Host Load Prediction with Bi-directional Long Short-Term Memory in Cloud Computing*

1st Hengheng Shen  
Institute of Computing Technology, Chinese Academy  
Beijing, China  
shenhengheng17g@ict.ac.cn

1st Xuehai Hong  
Institute of Computing Technology, Chinese Academy  
Beijing, China  
hxh@ict.ac.cn

Abstract—Host load prediction is the basic decision information for managing the computing resources usage on the cloud platform, its accuracy is critical for achieving the service-level agreement. Host load data in cloud environment is more high volatility and noise compared to that of grid computing, traditional data-driven methods tend to have low predictive accuracy when dealing with host load of cloud computing. Thus, we have proposed a host load prediction method based on Bi-directional Long Short-Term Memory (BiLSTM) in this paper. Our BiLSTM-based approach improve the memory capability and nonlinear modeling ability of LSTM and LSTM Encoder-Decoder (LSTM-ED), which is used in the recent previous work. In order to evaluate our approach, we have conducted experiments using a 1-month trace of a Google data centre with more than twelve thousand machines. our BiLSTM-based approach successfully achieves higher accuracy than other previous models, including the recent LSTM one and LSTM-ED one.

Index Terms—Host load prediction, Cloud Computing, Bi-directional Long Short-term Memory

I. INTRODUCTION

Cloud computing is a resource service model, computing model, and on-demand billing model that provides elastic and scalable virtualization through the Internet as a service, but the widespread use of cloud computing has led to an increasing cost of enterprise investment in data centers, which note that the cost of data centers accounts for about 25% of the total budget of the enterprise’s IT business. Although the data center has a large number of users and market share dominates, inefficient data centers can cause them to fail. One of the main causes of data center inefficiencies is low server utilization. Gartner and McKinsey report that server utilization in most enterprise data centers is only 6%–12% [1], and Amazon AWS server utilization is only 7%–17% [2]. To address the problem of underutilization of data center servers, we need to migrate virtual machines based on the load of the host. In this process, how to accurately predict the load of each physical host is a key issue. If you can accurately predict the load change trend for each physical host before scheduling, and advance the migration of virtual machines and resource scheduling to avoid violating service-level agreement (SLA), it will ultimately benefit the load balancing of the entire cloud platform.

Most previous works [3, 4, 5, 6, 7, 8, 9] on host load prediction have focused on the host load in traditional Grids. However, unlike the applications used in a Grid, the tasks in a Cloud tend to be shorter and more interactive. According to the comparison of work load set ween Cloud and Grid [10,11], the average noise in a Cloud is approximately 20 times larger than the average noise in a Grid. Therefore, predicting the host load in a Cloud is more difficult than in a Grid. Specifically, previous methods achieve limited accuracy when they are applied to the cloud environment.

In this paper, we predict the host load multi-step-ahead with a model called Bi-directional long short-term memory (BiLSTM) which is concise yet adaptive and powerful. During host load prediction, the quantity of history information required to predict future values may be variant in different load traces. Unlike previous methods, the BiLSTM model can learn how long does it really need instead of a manually control. Furthermore, this method is an end-to-end model which never requires an extra feature-extracted step. Experiment results show that our method achieves better performance than other start-of-the-art methods.

The outline of the paper is as follows. Section II gives an overview of the related work and comparisons between each other. The architecture of our proposed method is shown in Section III. In Sect. IV we present the experiment results and comparisons. Finally, we conclude the paper and future work in Section V.

II. RELATED WORK

Host load prediction in grid and cloud systems has gathered a lot of attention from researchers due to its benefits in improving resource allocation and utilization while satisfying service-level agreement (SLA).

