Forecasting Power Consumption of IT Devices in a Data Center

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***Abstract* – In recent years, estimation algorithms become more popular in terms of forecasting customer behavior or any required data for IT companies. Forecasting results can be used in different purposes such as improving the quality and capacity of production and services, reducing to greenhouse gas emissions, and minimizing the power consumption. The accurate forecasting results are also beneficial for data centers which are the significant participants in the electricity market in terms of consuming huge power demand and have a chance to reduce consumed power, electricity costs by rescheduling their flexible loads for the future period. In this paper, power-consuming devices and variables affecting power consumption are explained. Also, the brief information about artificial neural network and regression analysis methods has been provided. The power consumption of Information Technology devices is forecasted by nonlinear regression analysis and artificial neural network methods. The forecasting results show that artificial neural network method is more successful.**

***Index Terms* – Regression Analysis, Artificial Neural Network, Power Consumption Forecasting, Data Center**

I. INTRODUCTION

Nowadays, accurate forecasting becomes more important for both electric utilities and big electricity consumer companies in electricity market systems [1]. The utility sector, electricity generation, and distribution companies need realistic estimation results of electricity demand to plan generation, quality of service and meet power demand [1], [2]. On the other hand, for big power consumers which participate to the electricity market, the correct estimation is also significant in terms of the bidding for electricity price of the next day and determine their power management policy for the related day [3]. As the usage of the information and communications technologies has increased rapidly, the requirement of Data Centers (DCs) has also grown to satisfy the increasing demand and providing reliable low latency services to customers. Therefore, DCs have become a crucial power consumer and players in the power sector. According to [4], the worldwide power consumption of DCs was 270 TWh in 2012. Due to the fact that DCs consume huge power, forecasting of power consumption at each time interval of the next day turned into significant in terms of determining the correct power management option, distributing the workloads and participating to the electricity market.

This study aims to forecast power consumption of Information Technology (IT) devices which are the biggest power consumer in a DC [5]. The forecasting was carried out by considering what variables are affecting the power consumption of IT devices. While developing a power consumption model for IT devices, the mock-up historical data of each IT devices are used, and each variable's data are normalized by diving to the maximum value of it. The regression analysis method which allow to determine the shape, direction, and strength of the relationship between variables through mathematical equations [6] is used in this paper as one of two forecasting methods. The other one is the Artificial Neural Network (ANN) method which is successful in the selection and classification of the model, function estimation, data fitting, and data classification. ANN produces consistent results even if the mathematical models cannot be created or where there is no linear relationship between inputs and outputs. Because ANN can process in parallel, it can perform independent operations very quickly [7], [8], [9].

The remainder of this paper is organized as follows. Section II briefly describes the related works. In section III, the brief information about DCs and its power consuming parts are provided. A short preview of forecasting methods is explained in Section-IV. Section V presents the analysis and results of nonlinear power consumption models of IT devices, which are nonlinear regression analysis and artificial neural network method and the results of power consumption forecasting. Finally, the paper is concluded in section VI.

II. RELATED WORKS

Along with the reveal of the significance of data center as a power consumer in recent years, a large number of studies have been presented in this area. The most popular topic is the participation of data centers in the electricity market. In [10], it is explained how the data center can be a good candidate to balance the grid transmission and distribution system fluctuations which is caused by the renewable energy sources because of weather changing. Data centers are used as virtual power plants through participating in demand-side management (DSM). In terms of many studies about participation of data centers in DSM, the power consumption forecasting becomes

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crucial for minimizing data center power consumption and energy cost, optimization of the load balancing and data center power management [11] – [20].

In [11], the authors focus on minimizing power consumption as forecasting the future CPU idle time interval to use the idle mode efficiently. The dynamic prediction scheme is used for forecasting. In [12], the CPU utilization that assumed as the workload is forecasted using by Holt-Winters and autoregressive moving average methods. In terms of the indirect effect of workload on the energy consumption of data center, the forecasted workload is used in energy efficiency with load balancing. In other study based on to forecast the CPU utilization [13], the researchers forecast the CPU utilization to decide which VM (virtual machines) needs to be migrated for load balancing. In order to minimize the cost, the VM migration schedule has been determined before the VMs overloaded.

