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An Elman Neural Network-based Prediction Model for the Power Consumption of Servers

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Abstract. The growing number of the servers across the world has spurred the development of cloud computing. However, the appetite of the servers for power consumption is extraordinary because of the round-the-clock operation. This paper models the running process of the servers to be a nonlinear and time-variation system with uncertainties. An Elman neural network is established to find out the major factors that influence the power consumption of the server in different working conditions. Using the recommended input vector that consists of the major factors, the proposed Elman neural network correlate different kinds of performance data generated in the running of the server and transforms the data into energy information. The simulation results demonstrate that after training with the recommended input vector, the Elman neural network can provide the prediction results that has a high reliability.

Keywords: cloud computing, Elman neural network, mean impact value, power consumption prediction

1 Introduction

With the development of cloud computing and the global growth of data, the number of the servers in the data centers across the world is unceasingly increased. Currently, the appetite of the data center for power consumption is extraordinary because the servers in most data centers continue to slurp energy even when their processors are idle [1]. Thus, the power consumption of the data center has been in a prominent position. Against this backdrop, green data centers are put forward to reduce the power consumption without compromising availability or reliability [2]. There are many factors that might influence the power usage effectiveness (PUE) of a data center, such as cooling system, power density, server device, and the data center environment. The primary goal of the green data center is to timely predict the power consumption of the energy-consuming devices in the data center, and then prioritize opportunities to reduce the power consumption with available technologies and best practices.

Consuming 50-70% of the total power consumption, servers are the primary energy-consuming equipment in the data center. Predicting the power consumption of the server is an important research direction in the establishment of the green data center [3]. The components of a server include the

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motherboard, CPU, fans, memory, hard disk, network card, and power supply unit. Since these components have certain interactions during the operation of the server, the power consumption of the server is a complex and non-linearity process by effect of multiple factors. However, the power consumption of each component cannot be measured in a uniform way. Also, exactly describing the power consumption of each component by accurate mathematics is unrealistic. It is difficult to establish a precise model to obtain appropriate forecasting results using traditional mathematical models and statistical methods.

Domestic and international scholars have done lots of studies on predicting the power consumption of the physical machines and virtual machines. Lewis, Ghosh and Tzeng [4] summed up the power consumption of all functional modules with different weighting factors to predict the power consumption of the physical machine. Bircher and John [5] divided the physical machine into several subsystems and accumulate the power consumption of each subsystem. Bertarn, Gonzalez and Martorell [6] predicted the power consumption of the physical machine by monitoring the power consumption of each core contained in the physical machine. Many papers have been published to date on the use of linear regression models for predicting the power consumption of the virtual machines [7-11]. For example, Quesnel, Mehta and Menaud [12], proposed a linear regression model to calculate the power consumption of a single virtual machine. The proposed model considers the memory resource consumption and the CPU resource consumption independently. Jiang, Lu and Cm [13] established a two-dimensional table to describe the relationship between the LLC (Logical Link Control) and the CPU utilization. Given the number of LLC and the CPU utilization, the power consumption of the virtual machine can be obtained by looking up the table. However, existing strategies widely use linear regression model for power consumption prediction, ignoring the non-linear process when the server works in different conditions [14-15]. A performance comparison of existing linear power models is shown in Table 1.

Table 1. A performance comparison of linear power model

Linear Power Model	Model Element										Prediction error
	CPU	I/O	Chip	Disk	Memory	Bus	Cache	DRAM	HDD	Temperature	
[4]	√					√				√	4%
[5]	√	√	√	√	√						9%
[6]	√										1.89-6%
[7]	√			√	√						0.4-2.4W
[8]	√	√	√	√	√	√	√	√	√		3%
[9]	√				√				√		5%
[10]	√			√			√	√			6-7%
[11]	√			√	√		√				3.91%
[12]	√				√						5-6%
[13]	√				√						2.61W

