

## Research on the Remaining Load Forecasting of Micro-Grid based on Improved Online Sequential Extreme Learning Machine

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**Abstract.** In order to improve the forecast accuracy and stability of the micro-grid uncontrollable remaining load and provide a more reliable basis for micro-grid power generation plan, an ultra-short-term micro-grid uncontrollable remaining load forecasting model based on the improved online sequential Extreme Learning Machine is proposed. Aimed at the wind and solar power generation and load characteristics, the weight update of old and new training data is added to the Extreme Learning Machine. And the average value of multi-module is used to enhance the predict stability of the algorithm. After the real data from UCI Machine Learning Repository is analyzed, the result shows that the algorithm is superior to the traditional Extreme Learning Machine (ELM) and the online sequential Extreme Learning Machine (OS-ELM) and the proposed algorithm is feasible.

### Introduction

The micro-grid has been a hot topic of power system [1]. Micro-grid can be seen as the "power" can also be seen as a "burden". So it could be run standalone in some special places like in remote mountain areas or islets [2]. Micro-power supply of micro-grid mainly includes two categories [3] which are controllable and uncontrollable micro-power supply. Controllable micro-power supply ensures stability and regulation, to achieve stable and efficient operation of independent micro-grid [4]. Uncontrollable micro-power supply mainly includes wind turbines and solar panels.

Due to the small scale of micro-grid, so accurately ultra-short-term remaining load forecast can be said to be the micro-grid system planning basis. Yan Gang put forward a kind of prediction method based on Improved LS-SVM algorithm [5]. Algorithm based on evolutionary neural network and the short-term power load forecasting model of chaotic feature selection is put forward by Sajjad Kouhi [6]. Although both SVM and evolutionary Neural Networks have strong nonlinear identification ability, good accuracy, and good global search ability. There are defects such as weak generalization ability and slow training speed. Guang-Bin Huang put forward a new single hidden layer neural networks algorithm, called the Extreme Learning Machine (ELM) [7]. ELM and its extension have obtained good effect in wind [8] or solar [9] power prediction and load forecasting [10]. ELM has improved rapidly in training speed, but still need to be repeated scanning history data and update model to achieve the ideal predictive effect. The literature [11] put forward a kind of online sequential ELM (OS-ELM). When updating model, just enter the current training data blocks, without repeated scanning the historical data. Based on the literature [11], Sun Yigang came up with weighted OS-ELM (WOS-ELM) for discovering fault diagnosis of aircraft engine sensor [12].

Considering the old and new data and contingency of predicting remaining load, there came up with the concept of uncontrollable remaining load and multiple models WOS-ELM (MM-WOS-ELM) prediction algorithm, according to the literature [13] proposed the concept of remaining load. Adding the weight update of new and old training data on the basis of OS-ELM made the prediction model more focus on training data which had higher predicting accuracy. Because of predict accident of OS-ELM, there could be more than one model of OS-ELM and made the mean value of multiple models output as the final output of the prediction model. This paper

analyzes power load of multiple families and real wind data and illumination intensity per minute in micro-grid and compares with the predictive result of ELM, OS-ELM and WOS-ELM.

### The Micro-Grid Uncontrollable Remaining Load

The remaining load of micro-grid refers to the difference between the total of all loads with the sum of all output power of micro-powers.

Accurate ultra-short-term load forecasting uncontrollable micro-power supply can provide decision basis for generation of controllable micro-power. When the value is greater than 0, show the generation of uncontrollable micro-power cannot be met by total electricity load, it requires other micro-power supply. But when the value is less than 0, show the generation can.

The uncontrollable micro-power supply is very common by using wind or solar. The power output characteristics can be show through their mathematical model respectively. Their power model is important basis of forecasting. The formula of generated power  $P_{wind}$  which is changed with wind speed  $v_{wind}$  is described as follows [14],

$$P_{wind} = \begin{cases} P_R \frac{v_{wind}^3 - v_l^3}{v_R^3 - v_l^3}, & v_l \leq v_{wind} \leq v_R \\ P_R, & v_R \leq v_{wind} \leq v_h \\ 0, & v_h \leq v_{wind} \text{ or } v_{wind} \leq v_l \end{cases} \quad (1)$$

with  $P_R$  as normal power output of wind turbine,  $v_l$  as cut-in wind speed,  $v_h$  as cut-out wind speed and  $v_R$  as rated wind speed.