According to [14] , the energy consumption of data center can be minimized by allocating the power resources effectively with the network workload which is forecasted by autoregressive linear prediction and neural network prediction methods. It is assumed that there is a relation between power consumption and network workload without defining any mathematical function to show what kind of relationship they have. In [15], the power consumption of data center is forecasted by the Holt-Winters method and persistence approach using four different power consumption profiles to compare the efficiency of forecasting methods. The authors prefer to use time-based prediction methods and use power consumption lagged values as a predictor variable. In [16], the data center power consumption is forecasted using by Hidden Markov Model within the scope of participation of the data center to the electricity market and using data center as a virtual power plant. All historical data of the cooling devices and server load are used as training data set and the same data are used to test forecasting model efficiency contrary to ordinary. So, the low MAPE rate is obtained.

In [17], the authors focused on the relationship between the energy consumption of data center to weather conditions. The active and reactive power of data center is forecasted using by single variable linear regression method selecting atmospheric pressure, dew point temperature, rainfall, relative humidity, and wind chill as predictor variables individually and together. In another study [18], which is based to use the relationship between cooling devices and power consumption of data center, the outlet air temperature which affects cooling devices working performance and power consumption of the data center indirectly is forecasted by the machine learning method. So, the cooling devices can be optimized to minimize the power consumption of data center by ignoring the power consumption of IT devices

In [19], a neural network forecasting method which is based on forecasting each individual servers' power consumption is used to minimization of cost by deciding efficient load balancing scheme via an aggregator. In [20], one of the main focused issues is to solve the difficulties in measuring variables of different scaled internal parameters of IT equipment. Therefore, the author created software which name is DAEMS (Data Acquisition and Energy Management System) in C# programming language. Servers' internal variables are measured through DAEMS and assumed historical data of IT equipment. The historical data are used to forecast power consumption of IT equipment using by artificial neural network-based forecasting method.

According to present studies, researchers generally focused on forecasting induvial parameters such as CPU utilization, network workload, weather parameters which directly or indirectly affect to power consumption. Also, most of them assumed that the power consumption of data center or IT equipment is dependent these parameters in linear form. Additionally, it is assumed that power consumption IT equipment composed only servers. However, power consumption of networking equipment and storage units might be considered in IT equipment even the servers are the most power consuming devices [5],[21]. Additionally, because the power consumption has nonlinear characteristic, there should be nonlinear relation between power consumption and affected parameters [21], [22], [23], [24], [25]. Furthermore, the power consumption of data center or IT equipment is not only dependent on individual parameters but also affected by weather conditions, network workload, CPU utilization, daytime etc. together [21].

In this paper, we focus on forecast power consumption of IT devices included servers, storage units and networking equipment. We used nonlinear power consumption model including the effects of all possible independent parameters such as CPU usage, RAM usage, network load, temperature, humidity etc. The power consumption of IT equipment is forecasted by nonlinear regression and artificial neural network methods to minimize power consumption and energy cost within the scope of participation of the data center to the electricity market and allocate renewable energy sources and optimize power management systems.

III. DATA CENTER EQUIPMENT

DCs are places where high-speed computers (servers) and network equipment are gathered at a central location for collection, storage, processing, and distribution of digital information data. Any organization such as government agencies, educational institutions, telecommunication companies, financial institutions, health institutions, internet service providers and cloud services, needs a DC for all kinds of data whose they generate or use. According to Dayarathna et al. [21], power-consuming components of a DC categorized into two parts which names of *"IT equipment"* and *"infrastructure facilities".* Power consumption by servers, networks, and storage units was included in IT equipment part while power consumption by cooling and power conditioning systems were contained in infrastructure facilities. According to [5], power consumption responsibilities of these components for a typical DC are shared as; Servers: 56%, Cooling: 30%, power conditioning systems: 8%, Network Equipment: 5%, Lighting: 1%.

Because the power consumption models of IT equipment has been taken into account, the power consumption subcomponents of IT equipment explained briefly in the following sections in terms of defining the variables which affect the power consumption.

A. Power Consumption Models of Servers

Servers are significant computing components that make the main job and responsible for a major amount of power consumption in a DC. Servers consist of many subdivisions such as *processor, memory,* fan, *network interface*, etc. and the power consumption modeling of each part is available in various studies [26],[27],[28],[29].

One of the models developed by Roy et al. [27] includes the entire server's power consumption as a summation of its subcomponents such as *CPU* and *memory*. In another study, Song et al. [30] proposed a detailed model in which total energy consumption of a server is formulated by a function of *energy consumption of CPU, memory, disk, and network interface card*.