During the operation of the server, massive data will be produced. However, without fully mine the information contained in data, people confront the problem of rich data and poor knowledge. Different from existing work which model the server as a fixed linear system, this paper considers the running process of the servers to be a nonlinear and time-variation system with uncertainties. To fully exploit the value of data generated in the running process, an Elman neural network is established to find out the major factors that influence the power consumption of the server in different working conditions. Finally, using the major factors as input vector, the proposed Elman neural network is able to correlate different kinds of performance data generated in the running of the server and transforms the data into energy information. The technical achievements of our work is summarized as follows:

- Model the running process of the servers as a nonlinear and time-variation system with uncertainties.
- Figure out the major factors that influence the power consumption of a server in different working conditions through an Elman neural network-based mean impact value (MIV) algorithm.
- For a certain working condition, purely using the major factors as the input vector of the Elman neural network to predict the energy consumption of the server.
- Adjust the parameter of the Elman neural network and test the accuracy of its output.

The remainder of the paper is structured as follows: section 2 introduces the Elman neural network; section 3 describes the Elman neural network prediction model for the power consumption of servers; section 4 compares and analyzes the proposed prediction model with the conventional model; and section 5 describes the conclusions.

2 Elan Neural Network

This paper establishes an Elman neural network to predict the power consumption of the servers because the running process of the servers is a nonlinear and time-variation system with uncertainties [16-17]. The topology structure of an Elman neural network is shown in Fig. 1. The first layer is called the input layer. Besides the nodes for the input data, the input layer includes the output feedback. When a server switches from the standby state to low power state, or from the low power state to high power state, the power consumption of the server will not happen suddenly changes. It suggests that the energy consumed by the server one second before is correlated with the power consumption of the server after the second. Therefore, the introduction of the output feedback makes sense in the predicting the power consumption of the server. The second layer is the hidden layer, in which the number of nodes can be adapted dynamically. The transfer function used in the hidden layer can be either linear or nonlinear. The third layer is called the transition layer, which can be viewed as a lag operator. The function of the transition layer is to use the output of the hidden layer in previous time as additional input added in the current input. The last layer is called the output layer, which transforms the input data into results. The output result obtained by the Elman neural network can be expressed by Eq. 1:

$$y(k) = g(w^3 x(kj)) . \tag{1}$$

$$x(k) = f(w^3 x_c(k) + w^2(u(k-1))) . \tag{2}$$

$$x_c(k) = x(k-1) . \tag{3}$$

where $u \in R^p$, $U^T = \left[u_1, u_2, ..., u_p\right]$ is the input vector of the neural network, $x \in R^m$, $X^T = \left[x_1, x_2, ..., x_m\right]$ is the knot vector in the hidden layer. x_c is a feedback vector, w^2 is the connection weight between the input layer and the hidden layer, w^3 is the connection weight between the hidden layer and the output layer. *f(*)* and *g(*)* denote the transfer function used in the hidden layer and the output layer, respectively.

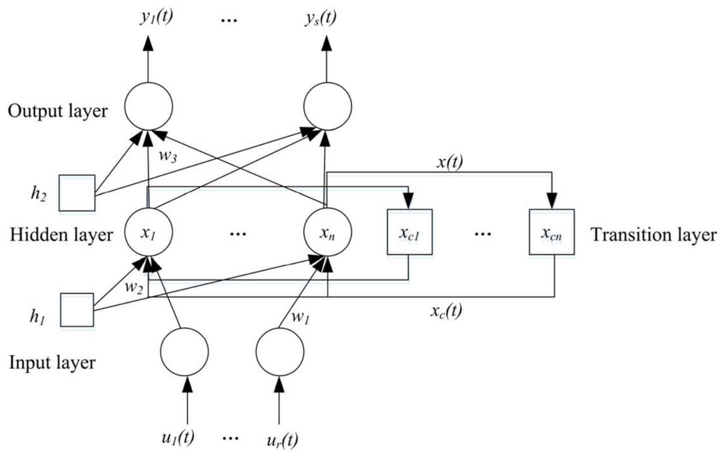

Fig. 1. Elman neural network topology structure

To evaluate and optimize the current output, Elman neural network computes error rate using the sum of error square as follows:

$$E(w) = \sum_{k=1}^{n} (y_k(w) - \tilde{y}_k(w))^2 . \quad \textbf{(4)}$$

Through continuously adjusting the connection weight for each layer in the learning procedure, the network is able to achieve the minimum sum of squared errors [18].

