consumption prediction for the year 2020

	Model	RMSE	MAE	MAPE	Total Error	Average Error	Rank
Linear Models	LPCPS (proposed)	0.7669	0.3876	0.0265	1.1809	0.3936	3rd
	ARMA (existing)	0.9352	0.6023	0.0404	1.5778	0.5259	4th
	TAPC (existing)	2.5245	2.3876	0.1389	5.0510	1.6837	6th
Non-Linear Models	PCoKFGA (proposed)	0.2091	0.1829	0.0127	0.4047	0.1349	1st
	ASUS (proposed)	0.4803	0.4466	0.0315	0.9584	0.3195	2nd

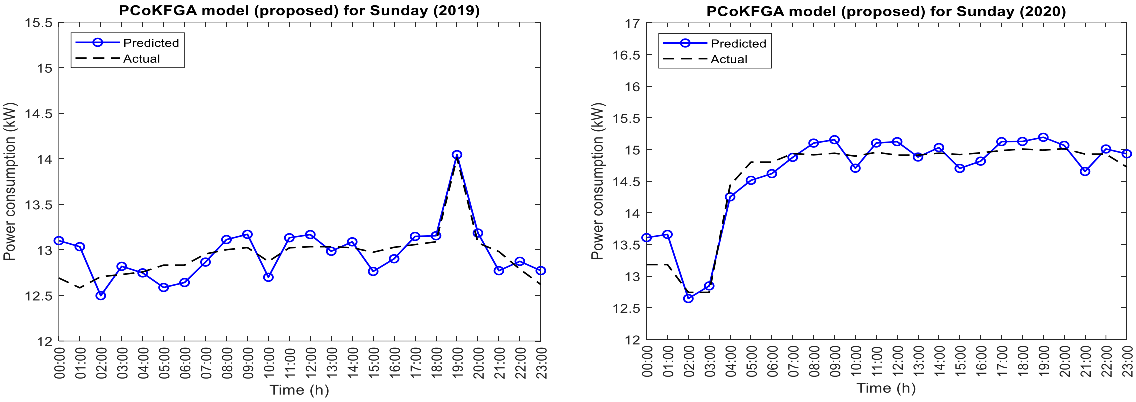

Figure 4. Prediction of power consumption of data centre by the PCoKFGA model for Sunday

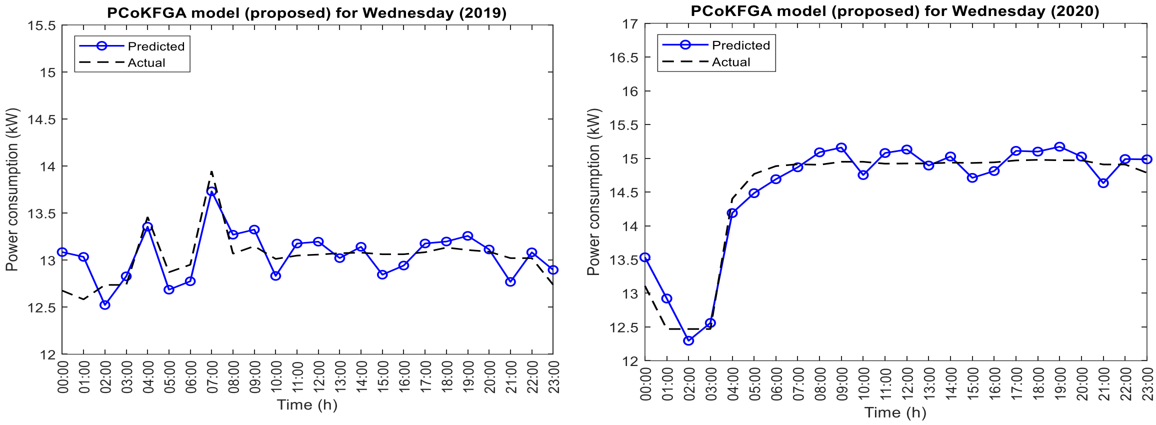

Figure 5. Prediction of power consumption of data centre by the PCoKFGA model for Wednesday

Analysis was done for each day of the week for all models (both existing and proposed) as shown above. This is because traffic usage would always follow almost the same partner for same day of the week in most areas unless something happens that would warrant a spike in traffic demand and vice versa.