Many efforts have been made toward host load prediction in Grids or HPC systems. Khan et al. [3] used the hidden Markov model to establish a CPU load prediction model based on self-similarity for the CPU load of the cloud data center. Dabrowski et al. [4] used Markov model modeling to predict host load data in a simulated cloud environment. Akioka et al. [5] proposed a load prediction framework by combining Gaussian Hidden Markov Model and seasonal variance analysis for the host load of the grid system, predicted the host load value of the grid system at the next moment. Firstly, the clustering method based on partitioning the underlying bipartite graph is used to capture the workload similarity characteristics of different groups of virtual machines, then the hidden Markov
model is used to model the time correlation, finally the different clusters are predicted. For the workload of each virtual machine, if the markov chain stochastic model works normally, on the one hand, the random process needs to have no memory, on the other hand, the system involved is stable. Obviously, the cloud computing resource allocation is dynamically changing, so the markov chain stochastic model can only be applied to short-term actual load prediction. Roy et al. [6] predicted the workload in the cloud computing environment based on the Exponential Moving Average (EMA) method. Yang et al. [7] proposed a prediction method for the CPU usage of the host, using the stability and trend assumptions of the time series, combined with the prediction error of the last time step and the observation data to dynamically adjust the parameters of the model. The experiment shows that the accuracy of the CPU load prediction obtained by the proposed trend seasonal prediction method is significantly higher than other linear-based prediction method. Kim et al. [8] proposed a combination method for cloud data center workload prediction which combining models such as ARMA, linear regression, and support vector machines, and using regression algorithms to dynamically determine the weight of each predictor, experiments show that the method can accurately predict the host load and workload of the data center.

The artificial neural networks are widely used on predict host load of grid and HPC systems, host load prediction research due to their high nonlinearity, adaptability and arbitrary function fitting. In addition, with the further advancement of deep learning, methods based on artificial neural networks have received unprecedented attention in academia and industry. Feedforward Neural Network (FNN) is a type of traditional neural network widely used in host load prediction, in which historical host load data is used for FNN input, and the host load value is directly used as the output of FNN, and iteratively adjusts its internal parameter values based on a specific optimization algorithm to model and analyze the highly nonlinear relationship between input and output. Prevost et al. [12] took the resource usage data of the cloud host as input, the workload resource usage of the cloud data center application as output, and trained the FNN based on the back propagation algorithm, and finally used the trained model for online workload prediction. Duy et al. [13] used the length of the ready queue maintained by the scheduler in the grid computing system as the CPU load index, and built a three-layer FNN to predict the CPU load in the future. Yang et al. [14] proposed a new method for the host load prediction problem of Google Cloud Data Center. This method combines the phase space reconstruction (PSR) method and the grouping data processing method based on evolutionary algorithm (EA-GMDH). The host load in the distributed environment and the host load in the cloud computing environment are predicted separately. Considering that the host load is a single variable time series, the PSR method is used to reconstruct the one-dimensional host load sequence in the multi-dimensional phase space, and the EA-GMDH method optimizes the model parameters of the FNN to select the best model. However, this method is limited by the number of neurons in the multi-step prediction task in advance and the FNN cannot learn long-term dependencies, so the prediction accuracy is poor. In order to solve the problem of multi-step early prediction of host load, Yang et al. [15] proposed to use an autoencoder as a feature extraction layer and an echo state network (ESN) as a prediction network to achieve multi-step early host load prediction. Since the random and sparse dynamic storage layer of ESN is used as the non-linear feature extraction layer and the input data storage layer, the accuracy is improved compared to the PSR+EA-GMDH model, but the ESN model uses manual selection of parameters, it reduces generalization ability of different loads, and ESN relies heavily on the features extracted from the auto-encoder, which adds additional workload for model parameter adjustment, so ESN is less effective in the actual cloud host load multi-step prediction task in advance.