3 The Elman Network Prediction Model for the Power Consumption of Servers

The choice of input variables is essential for a neural network to predict the power consumption of the server accurately. In this section, a large amount of factors that might influence the power consumption of the servers are analyzed by the Elman neural network, aiming to find out the major factors that determine the power consumption of the server in different working conditions. The major factors are finally used by the Elman neural network for power consumption prediction, with the purpose of reducing the dimension of the input vector without sacrificing the accuracy and efficiency of the prediction model.

3.1 Initial Input Variables in Elman Neural Network

As an integral part of the cloud data center, servers consist of motherboard, CPU, fan, memory, hard disk, network card as well as power supply unit. In the server run time, each component consumes a certain amount of electric consumption. For instance, when the server is in no load or idle state, electric is only consumed by the hardware units in the server. When the server is in load, besides the electric consumed by the hardware units, the server invokes CPU and memory for running processes. Moreover, since the server is located in the cloud data center, environmental factors affect the power consumption of the server to some degree. For example, if the air temperature in the cloud data center is high, the server will produce additional refrigeration power consumption.

The server selected as tester in this study is NF5270M3 made from Inspur. The initial variables that used as input in the Elman neural network include the temperature of each component in the server, ambient temperature and humidity, and workload. The temperature of each component in the server is collected by Intelligent Platform Management Interface (IPMI). The workload of the server in different working conditions is collected by the monitoring and management platform in the cloud data center. The ambient temperature and humidity are measured by hygrothermograph. Above-mentioned parameters are listed in Table 2. The parameters are recorded in hours and used as raw input to predict the power consumption of the server.

Table 2. Initial input variables in the Elman neural network

Types of variables	Target object	Variable name
Temperature	Central processing unit_0	T_{CPU0}
	Central processing unit_1	T_{CPU1}
	Dual In-line memory module_0	T_{DIMM_0}
	Dual In-line memory module_1	T_{DIMM_1}
	Dual In-line memory module_2	T_{DIMM_2}
	Dual In-line memory module_3	T_{DIMM_3}
	PCI bus_0	T_{PCIE_0}
	PCI bus_1	T_{PCIE_1}
	South bridge chip	T_{PCH}
	Intel ME_0	T_{ME_CPU0}
	Intel ME_1	T_{ME_CPU1}
	Indoor temperature	T_{Indoor}
Humidity	Indoor humidity	H_{Indoor}
Workload	CPU Utilization	η_{CPU}
	Memory utilization	η_{Mem}

3.2 Mean Impact Value of the Initial Input Variables

Although the parameters listed in Table 2 can reflect the power consumption of the server in different aspects, the dimension of the input vector is too large if all the parameters are selected as input variables. Besides, there are some multiple correlations between these parameters. Involving all the parameters in the Elman neural network will decrease prediction efficiency without any improvement in the precision. Thus, the major factors that determine the power consumption of the server in different working conditions are required to be identified.

In this study, a server is allowed to switch between the standby state, low power state and medium power state. If the running power of the server is less than ten percentage of its rated power, the server is in the standby state. If the running power of the server is larger than ten percentage of its rated power but less then fifty percentage of the rated power, the server is in the low power state. If the running power of the server is larger than fifty percentage of the rated power but less than seventy percentage of the rated power, the server is in the medium power state. The running power of server is not allowed to exceed seventy percentage of the rated power because high power state do harm to the hardware units in the server and increase the failure rate. In each working state, the major factors that influence the power consumption of the server is determined by an Elman neural network-based mean impact value (MIV) algorithm. The Elman neural network-based mean impact value (MIV) algorithm is able to evaluate the relevance of a certain input and the output of the Elman neural network. A large mean impact value indicates the corresponding input is of significance and should be retained. The steps of the Elman neural network-based MIV algorithm is as follows:

