ARTIFICIAL INTELLIGENT TECHNIQUES FOR SOLAR ENERGY GENERATION & HOUSEHOLD LOAD FORECASTING

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Abstract:

In this paper, two short-term power prediction method based on singular spectrum analysis (SSA) and Stacking ensemble learning framework have been proposed. A household load forecasting method based on multiple cycles self-boosted neural network named as MultiCycleNet was also proposed. Simulation results have been used to demonstrate the benefits for the methods.

Keywords:

Machine Learning; Solar Energy; Household Load

1. INTRODUCTION

Photovoltaic power generation is one of the main forces of clean energy. Due to the purpose of smooth transition to net zero by 2050, with zero fuel-cost, it is one of the most highly anticipated energy for electricity production [1]. The installed capacity of photovoltaic power generation will face a period of continuous growth, while the safety and stability of large-scale penetration photovoltaic power supply and power grid operation reliability will have been greatly challenged. These challenges are mainly due to high variability and non-dispatchability of photovoltaic power generations [2]. Therefore, precise photovoltaic power prediction has a significance influence on the stable operation of the power grid. In this aspect, the forecast for time series of active power plays an important role in the safe economic operation and reliable scheduling of the power grid scenario.

Some researchers believe that photovoltaics and electric vehicles (Solar-EV city) can jointly play a key role in deep decarbonization [3] and household load is an important component of electricity consumption. The accurate time series forecasting of photovoltaic active power and household load have a significant influence to the future. Photovoltaic power generation is greatly affected by the weather, and its output power is highly unstable. The uncertainty of household electricity load forecasting due to customers behavior and weather conditions when it comes to consuming energy [4] is a big issue to smart energy matter which is one the major domains in smart cities development [5].

In previous studies, many researches on time series forecasting mainly includes physical methods, statistical method, statistical methods and machine learning methods [6]. With the gradual emergence of artificial intelligence, machine learning methods have become most popular approach for solar irradiance forecasting [7]. Machine learning algorithm have shown superiority over time series prediction using multidimensional features as input variables [4]. Thus, the proposed time series forecasting model uses multidimensional features such as different weather features in PV active power forecasting and different applications in household load forecasting.

Derivative-Free Optimization (DFO) technique with deep learning models have been used an efficient feature selection via ensemble structures to predict a variety of renewable energy systems which are periodic and express repetitive behaviors [8]. Ensemble methods have been widely deployed for forecasting applications due to their ease of implementation [9]. Multiple models are combined in order to integrate the benefits of different models, the advantage of employing an ensemble approach over simple machine learning methods is that the ensemble models can enhance the prediction accuracy by integrating the benefits of multiple models [7].

The rest of this paper is organized as follows. In Section 2, two short-term power prediction method based on singular spectrum analysis (SSA) and Stacking ensemble learning framework are proposed. After that, the proposed methods are evaluated in Section 3. Finally, Section 4 gives some conclusions.
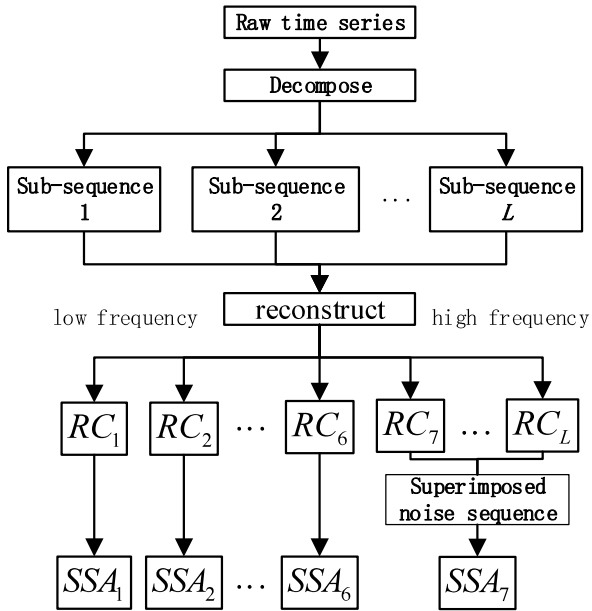
2. METHODOLOGY