B. Power Consumption Models of Storage Units

Storage controllers and directly attached storage units are located in the storage portion of a DC [31]. In literature, there are several power consumption models of storage units [21], [32], [33]. According to [21] and [32], the model depends on a function of *rpm of disk*, the radius of the platters and *idle* or *actively performing time*. Also, Hylick et al.[33] observed that total power consumption of storage unit composed of power of active time which means servicing N requests, seek power and the power of idle time working condition.

C. Power Consumption Models of Data Center Networks

When the modeling power consumption of DC networks, the power consumption of the entire network, including network connections and network devices should be considered [34]. A model, developed by Zhang et al. [35], includes the total power consumption of *network switches* and *links* in a core-level subgraph. In addition, *routers* and *switches* are also important devices in terms of operating the DC and consuming power [36]. According to [37], a *network interface card (NIC)* which is a circuit board installed on a computer and is used to connect the PC to a network, is another power-consuming device. It can be accepted that the *network traffic* affects the power consumption of network equipment indirectly because it is used as an input working parameter by all network equipment.

IV. FORECASTING METHODS

In terms of the different purpose of use, kinds of forecasting methods are existed in the literature [38]. The regression analysis and ANN methods are used and explained briefly.

A. Regression Analysis

The regression analysis is a method which defines the mathematical relationship between two or more variables. In this method, generally, the response variable is dependent on a function of one or more predictor variables. The coefficients of this function which describe the relationship between predictor variables and the response variable are forecasted [39]. The relation function can have one or more predictor (independent) variables and the relationship between predictors could be linear or nonlinear. The regression analysis can be examined by three subsections for forecasting: simple linear regression, multiple linear regression and nonlinear regression[40].

1) Simple Linear Regression

In simple linear regression method, cause and effect relationship is explained with a linear function between predictor and response variables as shown below.

$$Y_1 = a_1 + a_2 * X \tag{1}$$

X represents the predictor variable and the response variable is indicated by Y_1. The coefficients of function are a_1 and a_2. This function has only one predictor variable. Commonly, the least-squares method is used to calculate the coefficients that determine the best relations between predictor and response variables by minimizing the sum of the square of difference between forecasted response value and actual response value [41]. The general equation of the least-squares method is shown below:

$$\varepsilon = \sum[Y_1 - \hat{Y}_1]^2 \tag{2}$$

ε is a residual value. The forecasted response variable is represented by $\hat{Y}_1$ while the response variable is indicated by Y_1.

2) Multiple Linear Regression

In multiple linear regression, there are more than one predictor variables $(X_1 \ldots . X_n)$ affect one response variable (Y). According to [40], the general equation of multiple linear regression is shown as in (3)

$$Y = a_1 + b_1 * X_1 + b_2 * X_2 + b_3 * X_3 + \cdots + b_n * X_n \tag{3}$$

As it can be seen in the equation, the function is linear and there are "n" coefficients. The least-square method is generally used to find the coefficients which are $a_1, b_1, b_2, \ldots, b_n$ in multiple linear regression as well as in simple linear regression.

3) Nonlinear Regression

In nonlinear regression method, the response variable is calculated using a nonlinear function of predictor variables. The general mathematical form of nonlinear regression method can be shown as [42]:

$$y_i = f\left(x_{i,}\theta\right) + \varepsilon \tag{4}$$

y_i represents the ith observation of y which is the response variable and x_i indicates ith observation of predictor variable x. θ is the vector of coefficients. "ε" represents the random errors. The relation function (f) between x_i and y_i is nonlinear. The polynomial function is one of the most common used as a relationship function in nonlinear regression analysis to forecast the response variable and shown in (5).

$$Y = a_1 + b_1 * X_1 + b_2 * {X_2}^2 + b_3 * {X_3}^3 + \cdots + b_n * {X_n}^n \tag{5}$$

Y represents the response variable. The predictor variables are indicated as $X_1, X_2, \ldots, X_\mathrm{n}$. The coefficients of function are $a_1, b_1, b_2, \ldots, b_n$.

B. Artificial Neural Network

General information about ANN methods and learning algorithms are explained in brief.