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Algorithm 1: Mean impact value (MIV) algorithm
Procedure: Determine the mean impact value of each variable in the input vector U^T=[u1,u2,...,up]
Input: initial input vector U^T=[u1,u2,...,up], adjustment rate η;
For each ui ∈ U^T
    ui_increase = ui*(1+η);
    Replace ui with ui_increase in ui ∈ U^T;
    Use the Elman neural network to train the new vector U^T;
    The training result is yi_increase;
    ui_dncrease = ui*(1-η);
    Replace ui with ui_dncrease in ui ∈ U^T:
    Use the Elman neural network to train the new vector U^T;
    The training result is yi_decrease;
    MIV(ui) = abs(yi_increase-yi_decrease)/p;
End For
End Procedure
```

Using all the parameters in Table 2 as the input, the Elman neural network is established to predict the power consumption of servers in the standby state, low power state and medium power state, respectively. In the process of sample training, 2250 groups of data were selected as training data and 55 groups of data were used to verify the accuracy of the prediction model. The time of training was 50. The learning rate was 0.03 and the error goal was 0.001. The adjustment rate ranged from 0.1 to 0.3 with a step of 0.05. The number of node in hidden layers is determined based on the optimal prediction.

Fig. 2 depicts the prediction error obtained by the Elman neural network when the server is in the standby state. The optimal prediction can be obtained when the number of hidden nodes is 15. It can be observed that the prediction error had a margin of error of plus or minus 0.5. The maximum margin of error was of plus or minus 1.5. Thus, most of the prediction were within the range of the admissible error. The MIV of each variable is shown in Table 3. It can be observed that when the server was in the standby state, most energy were consumed to support the operation of each hardware in the server. Furthermore, south bridge, CPU and memory had little effect on the power consumption and because there was no process or thread running in the server. Therefore, the power consumption of the server in the standby state is mainly determined by the temperature of each hardware.

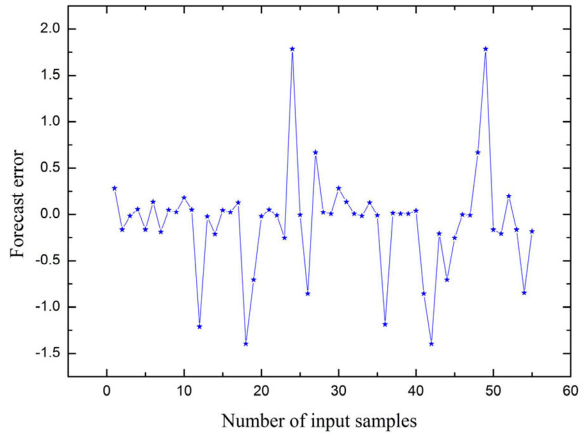


Fig. 2. The output result error when the server is in the standby state

Table 3. MIV of each variable in the standby state

Input variables	Adjustment rate				
	10%	15%	20%	25%	30%
T_{CPU0}	1.7862	0.7466	15.4868	4.8020	3.7344
T_{CPU1}	1.4535	12.0178	16.0246	5.3245	8.1504