FIGURE 1 Singular spectrum analysis process

This section proposes a short-term PV power prediction method based on SSA and Stacking ensemble learning, which decomposes the weather feature input and power output into multi-subsequences of level-0 learner for training. Considering the similarity of the same weather type, the original sample set is divided into three weather types (sunny, cloudy and rainy). And then these weather sets are used as the input feature series, while the historical PV active power is used as the output variable series. As shown in Figure 1, SSA is performed on the input feature sequence and output variable sequence respectively, and 7 sub-sequences with different frequencies are decomposed respectively and, in which are sub-sequences reconstructed by SSA respectively. RC is defined as the reconstructed sequence.

Figure 2 illustrates the Stacking ensemble learning framework. Firstly, the recurrent neural network (RNN), long short-term memory (LSTM) and gated recurrent unit (GRU) are used as the learner to train sub-sequence prediction model, and $\{\hat{y}_1^{RNN}, \hat{y}_2^{RNN}, ..., \hat{y}_7^{RNN}\}$, $\{\hat{y}_1^{LSTM}, \hat{y}_2^{LSTM}, ..., \hat{y}_7^{LSTM}\}$ and $\{\hat{y}_{1t}^{GRU}, \hat{y}_{2t}^{GRU}, ..., \hat{y}_{7t}^{GRU}\}$ level-0 sequences are predicted. These forecasts serve as the input feature set for the learners of the level-1, in which RNN, LSTM and GRU are used as the learner to train the level-1 prediction model, and the results of the level-1 prediction model is $\{\hat{y}^{RNN}, \hat{y}^{LSTM}, \hat{y}^{GRU}\}$. And then these results are used as the input feature set for the learner of

the level-2 prediction model under different weather conditions. After the model training in three stages, the ensemble learning PV power prediction framework based on SSA-Stacking in different weather conditions is obtained, and the prediction result sequence $\hat{y}$ is obtained.

After that, a household load forecasting method based on multiple cycles self-boosted neural network named as Multi-CycleNet was proposed [10], which is shown in Figure 3. With the household load information in similar historical cycle, the method tries to realize the learning of power consumption rule.
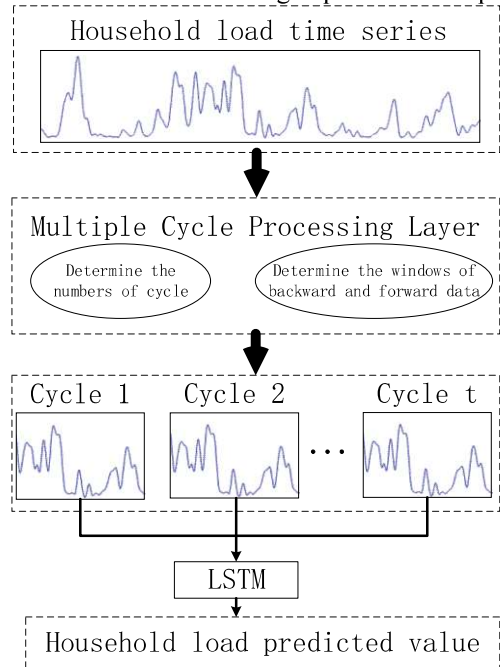

FIGURE 3 The key processes of the MultiCycleNet framework

3. RESULTS

To evaluate the effect of the model, Mean Absolute Percentage Error (MAPE) is selected as the main index for the prediction performance of each model, while the Root Mean Square Error (RMSE) and the Mean Absolute Error (MAE) is selected to evaluate the dispersion degree of the predicted values.