1) Specification of ANN

An artificial neural network model, inspired and developed from the human brain, is a computational model based on the structure and functions of biological neural networks which are connected to each other by various weights and each has its own memory [9], [43], [44], [45]. It can be assumed that the ANN is a kind of program which mimics biological neural networks and has similar working principles. It has self-learning capability without requiring any programmer. Neurons come together in the same direction to form layers. The ANN Network consists of input, hidden and output layers that are receiving, processing, and transmitting information, respectively [9], [46].

The Input Layer is a connection with the outside world into the artificial neural network. The neuron number of input layer is equal to the number of input variables. The input variables are transmitted to the hidden layer without any processing. Each input neuron indicates the independent variable that influences the output of the ANN. Hidden Layer processes the information which is received from the input layer and transmits it to the next layer. Cell numbers in hidden layers are independent of input and output neuron numbers. Output Layer processes the information coming from the hidden layer and sends the generated information to the outside world. The number of cells in the output layer can be more than one. Each output cell has one output and each cell is tied to all the cells in the previous layer.

2) ANN Methods

In terms of modeling, ANN is divided into feedforward ANN and feedback ANN. There are no delays in the feedforward ANN and the operation proceeds from inputs to outputs in only one direction. An error function is obtained by comparing the output values, which are taken from the supervisor, with the desired output values then the weights are updated [7],[9]. The most commonly used learning algorithm in feedforward ANN is the backpropagation algorithm.

In feedback ANN, the unsupervised learning algorithm is generally used and it has delays [47]. A feedback neural network is derived from a feedforward ANN by connecting the outputs to the inputs.

3) ANN Learning Algorithms

Generally, the learning algorithms are subdivided into two headings: supervised and unsupervised algorithms. In supervised learning, a supervisor is needed, and it learns from examples. There is a sample training set with correct responses (targets) [9], [46]. The algorithm which is trained by training set reacts correctly to all different possible inputs. The testing procedure makes it possible to see if the ANN method is making a sufficient generalization. If the desired success is achieved in the training and testing stages, then the ANN method can be used for forecasting. Unlike supervised learning, unsupervised learning has no training set with examples of correct responses [46]. Gaussian mixture models and clustering algorithms which are hierarchical clustering, k-means clustering can be given as examples of unsupervised learning techniques. The other learning method is called Kohonen's self-organizing maps (SOM). Because of its easier implementation, Hebbian learning is also commonly used in unsupervised learning algorithms.

In the following sections, it is examined how the nonlinear regression analysis and artificial neural network methods are used for the power consumption forecasting of IT devices in a DC and which results are obtained.

V. ANALYSIS AND RESULTS

Each power consumer component of IT equipment has several independent variables which affect the total power consumption. As a consequence of section II analysis, it is determined that nine independent variables (predictor variables) affect the power consumption of servers. The power consumption of storage units and network equipment are dependent on five independent variables. Each variable of power consumption model of server, storage units and network equipment is shown in the related section below. The same predictor and response variables are used in both forecasting methods which are nonlinear regression analysis and artificial neural network methods. End of each forecasting step, the real and forecasted data are shown in the graph. Also, the mean absolute percentage error (MAPE) which can show the accuracy of forecasting are calculated.

A. Forecasting the Power Consumption of IT Devices Using Nonlinear Regression Analysis Method

In this section, the total power consumption of servers, storage units, and network equipment are forecasted using nonlinear regression analysis method. Due to the equation of power consumption of a device is nonlinear, polynomial regression function is used to forecast P_{server}, $P_{storage}$, $P_{networking}$ which represent power consumption of server, storage units, and network equipment, respectively. Power consumption of each component has been forecasted in Matlab. The nonlinear regression part under statistics and machine learning toolbox includes different functions to fit nonlinear regression models or predict the response of nonlinear regression method. The "nlinfit" and "fitnlm" functions are two of them. In this study, "nlinfit" function is used to create a nonlinear regression model.

1) Power Consumption Model of Servers

The power consumption of servers which is represented as P_{server} is affected by nine independent variables which are temperature and humidity of room, time, RAM usage, power consumption of disk, CPU usage, and load traffic. In addition, the information on which day of the week, and whether it is a holiday or working day, are considered as predictor variables. All these parameters are indicated x_1 to x_9 and are shown in Table I.