T_{DIMM_0}	0.3225	2.2603	7.1362	2.4242	0.4191
T_{DIMM_1}	0.1128	1.6066	0.2274	1.6196	0.538
T_{DIMM_2}	1.2376	3.7133	2.3511	2.8195	3.5537
T_{DIMM_3}	1.3568	1.6357	4.5866	0.0305	3.1210
T_{PCIE_0}	2.2760	6.6248	34.0106	0.9798	44.3527
T_{PCIE_1}	21.8201	15.5274	32.1684	16.6366	4.4518
T_{PCH}	0	0	0	0	0
T_{ME_CPU0}	0	0	0	0	0
T_{ME_CPU1}	0	0	0	0	0
η_{CPU}	0.0768	0.1958	0.7843	0.9994	0.1078
η_{Mem}	0.0189	0.3711	0.3025	0.7467	0.8339

Fig. 3 depicts the prediction error obtained by the Elman neural network when the server is in the low power state. The prediction is satisfying when the number of hidden nodes is 13 or 35. To reduce the complexity of the network, 13 hidden nodes is finally added in the hidden layer. It can be observed that the prediction error had a margin of error of plus or minus 3. The MIV of each variable in the low power state is shown in Table 4. It can be observed that the power consumption of the server was greatly influenced by both CPU utilization and memory utilization. This is because a number of processes and threads are running in the server while energy consumed by the hardware units of the server decreases.

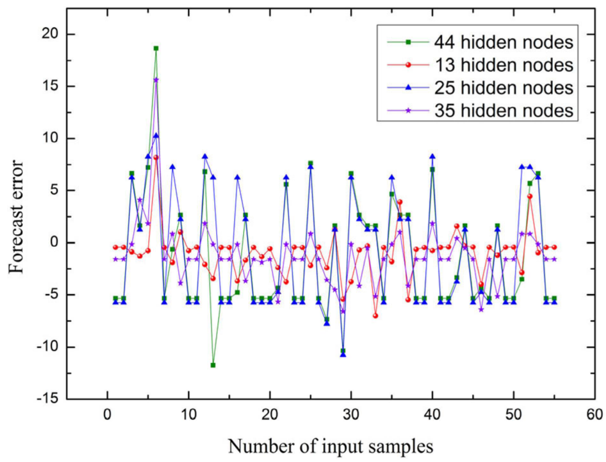


Fig. 3. The output result error when the server is in the low power state

Table 4. MIV of each variable in the low power state

Input variables	Adjustment rate				
	10%	15%	20%	25%	30%
T_{CPU0}	0.6328	1.4656	2.7775	8.8467	2.4279
T_{CPU1}	0.7184	1.0868	4.1865	7.8862	3.0986
T_{DIMM_0}	0.7397	1.4778	0.4487	1.1569	7.4912
T_{DIMM_1}	0.8880	0.4902	0.7479	12.4641	2.7682
T_{DIMM_2}	0.3316	1.3490	0.2167	5.1266	12.1210
T_{DIMM_3}	1.6409	4.4449	4.3647	24.1407	21.1210
T_{PCIE_0}	25.3844	1.3345	10.8753	75.2558	14.8492
T_{PCIE_1}	4.7408	55.3875	57.0698	34.3933	122.9817
T_{PCH}	3.3025	3.5638	21.8603	73.9012	8.5510
T_{ME_CPU0}	0.3592	0.5034	0.7313	0.3700	0.0198
T_{ME_CPU1}	0.2505	0.9243	0.0098	0.1736	0.0840
η_{CPU}	3.0893	5.5693	7.2032	5.6595	14.6525
η_{Mem}	10.2381	1.7715	3.1657	1.5912	12.3486

Fig. 4 depicts the prediction error obtained by the Elman neural network when the server is in the medium power state. The prediction is satisfying when the number of hidden nodes is 16. It can be observed that the prediction error had a margin of error of plus or minus 1. The maximum margin of error was of plus or minus 2. The MIV of each variable in the medium power state is shown in Table 5. Similar to the low power state, the power consumption of the server in the medium state is more controlled by both CPU utilization and memory utilization. This is because a number of processes and threads are running in the server while less energy is consumed by the hardware units of the server.