6.1. Energy Consumption (EC) and Power Usage Effectiveness (PUE)

The calculated Energy Consumption (EC) and Power Usage Effectiveness (PUE) of the models for the year 2019 are contained in Table 9. The lowest possible EC and the PUE of approximately 1.0 is the target of any data centre [23-26]. The PCoKFGA model gave the lowest EC of 313.354 kWh while the conventional model gave the highest EC of 633.600 kWh. On the other hand, the ASUS model gave the best PUE with a value of 1.07, while the other models gave the same PUE value of 1.68 because it was assumed that all the servers or equipment were on at all times. The calculated ECs and PUEs for the year 2020 are contained in Table 10. The ASUS model gave the lowest EC of 343.410 kWh while the conventional model gave the highest EC of 633.600 kWh. The ASUS model also gave the best PUE with a value of 0.97 (closest to 1.0 target), while the other models gave the same PUE value of 1.54. The performance of the developed ASUS model is in line with the results of adapted power consumption strategy proposed by [23, 27, 28].

Table 9. EC and PUE of data centre for the year 2019

Model	EC (kWh)	PUE	Rank
Conventional	633.600	1.68	6th
ARMA (existing)	318.476	1.68	3rd
ASUS (proposed)	323.698	1.07	1st
LPCPS (proposed)	328.607	1.68	4th
PCoKFGA (proposed)	313.354	1.68	2nd
TAPC (existing)	382.545	1.68	5th

Table 10. EC and PUE of data centre for the year 2020

Model	EC (kWh)	PUE	Rank
Conventional	633.600	1.54	6th
ARMA (existing)	357.971	1.54	4th
ASUS (proposed)	343.410	0.97	1st
LPCPS (proposed)	356.419	1.54	3rd
PCoKFGA (proposed)	349.918	1.54	2nd
TAPC (existing)	406.246	1.54	5th

6.2. Effectiveness of the PCoKFGA Model

The PCoKFGA model developed in this study is applicable for forecasting the next hour's power consumption by using the knowledge of some immediate previous hours' values. The PCoKFGA model was able to achieve almost accurate predictions due to the use of the best possible KF parameters' values that were optimized by a genetic algorithm. Consequently, the PCoKFGA model gave a relatively good average prediction absolute error of 0.002 (0.2%) and 0.003 (0.3%), for the years 2019 and 2020, respectively. Furthermore, it is worthy of note that the prediction error of the PCoKFGA model is negligible; hence, the power consumption value predicted by the PCoKFGA model requires no adjustment and can be used directly in the power supply budget. Thus, the model is of practical use where a high level of prediction accuracy is required. On average, the developed PCoKFGA model proposed outperforms all the other prediction models investigated in this study in the area of prediction error, but inferior to the ASUS model in the area of implementation cost. Furthermore, the computational complexity of PCoKFGA is relatively lower than the ARMA and conventional method.

7. CONCLUSION

In this study, real-time data obtained from a DC for the years 2019 and 2020 to investigate the applicability of some power consumption prediction models. The analysis carried out on the DC's data revealed that the amount of power consumed by a DC has a direct proportionality to network traffic being handled by the DC. Furthermore, ambient temperature of the DC could also have an impact on the power consumption. In addition, it was observed in this study from the comparison between the data of 2019 and 2020 that the average daily power consumption levels in a given year may be different from that of another year. Hence, 2019 data could not be used to create a model for forecasting 2020 data. However, the data of the first few weeks of a given year is suitable for creating a prediction model for the rest of that year. PCoKFGA model is proposed for the prediction of power consumption in order to minimize wastage or idle power in DCs. The performances of the developed model is compared to two existing models named ARMA and TAPC (Temperature Aware Power consumption, which is an existing model) using prediction error measurements, energy consumption and Power Usage Effectiveness (PUE). The PCoKFGA model's prediction was based on estimation using Kalman filter (KF) and optimized KF parameters by genetic algorithm. The developed models gave improved performance over the existing models, and could be applicable to multivariate time series. The PCoKFGA model would be most useful where accuracy in prediction is of utmost importance, and for run-time application.

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