Rated power output of photovoltaic power generation is calculated in the standard state. The output power formula of photovoltaic power generation is described as follows [15],

$$P_s = \begin{cases} P_{STC} \frac{G_s}{G_{STC}} (1 + k(T_c - T_R)), & G_s > C \\ 0, & G_s \leq C \end{cases} \quad (2)$$

with  $P_s$  as the output power when light intensity is  $G_s$ ,  $P_{STC}$  as the maximum output power under standard state,  $G_s$  as real-time light intensity,  $G_{STC}$  as the light intensity under standard state,  $k$  as the output correlation coefficient of temperature and power.  $T_c$  as real-time temperature of photovoltaic cells,  $T_R$  as the temperature under standard state and  $C$  which is constant as the basic threshold of light intensity.

### The Online Sequential Extreme Learning Machine

OS-ELM makes the training data block as the unit and adds new historical data block to training network which avoids consuming a lot of time in training. OS-ELM can be divided into two steps as a whole, including initial stage and continuous learning stage.

In initial stage, setting the number of hidden layer nodes ( $L$ ) and making a portion of the training sample as initialize learning. If the count of initial training sample is  $N_0$ ,  $N_0 \geq L$  is necessary. Then, weight vector ( $W_j$ ) and bias ( $b_j$ ) in hidden layer are generated, and calculating initial output matrix ( $H_0$ ) in hidden layer. The initial output weight vector ( $\beta_0$ ) could be calculated as follows,

$$\beta_0 = P_0 H_0^T T_0 = (H_0^T H_0)^{-1} H_0^T T_0 \quad (3)$$

with  $T_0$  as expectations.

In continuous learning stage, suppose the first  $k+1$  training data is  $X_{k+1} = \{(X_t, T_t)\}_{t=1+\sum_{j=0}^k N_j}$  and the number of its samples is  $N_{k+1}$ , the output matrix ( $H_{k+1}$ ) can

be confirmed. Now suppose the first  $k$  training data has successfully enter the model, and there is  $K_k = H_k^T H_k$ . When the first  $k+1$  data block compares to input,  $K_{k+1}$  can be represented by  $H_k$  and  $H_{k+1}$  as follows,

$$K_{k+1} = \begin{bmatrix} H_k \\ H_{k+1} \end{bmatrix}^T \begin{bmatrix} H_k \\ H_{k+1} \end{bmatrix} = K_k + H_{k+1}^T H_{k+1} \quad (4)$$

Now,  $K_{k+1}^{-1} = P_{k+1}$  and updating output bias as follows,

$$\beta_{k+1} = \beta_k + P_{k+1} H_{k+1}^T (T_{k+1} - H_{k+1} \beta_k) \quad (5)$$

Because calculating inverse matrix of  $K_{k+1}$  can cost a lot of time, in order to avoid inverting matrix and  $K_{k+1}^{-1} = P_{k+1}$ , according to Eq. (4), there is a formula as follows

$$P_{k+1} = P_k - P_k \times H_{k+1}^T \times (I + H_{k+1} \times P_k \times H_{k+1}^T)^{-1} \times H_{k+1} \times P_k \quad (6)$$

Then  $k = k + 1$  and continue, until the next training data block is none.

### Algorithm Design Based on the Multi-Module Weighted Online Sequential ELM

Basis on Eq. (4), the matrix, which has old and new training data can be added weight on, is shown as follows,

$$K_{k+1} = \begin{bmatrix} H_k \\ \alpha H_{k+1} \end{bmatrix}^T \begin{bmatrix} H_k \\ \alpha H_{k+1} \end{bmatrix} \quad (7)$$

where  $\alpha$  is weight of new data block which is decided by last Root-Mean-Square Error (RMSE).

If  $RMSE \in [a, b]$ ,  $\alpha = 1$ . If  $RMSE < a$ ,  $\alpha = 0.995$ . If  $RMSE > b$ ,  $\alpha = 1.005$ . Calculating Eq. (7) and get function as follows,

$$K_{k+1} = K_k + \alpha^2 H_{k+1}^T H_{k+1} \quad (8)$$

Inversing Eq. (8) on both sides of the equal sign and  $K_{k+1}^{-1} = P_{k+1}$  and  $K_k^{-1} = P_k$ , there are equation as follows,

$$P_{k+1} = P_k - P_k \times H_{k+1}^T \times (I/\alpha + H_{k+1} \times P_k \times H_{k+1}^T)^{-1} \times H_{k+1} \times P_k \quad (9)$$

In this paper, the WOS-ELM model is processed aimed at the predict error.