Song et al. [16] used the advantages of long short-term memory in the recurrent neural network to model time series data, and realized the time-correlation modeling and multi-step advancement of the host load prediction in the cloud computing environment and grid computing system. Peng et al. [17] apply the gated recurrent units to cloud computing host load prediction, and adopted the encoder-decoder network (GRUED) based on the gated recurrent units as the load prediction network, using traditional dataset ‘Dinda’ of grid computing system and Google cluster trace dataset to verify. The experimental results show that the GRUED model performs better than the prediction model based on long short-term memory on the two datasets. Nguyen et al. [18] proposed a composite deep neural network structure model based on long short-term memory encoder-decoder network (LSTM-ED) and FNN which normalized and serialized host load data, and realized the time-correlation modeling and multi-step early host load prediction task in advance.

III. Our Method

A. Overview of proposed method

Figure 1 presents the architecture overview of our proposed model. At the center of our methods, we use a model called Bi-directional Long Short-Term Memory (BiLSTM) for host load prediction. The BiLSTM consists of two main components, including a forward LSTM computing procedure which using historical host load to update hidden state with forwarding, and a backward LSTM computing procedure which using future host load to update hidden state with backwarding.

It can be seen from the Figure 1 that the time-correlation features hidden in the input sequence data are first extracted. The extraction process is implemented by the BiLSTM network. Specifically, the BiLSTM network will perform feature extraction on the long-term dependence of the input sequence layer by layer and adopt the forward and backward calculation processes respectively; secondly, the extracted features are
further feed into the fully connected layer; finally the future host load is predicted through a linear regression output layer.

The host load time series is divided into consecutive ‘history’ sequences of fixed size; each of this ‘history’ sequence is accompanied by a ‘prediction’ sequence of fixed size. The history and prediction sequences are used as inputs and supervised outputs/labels for the BiLSTM, respectively. Depending on the performed tasks, these ‘prediction’ sequences can be either real host load values or mean load values over future time intervals.

In addition, the Google load trace provides measurements taken at 1-s intervals, which is too small compared to the usual CPU load fluctuations in the trace. Thus, in this work the smallest interval we have used to take samples from the trace is 5 min, which is the same as previous works that used this case for comparison purpose.

### B. Recurrent neural network

Recurrent Neural Network is a type of network with loops in them to allow information to persist. This type of network can be used for our host load prediction task by predicting the next value based on historical load values. Figure 2 shows the architecture of a Recurrent Neural Network (RNN) with one hidden layer together with its unrolled form, in which at time step $t$ in the network $x_t$ is the input, $h_t$ is the hidden state, and $y_t$ is the output.

In our host load prediction task, $x_t$ can be the historical load value (possibly after normalization). Then the hidden state $s_t$ of RNN can be calculated based on the previous hidden state and the output at the current time step:

$$ h_t = \sigma \left( U x_t + W h_{t-1} + b_h \right) $$

where $\sigma$ is usually a nonlinear function like $\tanh$ or $\text{ReLU}$. To calculate the first hidden state, $h_{-1}$ is typically initialized to zeros.

The output state $y_t$ can be calculated based on the hidden state $h_t$ as follows:

$$ y_t = V h_t + b_y $$

Different from a traditional deep neural network, RNN uses the same set of parameters $(U, V, W)$ across all steps, which greatly reduces the number of parameters the network needs to learn.

### C. Long short-term memory

Long Short-Term Memory (LSTM) is a special kind of RNN, which can resolve the vanishing gradients issue and is capable of learning long-term dependencies. Introduced by Hochreiter et al. [19] in 1997, there have been many works which apply LSTM. These include the recent previous work by Song et al. [16], where they optimized the parameters and showed that their LSTM model outperformed other previous models in the Google load trace.

Figure 3 shows that architecture overview of a LSTM cell, which consists of the following components:

- $x_t$: external input at time step $t$. 
- $c_{t−1}$: cell state at time step $t−1$.
- $h_{t−1}$: hidden state at time step $t−1$.
- $h_t$: hidden state at time step $t$.
- $c_t$: cell state at time step $t$.
- $f_t$: forget gate at time step $t$.
- $i_t$: input gate at time step $t$.
- $o_t$: output gate at time step $t$.
- $\sigma$: activation function (e.g., $\tanh$, $\text{ReLU}$).