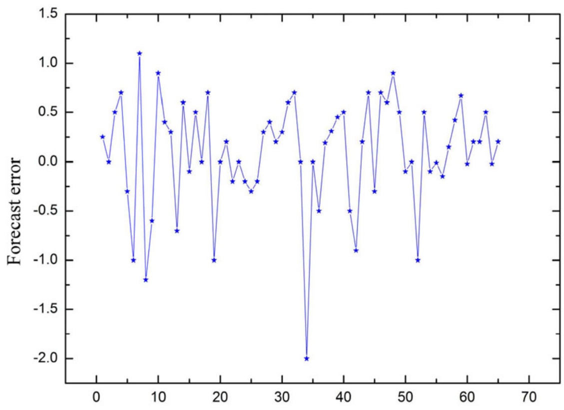


Fig. 4. The output result error when the server is in the medium power state

Table 5. MIV of each variable in the medium power state

Input variables	Adjustment rate				
	10%	15%	20%	25%	30%
T_{CPU0}	0.5547	3.1698	3.3364	10.7987	3.5630
T_{CPU1}	0.4592	2.7597	3.4912	10.3994	5.5742
T_{DIMM_0}	1.3359	0.7795	0.6518	0.5511	2.4100
T_{DIMM_1}	3.2483	3.7632	7.0214	18.5359	14.8099
T_{DIMM_2}	0.6566	1.4828	1.4050	2.9420	3.6545
T_{DIMM_3}	2.9931	9.5700	30.4528	1.0494	18.4890
T_{PCIE_0}	52.6172	12.9500	53.3743	84.9625	10.008
T_{PCIE_1}	18.9635	33.9339	21.1260	88.9472	44.4697
T_{PCH}	0.9427	2.8123	8.9663	32.6140	9.7235
T_{ME_CPU0}	0.4027	0.7378	0.6450	0.5244	0.4546
T_{ME_CPU1}	0.2650	0.2422	0.2252	0.9348	0.7655
η_{CPU}	10.5780	15.1423	24.8659	77.0669	26.0305
η_{Mem}	1.7765	1.6898	1.1893	5.1859	12.0087

3.3 The Determination of the Recommended Input Variables

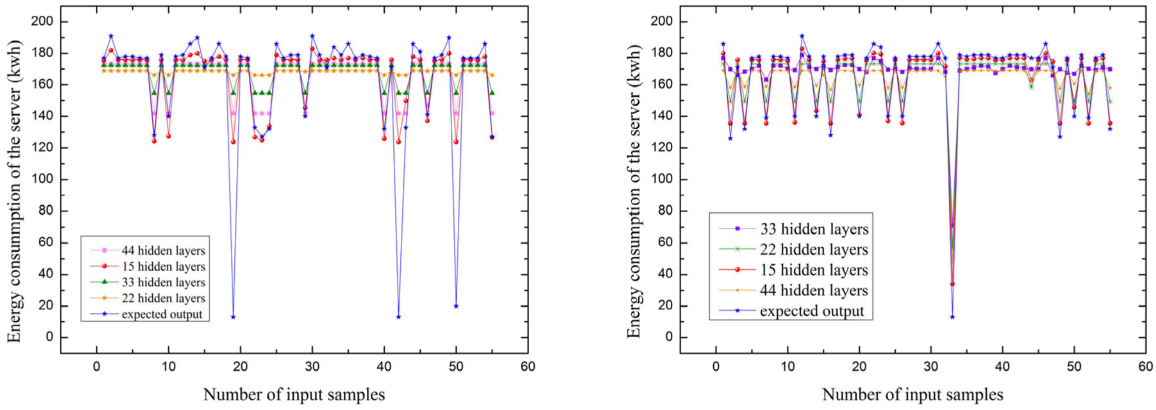
Based on the above-mentioned results, the major factors that influence the power consumption of the server in different working states are summarized from Table 3 to Table 5. In case of the standby state, TPCH, TME_CPU0, TME_CPU1, η_{CPU} and η_{memory} can be removed from the raw input without decreasing the precision of the output. Thus, the recommended dimension of the input vector in the standby state is 8. Similarly, in case of the low power state or medium power state, T ME_CPU0, TME_CPU1 can be removed from the raw input to reduce the dimension of the input. The recommended input vector in the low power state and medium power state is the same and the dimension of the input vector is 11. However, the Elman neural network cannot use two groups of input to predict the power consumption of the server in different states because the working state of the server is unknown to the Elman neural network. The strategy proposed in this paper is to merge the two recommended input vectors into one vector and handle corresponding variables in the vector based on the judgment of the working state. It is noticed that the recommended input vector in the standby state is a subset of the recommended input vector in both the low power state and the medium power state. The union of the two recommended input vector is the the recommended11-dimensional input vector in both the low power state