Multiple model prediction is combined with WOS-ELM modules which number is M. To avoid the error of output is too large, figuring up the average of all WOS-ELM modules output as follows,

$$o_t = \frac{1}{M} \sum_{j=1}^M o_t^j \quad (10)$$

where  $o_t^j$  is the first j model output.

The main idea of MM-WOS-ELM is to update weights and to calculate the average of modules.

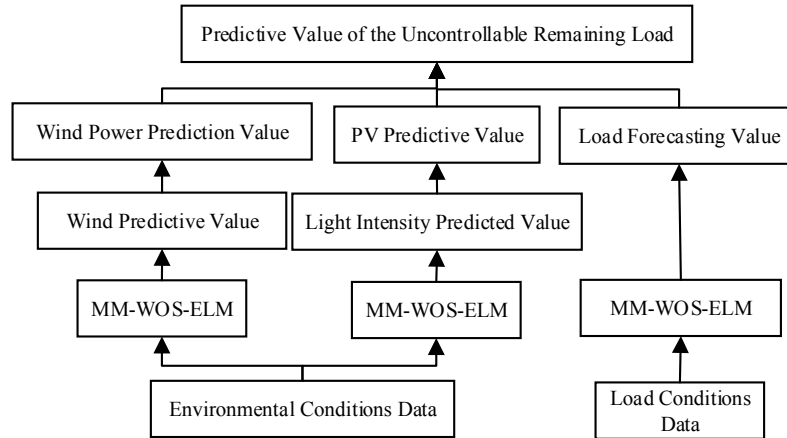


Fig.1. Uncontrollable remaining load forecasting model based on MM-WOS-ELM

The specific steps of MM-WOS-ELM are shown as follows,

- (1) Getting historical training data sets and the data sets were input to WOS-ELM modules.
- (2) According to the WOS-ELM training logic, train these WOS-ELM modules respectively.
- (3) After getting results of modules, the average must be calculated. This value is regarded as the final prediction value of the whole model.
- (4) Slide along the data time axis and access to new historical data, each WOS-ELM modules update their own training data right weight values based on the last real historical data. Then return to the step (1) for next circulation.

The uncontrollable remaining load forecasting model based on MM-WOS-ELM is shown in Figure 1.

## Experiment and Example Analysis

The remaining load forecasting accuracy uses the Root Mean Square Error (RMSE) for testing indicators as follows,

$$RMSE = \sqrt{\frac{1}{N} \sum_{t=1}^N (o_t - T_t)^2} \quad (11)$$

where  $N$  is the number of prediction values one time,  $o_t$  is the first  $t$  prediction value and  $T_t$  is the first  $t$  true value.

The stability of the algorithm uses the Standard Deviation (SD) as a measure. The formula is described as follows,

$$SD = \sqrt{\frac{1}{N} \sum_{i=1}^N (RMSE_i - \overline{RMSE})^2} \quad (12)$$

where  $N$  is the total number of test errors,  $RMSE_i$  is the first  $i$  of  $RMSE$  and  $\overline{RMSE}$  is the average of  $RMSE$  under several tests.

Considering the algorithm running time, forecasting accuracy and forecast stability, add the three normalized data as a comprehensive index.

$$Syn = Time_{norm} + RMSE_{norm} + SD_{norm} \quad (13)$$

with  $Syn$  as comprehensive index of algorithm,  $Time_{norm}$  as algorithm running time,  $RMSE_{norm}$  as the  $RMSE$  of prediction algorithm and  $SD_{norm}$  as the SD of forecasting accuracy.

The input samples include two classes. One is the training data set of load which includes date, time and temperature. Another is the training data set of environment including date, time, temperature, precipitation and atmospheric humidity. Both two training data sets are normalized. The experimental targets are predicting wind speed, light intensity and electricity load, and then calculate the uncontrollable remaining load.

Micro-grid data, which is from 11:45 on March 13, 2012 to 2:00 on April 4 provided by UCI Machine Learning Repository website, used in this experiment. Determining the number of WOS-ELM modules based on integrated indicators. And MM-WOS-ELM was compared with ELM, OS-ELM and WOS-ELM in forecast accuracy and stability. By comparing with these three algorithms, test the MM-WOS-ELM prediction performance of the algorithm in this paper.