Fig. 1: The architecture of our proposed method.

Fig. 2: Recurrent Neural Network and its unfold structure.

Fig. 3: The LSTM memory block.
- \( h_{t-1} \): hidden state at times \((t-1)\) or \(t\). This is also used as output or input for the next layer of LSTM cells (in multi-layer LSTM).
- \( c_{t-1}, c_t \): the ‘cell state’ or ‘memory’ at time step \(t-1\) or \(t\).
- \( f_t \): the result of the forget gate, which controls whether to forget (for values close to zero) or remember (for values close to one) the memory \(c_{t-1}\).
- \( i_t \): the result of the input gate, which determines the degree of importance of the (transformed) new external input.
- \( \tilde{c}_t \): the result of the candidate cell state, which performs a nonlinear transformation of the new external input \(x_t\).
- \( \sigma_t \): the result of the output gate, which controls the amount of the new cell state \(\tilde{c}_t\) that goes to the output and the hidden state.

Every time the LSTM takes an input \(x_t\), the three gates \(f_t, i_t, o_t\) and the candidate cell state \(\tilde{c}_t\) are updated as follows:

\[
\begin{align*}
i_t &= σ(Wh_u[h_{t-1};x_t] + b_u) \\
f_t &= σ(Wf[h_{t-1};x_t] + b_f) \\
o_t &= σ(wo[h_{t-1};x_t] + b_o) \\
\tilde{c}_t &= tanh(we[h_{t-1};x_t] + b_c)
\end{align*}
\]

where we use sigmoid function for \(σ\) in this work.

The cell state at the current time step can be updated using the results from the cell gate and the cell state at the last time step as follows:

\[
c_t = f_t \odot c_{t-1} + i_t \odot \tilde{c}_t
\]

Finally, the hidden state (or output) can be updated using the results from the output gate and the cell state at the current time step as follows:

\[
h_t = o_t \odot tanh(c_t)
\]

**D. Bi-directional long short-term memory**

In order to further improve upon the previous works LSTM model that shows longterm dependencies learning capability, in this work we have used a model called Bi-directional Long Short-Term Memory (BiLSTM). The BiLSTM model consists of two directional LSTM RNN units that act as an forward and backward pair, as illustrated in Figure 4.

![Bi-directional LSTM network](image)

In summary, it can be seen from Figure 4 that the host load prediction model based on our proposed method mainly includes three steps, and the technical details of the model are now described as follows:

1. **Step 1**: Feed the input data \(X_t = [x_1, \cdots, x_{W_{in}}]\) into the BiLSTM network to extract the temporal features of the host load. The output features can be calculated as follows:

\[
H_t = [h_1, \cdots, h_{W_{in}}] = f_1(X_t; \tilde{Θ}_{LSTM}, \tilde{Θ}_{LSTM})
\]

where \(f_1(\cdot)\) represents the hidden state update function of the BiLSTM network and specifically described by Equation. 6 — Equation. 7. It is necessary to point out that the complete output at each time point are all a fusion feature obtained by weighting and summing the elements forward and backward according to the elements. Taking the time \(t\) as an
example, the complete output $h_t$ can be calculated by the following formula:

$$h_t = \lambda_1 \cdot \tilde{h}_t + \lambda_2 \cdot \bar{h}_t$$  \hspace{1cm} (9)$$

b) Step 2: The output features extracted through the BiLSTM network are fed into a FNN layer. The process is described as follows:

$$o_i = f_2(H_i; \Theta_{FC}) = g(W_F H_i + b_F)$$  \hspace{1cm} (10)$$

where we use ReLU function for $g$ in this work.