Table I. The Predictor Variables of Power Consumption of Server

x_1: $Temperature$	x_4: $Weekday$	x_7: $RamUsage$
x_2: $Humudity$	x_5: $IsworkingDay$	x_8: $CPUusage$
x_3: $Time(h)$	x_6: $Pdisk$	x_9: $LoadTraffic\ (Byte)$

Then, the equation of power consumption of server is established as in (6).

$$P_{server} = \sum_{1}^{i} [a + (b_1 * X_{1,i} + b_2 * X_{2,i} + \cdots b_9 * X_{9,i}) + (c_1 * X_{1,i} + c_2 * X_{2,i} + \cdots + c_9 * X_{9,i} + d_1 + d_2 + \cdots + d_9)^2] \tag{6}$$

where (i) is the observation number and the coefficients of the equation are represented by (a), (b), (c) and (d). This equation is applied in Matlab to forecast power consumption of server using "nlinfit" function. It uses iterative least square estimation with initial conditions and the Levenberg-Marquardt nonlinear least-squares algorithm. The historical data which belong to predictor and response variables are divided as training and test dataset to be used nonlinear regression analysis. Then the nonlinear model is set by "nlinfit" function and the coefficients of the power consumption equation are forecasted. After that, the test dataset is applied to the model for comparing the forecasted and real power consumption of server. The power consumption of server is forecasted with a 3.99% ratio of MAPE. The results graph is shown in Fig. 1.

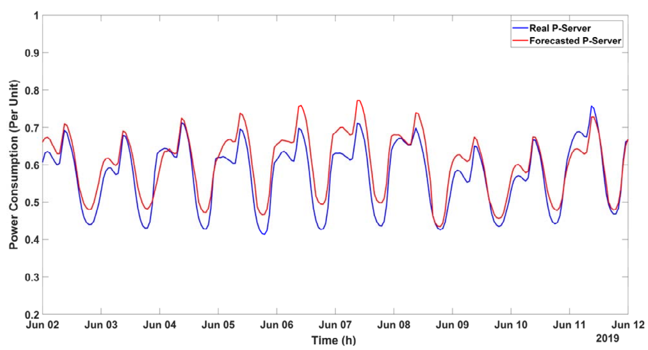

Fig. 1. The Comparison of Real and Forecasted Power Consumption of Server using Regression Analysis Method

2) Power Consumption Model of Storage Units

Storage systems are another significant part that is responsible for a huge amount of power consumption. The first step of forecasting is similar to the forecasting power consumption of servers. The predictor variables which are determined in section II are shown in Table II.

Table II. The Predictor Variables of Power Consumption of Storage Units

x_1: *Idle Time*	x_4: *Total Active Time*	x_3: *Read Time*
x_2: *Write Time*	x_5: *RPM of Disk*	

The equation of power consumption of storage units is established as:

$$P_{storage} = \sum_{1}^{i} [a + (b_1 * X_{1,i} + b_2 * X_{2,i} + \cdots b_5 * X_{5,i}) + (c_1 * X_{1,i} + c_2 * X_{2,i} + \cdots + c_5 * X_{5,i} + d_1 + d_2 + \cdots + d_5)^2] \tag{7}$$

The observation number is represented by (i) and (a),(b),(c),(d) indicate coefficients of the power consumption equation. $P_{storage}$ is forecasted using equation (7) in Matlab. The MAPE rate is % 4.60. The result graphs are shown in Fig. 2.

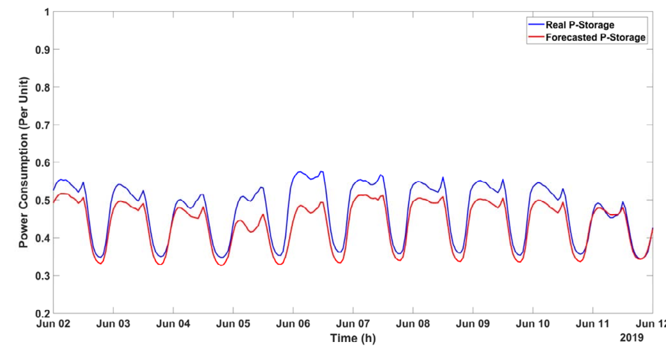

Fig. 2. The Comparison of Real and Forecasted Power Consumption of Storage Units using Regression Analysis Method.

3) Power Consumption Model of Network Equipment

The power consumer components of network equipment in a DC are composed of switches, network links, routers, network interface card and network load traffic. These are considered as predictor variables to forecast the power consumption of network equipment also are shown in Table III.