and the medium power state. Then, the server is assigned with the ability to judge whether it is in the standby state by inquiring the temperature of the south bridge as well as the cpu utilization. Only when the temperature of the south bridge as well as the cpu utilization are at a low level, the server determines that it is in the standby state and set the value of TPCH, η_{CPU} and η_{memory} to 0 in the 11-dimentional input vector. Otherwise, the true value of each variable is given in the input vector.

4 Simulations

The final Elman neural network used for predicting the power consumption of the servers synthesizes the network structure applied for each working state in section 3. The number of hidden nodes was 15. The learning rate was 0.03 and the error goal was 0.001. The maximum time of training was 1000. The piece of the hidden layer was set to 15, 22, 33 and 44. In the process of sample training, 8650 groups of data were selected as training data and 55 groups of data were used to verify the accuracy of the prediction model. The Elman neural network used the raw input vector that contains 15 variables and the recommend input vector that contains 11 variables to predict the power consumption of a server, respectively.

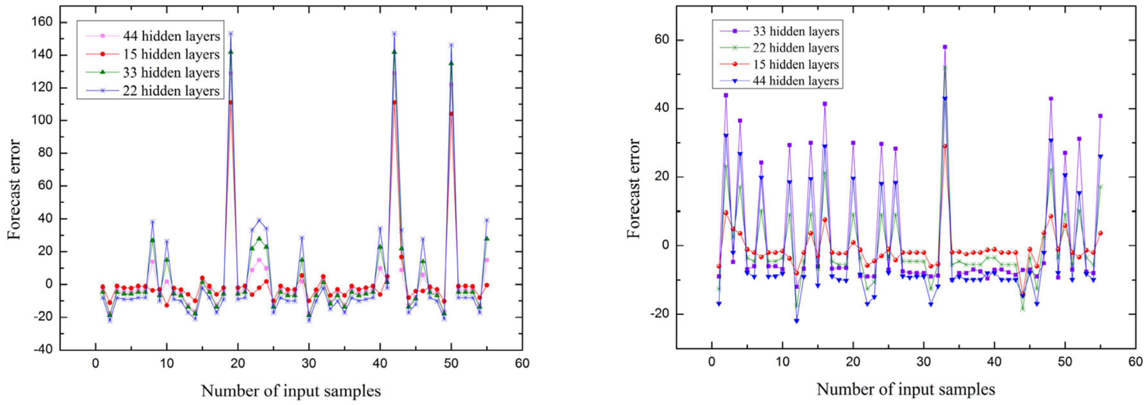
Fig. 5(a) and Fig. 5(b) show the worst and the best output of the Elman neural network, using the raw input vector. In either the worse or the best case, it can be observed that better prediction results can be obtained when the piece of the hidden layer was 15 or 44. Specifically, as shown in Fig. 6(a), in the worse case, the forecast error was less than 20 if the server held its working state. When the working state of server changed, a great error of prediction result existed. As shown in Fig. 6(b), in the best case, the forecast error was less than 10 if the server holds its working state and was no more than 30 when the server's state changed. It can be concluded that after training with the raw input vector, the Elman neural network cannot provide the prediction results that match the expected outputs well.

Fig. 7(a) and Fig. 7(b) show the worst and the best output of the Elman neural network, using the recommended input vector. In either the worse or the best case, it can be observed that better prediction results can be obtained when the piece of the hidden layer was 15 or 33. Specifically, as shown in Fig. 8(a), in the worse case, the forecast error was less than 10 if the server held its