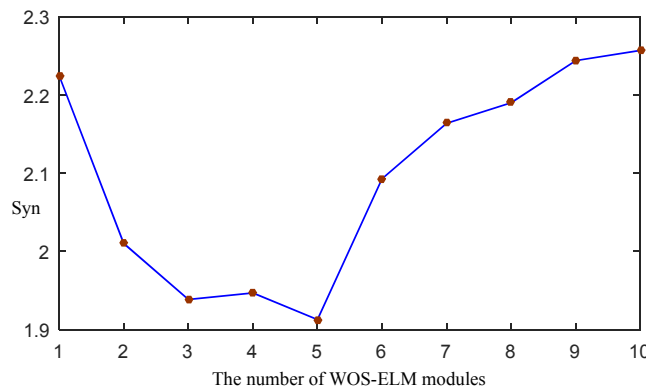


Fig.2. Integrated indicators of algorithm which has different number of WOS-ELM modules

For confirming the number of WOS-ELM modules through test data, this experiment took calculating comprehensive index as the objective function. In order to ensure the objectivity of the experiment, the number of modules was tested from 1 to 10 one hundred times, and used the average as the final result. The relationship between the number of modules and integrated indicators is shown in Figure 2. As it is shown in Figure 2, when the module number is 5,  $Syn$  is minimum. Therefore, the following experiments were carried out based on the number of modules is 5.

Observe the algorithm prediction accuracy through RMSE. In order to ensure the accuracy and objectivity of predictions, experimented 50 times and the average value as a result of each algorithm. The RMSE of remaining load forecasting by using 4 algorithms is shown in Table 1. From Table 1, it can be seen that the RMSE of MM-WOS-ELM is minimum. It means that the performance of MM-WOS-ELM is better than ELM, OS-ELM, WOS-ELM.

Test data was used as predicted data which was from 18:45 on April 3, 2012 to the next day 2:00. Figure 3 are the charts which MM-WOS-ELM compared with ELM, OS-ELM and WOS-ELM respectively.

Tab.1. Prediction RMSE based on MM-WOS-ELM, OS-ELM, OS-ELM and WOS-ELM in test samples

Prediction Algorithm	RMSE
MM-WOS-ELM	2.2956
ELM	2.7976
OS-ELM	2.4817
WOS-ELM	2.3620

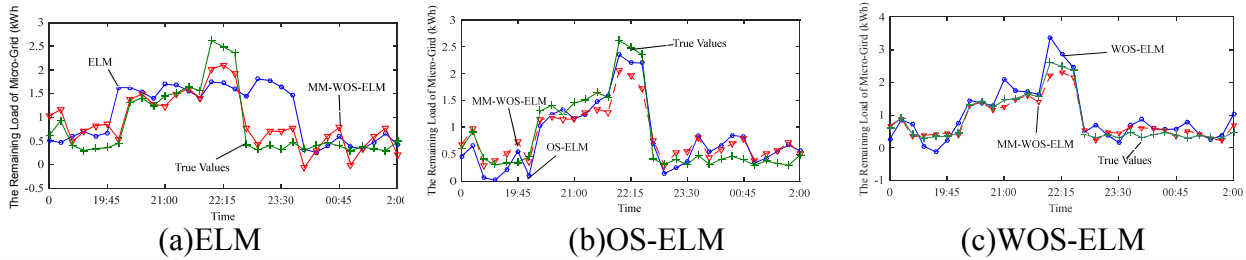


Fig.3. Comparisons of the actual uncontrollable remaining load profile and the predicted ones by MM-WOS-ELM and others from 18:45 on April 3th, 2012 to 2:00 next day

Predict stability was calculated by using the Standard Deviation of RMSE. And stability of MM-WOS-ELM was compared with that of ELM, OS-ELM and WOS-ELM. This experimented 100 times to obtain the value of each of the RMSE and the average of these values as Table 2. From Table 2, the Standard Deviation of MM-WOS-ELM is minimum and that of ELM is maximum.

Tab.2. Comparisons of the Stability of RMSE based on MM-WOS-ELM, OS-ELM, OS-ELM and WOS-ELM in test samples

Prediction Algorithm	DS of RMSE
MM-WOS-ELM	0.0435
ELM	0.1324
OS-ELM	0.0950
WOS-ELM	0.1049

## Conclusion

With the development of distributed energy, as well as the popularity of the smart grid, micro-grid has also gradually become the research target of people. Micro-grid which is an important part in the field of smart grid, has broad application prospects in the commercial and industrial area, city area and in remote areas. However, the investment and operational cost of micro-grid are higher. So we need to balance the power load and the generation of micro-power supply, and develop appropriate power plan to make the lowest cost. This article in view of the remaining load forecasting, puts forward the prediction algorithm of MM-WOS-ELM, which not only can accurately predict the relationship between the power load and the uncontrolled generation of micro-power supply, but also improve the stability of prediction.

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