Table III. The Predictor Variables of Power Consumption of Network Equipment

x_1: *Power Consumption of Network Switches*
x_2: *Power Consumtion of Networking Link*
x_3: *Power Consumption of Router*
x_4: *Power Consumption of Network Interface Card*
x_5: *Load Traffic (Byte)*

The equation of power consumption of network equipment is established as:

$$P_{Networking} = \sum_{1}^{i} [a + (b_1 * X_{1,i} + b_2 * X_{2,i} + \cdots b_5 * X_{5,i}) + (c_1 * X_{1,i} + c_2 * X_{2,i} + \cdots + c_5 * X_{5,i} + d_1 + d_2 + \cdots + d_5)^2] \tag{8}$$

(i) is the observation number and the (a), (b), (c) and (d) are the coefficients. Similar to power consumption forecasting of server and storage units, the power consumption of network equipment in a DC is forecasted by nonlinear regression method in Matlab using "nlinfit" function. The MAPE rate of forecasting is 2.54%. The result graphs are shown in Fig. 3

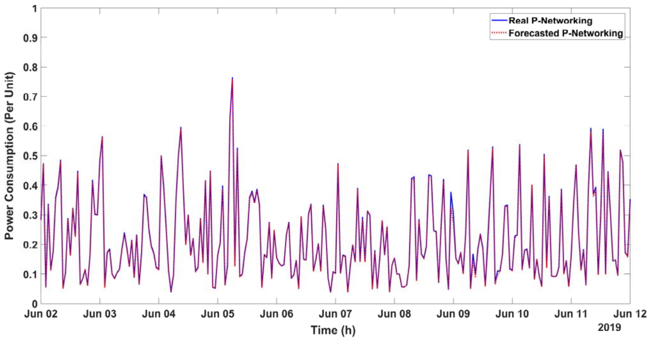

Fig. 3. The Comparison of Real and Forecasted Power Consumption of Network Equipment using Regression Analysis Method.

B. *Forecasting the Power Consumption of IT Devices Using Artificial Neural Network*

Power consumption of server, storage units, and network equipment are forecasted though "fitnet" and "train" functions of Matlab. Because the used methods and progress steps are the same for forecasting power consumption of server, storage units and network equipment with ANN, the following are the same for all three consumers. The feedforward ANN method and supervised learning algorithm are used to forecast power consumption in Matlab. First, the network of input, hidden and output layers are initialized. The numbers of neurons in each layer are determined. Then, a neural network is fitted by "fitnet" function with hidden layer size which is initialized before. After that, the network is trained by "train" function which is one of the fastest backpropagation algorithms in Matlab ANN ToolBox and uses the Levenberg-Marquardt optimization technique. At the end of the training, the network is tested with test data. Then, the MAPE rate of the forecasted power consumption is calculated for each consumer component. The forecasting results of server, storage units, and network equipment are explained below, respectively.

1) *Power Consumption Model of Servers*

Because the power consumption of server is dependent by nine predictor variables are shown in Table I, the ANN network has 9 neurons for input layer and 1 neuron for the output layer. Also, it is decided that the hidden layer should have 10 neurons. End of the forecasting process, the power consumption of server is forecasted with a 1.72% ratio of MAPE. The result graphs are shown in Fig. 4.

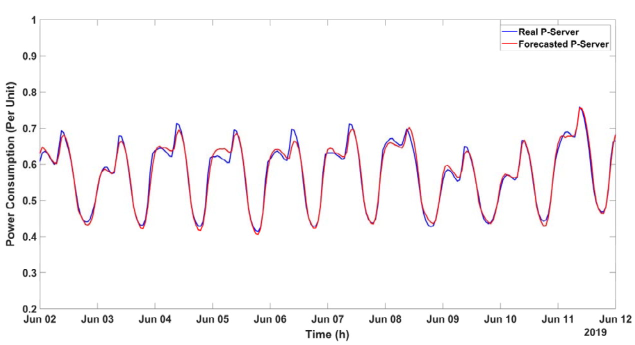

Fig. 4. The Comparison of Real and Forecasted Power Consumption of Server using ANN Method.