working state. When the working state of server changed, the prediction error was still in the acceptable scope. as shown in Fig. 8(b), in the best case, the forecast error was less than 5 if the server held its working state and was no more than 10 when the server's state changed. It can be concluded that after training with the recommended input vector, the Elman neural network can provide the prediction results that has a high reliability.



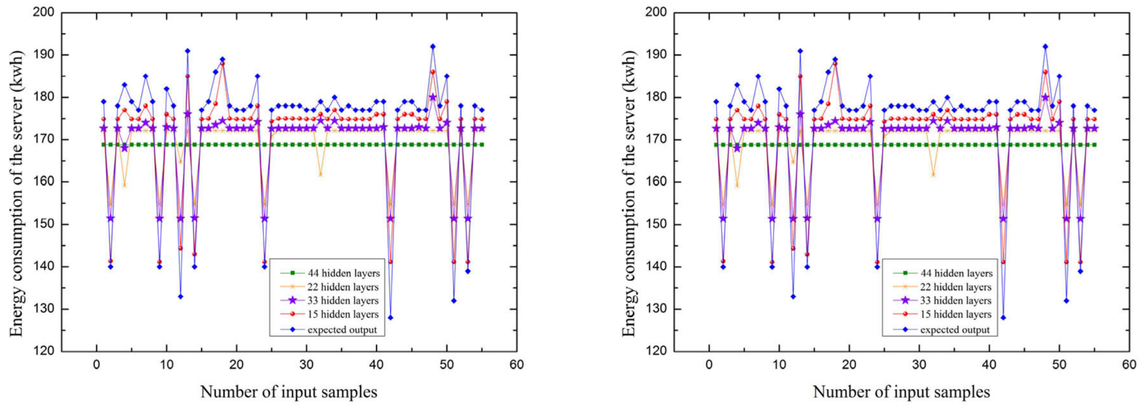
(a) (b)

Fig. 5. Target and predicted values for power consumption using the raw input vector



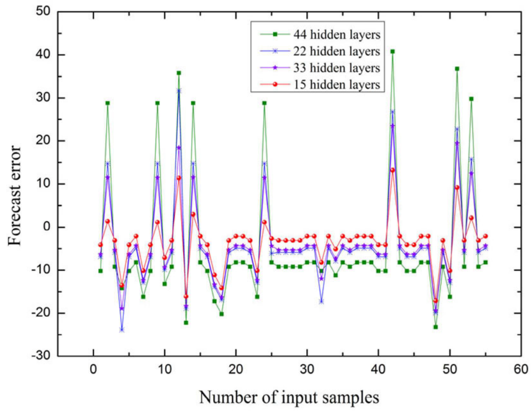
(a) (b)

Fig. 6. Forecast error induced by the raw input vector

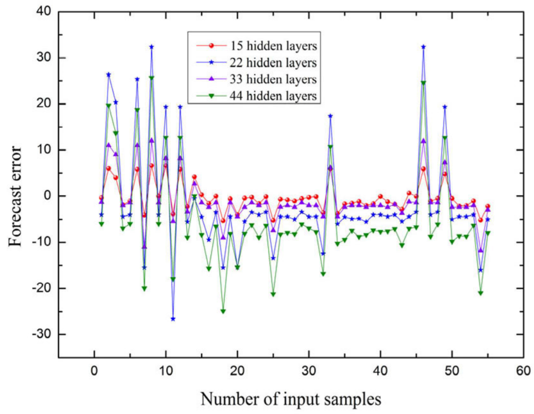


(a) (b)

Fig. 7. Target and predicted values for power consumption using the recommended input vector



(a)



(b)

Fig. 8. Forecast error induced by the recommended input vector

5 Conclusion

Power consumption prediction for servers is of significance to optimize the management of the cloud data center. In this paper, the running process of the servers is modeled to be a nonlinear and time-variation system with uncertainties. To fully exploit the massive data generated in the standby state, low power state and medium power state, an Elman neural network is established and analyze the mean impact value of each type of data, aiming to find out the major factors that influence the power consumption of the server in different working conditions. Using the major factors as input vector, the proposed Elman neural network correlate different kinds of performance data generated in the running of the server and transforms the data into energy information. The simulation results show that the Elman neural network can provide more accurate forecasting results with low dimensional input. The foresting results have referential value to inspecting and processing power consumption anomalies, speeding up the establishment of the green data center.

Due to the difficulty of data acquisition, our work only selects the server NF5270M3 made from Inspur as a test object. However, in the future, different models of servers will be hopefully established as an unified network model. Then, the model number of a particular server can be identified using the model that is built during training. Using correspond feature vectors, the unified model is able to predict the energy consumption of different types of servers.

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