c) Step 3: The output feature $o_i$ of the fully connected layer is finally input to a linear regression layer to calculate the host load prediction value $\hat{y}_i = \langle \hat{x}_{t+1}, \hat{x}_{t+2}, \ldots, \hat{x}_{t+m} \rangle$, the process can be described by the following formula:

$$\hat{y}_i = f_3(H_i; \Theta_R) = W_R o_i$$  \hspace{1cm} (11)$$

where $\hat{y}_i$ and $W_R$ are the predicted value of the host load and the weight vector of the last linear regression layer. It is worth noting that, Depending on the performed tasks, these prediction sequences can be either real host load values or mean load values over future time intervals. The input and output dimensions will also be different, respectively.

E. Parameters of our model

To train our network, we have used the backpropagation through time (BPTT) algorithm [20], which consists of repeated applications of the chain rule. Similar to the previous Google host load prediction work using LSTM, we 'clip' the gradient before parameters update when it becomes too large to prevent exploding gradients. We have also used similar input layer size, hidden layer size, batch size, number of epochs, and learning rate, which is also annealed by 0.1 every 30 epochs.

In addition, due to the long length of our prediction method, we have used ‘truncated backpropagation through time’ to reduce the cost of a single parameter update, similar to the previous LSTM work. The truncated length is kept at 39 for the mean load prediction task; however, different from the previous LSTM work, this length is reduced to 26 for the real values prediction task due to long-term dependencies learning ability of LSTM-ED method. The parameters values of our LSTM-ED method are summarized in Table I.

| Parameter       | Value |
|-----------------|-------|
| Input layer size| 24/64 |
| Hidden layer size| 128   |
| Batch size      | 128   |
| Global gradient clipping norm | 5     |
| Truncated length| 36/39 |
| Epoch           | 90    |
| Dropout rate    | 0.01  |
| Early stop rate | 10    |

IV. EXPERIMENT RESULTS

In order to evaluate our method, we have predicted both the actual load value and mean load value of the Google cluster workload traces [21]. Before training of our method and all other benchmark methods, the input data are standardized by removing the mean and scaling to unit variance to help with the convergence of gradient descent and performance of the methods.

A. Google load traces and baseline model

The Google cluster records tracking data from more than 12,500 compute nodes for 29 days, with approximately 67,2074 jobs, more than 26 million resource usage data for more than 26 million tasks, and a measurement cycle of 5min per record, each of which is divided into at least one task, each with corresponding scheduling constraints, resource constraints, and detailed resource usage.

In order to be able to obtain load data for each machine, our proposed method uses the CPU of all tasks that are running at the current time of each machine as the current host load, and obtains the naturalized data through data preprocessing such as normalization to speed up the convergence of training. Figure 5a and Figure 5b give the host load data with machine number 563849022, where Figure 5a shows the load data for the full measurement period, and Figure 5b clearly depicts the fluctuation of the host load in the first 6 hours.

(a) Host load of the whole 29 (b) Host load of the first 6 hours.

Fig. 5: Host load of a single machine with id 5638349022 in Google load traces

In order to be able to follow up on the model of BiLSTM network sequence data modeling and host load regression analysis, our method uses a random sampling of 1000 machines as a data set to verify the validity of the BiLSTM network, first of all, 1000 machines 29 days of tracking data divided into training set, validation set and test set, the first 20 days of tracking data as training data to calculate the parameter set of BiLSTM. The 21-26-day tracking data is used as a validation dataset to select model superparameters to avoid model overfitting, and 27-29 days of tracking data as a test dataset to evaluate the proposed model.

B. Accuracy metrics

a) Mean load prediction: To make the results comparable with other methods, we first used LSTM model to predict the mean load. The metric named exponentially segmented
pattern (ESP) was used to characterize the host load fluctuation over consecutive time intervals whose lengths increase exponentially.