2) *Power Consumption Model of Storage Units*

In forecasting of power consumption of storage units process, there are five predictor variables which are shown in Table II. So, the ANN network should have 5 neurons for input layer and 1 neuron for the output layer and the hidden layer has 10 neurons. The power consumption of storage units is forecasted with a 3.49% MAPE rate. The result graph is shown in Fig. 5.

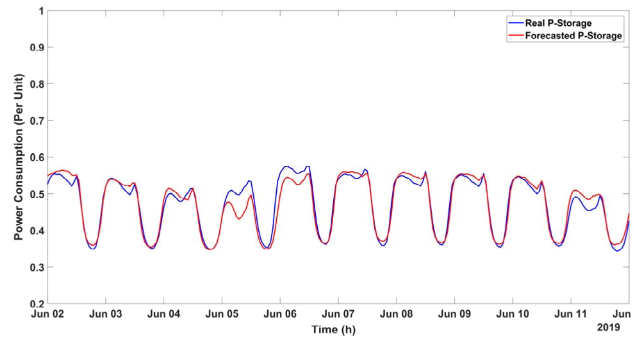

Fig. 5. The Comparison of Real and Forecasted Power Consumption of Storage Units using ANN Method.

3) *Power Consumption Model of Network Equipment*

In forecasting of network equipment's power consumption, there are one response variable and five predictor variables which are shown in Table III. The ANN network has 5 neurons for input layer and 1 neuron for the output layer and the hidden layer has 10 neurons. The power consumption of network equipment is forecasted with a 1.25% MAPE rate. The result graph is shown in Fig. 6.

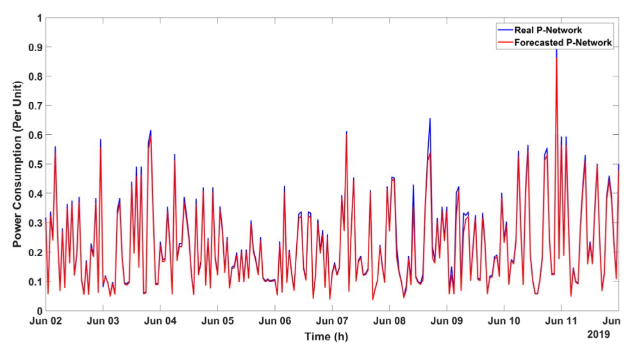

Fig. 6. The Comparison of Real and Forecasted Power Consumption of Network Equipment using ANN Method.

Both forecasting methods results are summarized in Table IV. It is seen that the power consumption of servers is forecasted with 3.99% of MAPE rate while it is 1.72% with ANN Method. So, the ANN method gives 56.89% better results than the nonlinear regression method.

Table IV. The result of MAPE rates of forecasting methods

IT Devices	The MAPE Rates of Nonlinear Regression Method	The MAPE Rates of ANN Method
Servers	3.99%	1.72%
Storage Units	4.60%	3.49%
Network Equipment	2.54%	1.25%

Also, the MAPE rate of the ANN method result is 24.13% less than nonlinear regression method's MAPE rate for forecasting power consumption of storage units. Finally, the power consumption of network equipment is forecasted with 2.54% and 1.25% MAPE rates by nonlinear regression and ANN methods, respectively. So, the ratio of ANN MAPE is 50.78% better than the ratio of nonlinear regression MAPE.

VI. CONCLUSION

In this paper, it has been mentioned that the demand of DCs, which composed of a large number of servers, large-scale storage units, network equipment, is grown significantly. The equipment of DC and its power consuming subcomponent are explained. The variables that affect the power consumption of IT equipment of a DC are explored. It has been also described the significance of correct estimation of IT devices' power consumption. Then, the most commonly used forecasting methods in the literature have been summarized. After that, nonlinear power consumption models for each IT devices are developed and used in both nonlinear regression analysis and ANN methods to forecast power consumption of IT devices.

On observation of each power consumption forecasting of servers, storage units, and network equipment, it is apparent that both forecasting methods give acceptable results with low MAPE rates. The main ambition of this study is to determine to most convenient method to forecast the power consumption of IT devices which are the biggest power consumer in a DC. Thus, the forecasted results can be used in order to minimize power consumption and energy cost in the context of participation of the data center to the electricity market and allocate the renewable energy sources and optimize power management systems.

According to results, it is obviously said that ANN Methods give better results than the nonlinear regression methods. In future work, the analysis of parameters more affecting power consumption of a DC will be examined in detail to obtain more certain forecasting results.

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