The mean segment squared error (MSSE) defined as follows was applied to quantify the performance of mean load prediction:

\[
\text{MSSE}(s) = \frac{1}{s} \sum_{i=1}^{n} s_i (l_i - \hat{l}_i)^2 \quad (12)
\]

where \( s_1 = b, s_i = b \cdot 2^{i-2}, s = \sum_{i=1}^{n} s_i \), \( b \) is called baseline segment, which is set to 5 min, similar to previous LSTM work [16] and LSTM-ED work [18]; \( l_i \) is the predicted mean value. \( L_i \) is the true value, \( n \) is the number of segments in the consecutive prediction interval. In practice, the load pattern is converted from single load interval.

b) Actual load prediction: Because the length of the segment shows an exponential growth trend across time in the mean load prediction task, so as the length of the segment increases, the average load value based on the segmentation mode can no longer fully capture the actual fluctuation of the load, so we also specifically considers the actual load prediction task. The forward load of the model can be used to obtain the actual load sequence for a period of time in the future. It is similar to the actual load prediction model of others [17, 16, 18], and the evaluation method based on the Mean Squared Error (MSE) is defined to measure the model:

\[
\text{MSE} = \frac{1}{N} \sum_{i=1}^{N} (\hat{y}_i - y_i)^2 \quad (13)
\]

where \( N \) is the length of the prediction step, and \( y_i \) and \( \hat{y}_i \) are the actual and forecast values, the interval length between two consecutive host load values is set to 5 min for the Google cluster trace dataset, respectively.

C. Analysis of different prediction lengths

Table II shows the impact of the five different prediction steps on the mean load prediction. From the table, it can be clearly seen that the proposed method has a good performance in the short-term mean load forecasting task. As the prediction steps increases, the MSSE also increases, which can be explained mainly from two aspects. Firstly, the BiLSTM network extracts effective temporal features by learning past and future load changes, and ultimately produces good short-term load prediction results. Secondly, when the number of prediction steps increases, although the input sequence data already contains more temporal information, the BiLSTM network still has deficiencies in capturing long-term dependencies.

TABLE II: Impact of prediction length on mean load forecast.

| Prediction length (5 min) | MSSE    | Training Time (s) |
|--------------------------|---------|-------------------|
| 0.7h                     | 0.00055 | 2.3745            |
| 1.3h                     | 0.00059 | 2.3694            |
| 2.7h                     | 0.00109 | 2.4495            |
| 5.3h                     | 0.00139 | 2.4189            |
| 10.7h                    | 0.00151 | 2.4331            |

D. Mean load prediction

As you can see from the Figure 6, Compared with the methods based on Bayes [11], PSR+EA-GMDH [14], AutoEncoder+ESN [22], LSTM [16], etc., our proposed methods are significantly better than other methods in the mean load prediction task. Compared with the state-of-art methods, such as LSTM-ED [18], the prediction performance of our method also has advantages. Although the prediction performance based on the LSTM-ED method with the increase of the prediction length is relatively stable, this is because the method uses the encoder-decoder structure and introduces the context vector to save the feature information for a long time, which can enable the model to obtain longer temporal information. Compared with the method based on LSTM-ED, the method based on BiLSTM network mentioned has achieved better prediction performance for the mean load prediction task on the Google cluster trace dataset.

Figure 7 shows the comparison of host load prediction performance between our proposed model and AutoEncoder+ESN [15], LSTM [16], and LSTM-ED [18] under different prediction lengths. Figure 7 clearly shows that the prediction accuracy of the model proposed is better than...
the other three models at all prediction lengths. Different from the AutoEncoder+ESN model, different from the LSTM and LSTM-ED models, the BiLSTM model mentioned can not only model the temporal dependency from the historical information of the host load, but also extract the feature information from the future host load changes. Compared with LSTM and LSTM-ED, BiLSTM-based model can obtain more powerful nonlinear generalization ability.

E. Actual load prediction

In order to better show the actual load prediction performance comparison, our method also considers the cumulative distribution function (CDF) of all comparison models MSE, that is, the probability distribution of all data less than or equal to the current MSE value, CDF is accurate for the analysis model Harmony and stability are of great help. In the field of host load prediction, many studies [16,15,18] have adopted MSE’s CDF as an indicator to evaluate the accuracy of the model. In particular, the MSE’s CDF graph can clearly depict the distribution of different models’ MSE. Figure 8 depicts the CDF of the MSE results of seven different prediction methods. Each data point in the CDF curve describes the proportion of all MSE values that are less than or equal to the horizontal coordinate of the point (that is, the value corresponding to the vertical coordinate of the point), it is worth noting that the closer the CDF curve is to the vertical axis, the higher the accuracy of the corresponding model. It can be seen from Figures 8 that the AR-based model [23] and the ANN-based model [13] are different from the CDF curve of other models. Under different predicted lengths, the ordinate value corresponding to 0.025 on the horizontal axis of the CDF Significantly less than 1, that is, the proportion of all data points whose MSE is less than or equal to 0.025 is significantly less than 1. Therefore, they have poor accuracy, leading to low accuracy for two main reasons: (1) their non-linear generalization ability is poor and they cannot complete the multi-step prediction task in advance; (2) they cannot effectively use the historical host load fluctuation information. In addition, you can see that the AutoEncoder+ESN, LSTM, LSTM-ED, and our proposed method, all MSE values on 1000 machines are basically less than 0.025. This is mainly because they are all RNN-based models. The load data is modeled, and it can be seen that as the predicted length increases, the CDF curve of MSE also shifts to the right. The corresponding map 3-10 depicts the MSE distribution of the different prediction methods under the load data of all test hosts.

Figure 9 is expressed in the form of a box plot. The box plot can clearly see all the prediction errors under different prediction lengths. The median is smaller than the other 6 prediction models. Therefore, under all prediction lengths, our proposed method has better prediction accuracy than the other 6 models.
F. Prediction results

In order to give an insight into the predictions, two results are present in Figure [10] and Figure [11], which both have poor autocorrelation and drastic fluctuates. One is the host cpu load on the Google cluster data in different prediction length. The other is the host memory utilization prediction results with different prediction length which machine_id=5411731657 in Google cluster data. In this case, Our method can give satisfactory performances and perfect predictions for six different prediction lengths.

V. CONCLUSION

We have proposed a method based on Bi-directional Long Short-Term Memory (BiLSTM) for host load prediction. The proposed method can effectively perform the mean load prediction task and the actual load prediction task using Google load trace data. Different from other deep learning based methods, our proposed method can simultaneously consider the historical information and future information of the host load. Because our proposed model is limited with size, the discarding method and the early stopping method are used to alleviate the overfitting problem in the model training process. The effect of further prediction length on the prediction performance of the proposed method is analyzed through numerical examples, and the effectiveness of the proposed method in short-term load and long-term load prediction tasks is further verified through comparative experiments. Finally, the prediction performance of our proposed method is compared with the state-of-art methods, and the results also verify the effectiveness of our proposed method. In addition, our proposed method can concisely and effectively implement a series of tasks such as Google cloud trace data collection and host load prediction. Therefore, the research can provide new solutions and ideas for end-to-end host load prediction in cloud computing environment.

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Fig. 10: The actual CPU load prediction results with different prediction lengths in Google cluster data.

Fig. 11: The actual memory load prediction results with different prediction lengths in Google cluster data.

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Xuehai Hong is received the Postdoctoral in department of computer science from Beijing University in 2003. He is an professor level senior engineer in the Institute of Computing Technology, Chinese Academy. His research interests are in Cloud Computing and Machine Learning.

Hengheng Shen is received Bachelors degree in Computer Science and Technology from Anyang Institute of Technology in 2017, Anyang, China. Masters degrees in Institute of Computing Technology, Chinese Academy, Beijing, China. His research interests are in Cloud Computing and Machine Learning.