Actual data of Alice Spring photovoltaic power plant in Australia is used for model comparison. The total number of training samples is 700 days, 70% of which are taken as training set and others for verification. The meteorological information collected by the photovoltaic generation includes Global Horizontal Radiation(W/m2), Diffuse Horizontal Radiation (W/m2), Weather Temperature Celsius (℃), Weather Relative Humidity (%), Wind Speed (m/s), Wind Direction

(Degrees) and Weather Daily Rainfall (mm). The data sampling period is 5min, that is, 288 sets of data are collected every day and the output variable is Active Power (kW).

The sub-sequence after SSA and the raw sequence (Raw) without mode decomposition are compared by using level-1 or level-2 learner. Three groups of comparison experiments are conducted for sunny, cloudy and rainy weather conditions. The experimental results are shown in Figure 4, and the forecasting errors are shown in Table I.

It can be seen that MAPE decreases 85%, 14.1% and 16.7% with SSA-Stacking compared to raw-Stacking on sunny, cloudy, and rainy day, respectively. SSA-Stacking improves forecasting accuracy based on the smoothness of the Lever-1 model forecasting curves, coupled with SSA-Stacking performance.

4. CONCLUSIONS

In this paper, hybrid techniques based on artificial intelligence have been proposed and with simulation results, this demonstrated that the proposed approaches and methods are feasible and better than the state-of-the-art techniques. For future work, it is essential to test the methods with more real-life data. The potential in using artificial intelligence should further be considered to formulate some recommendations for standards development too.
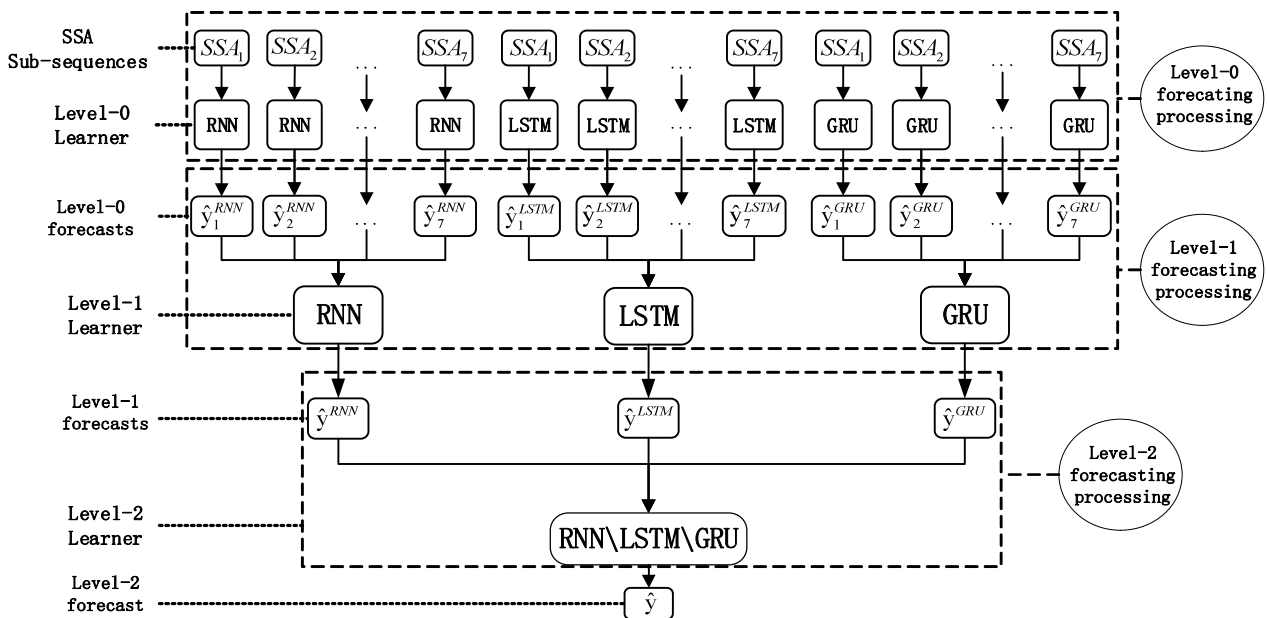

FIGURE 2 Short-term PV power time series forecasting method based on SSA-Stacking ensemble learning framework
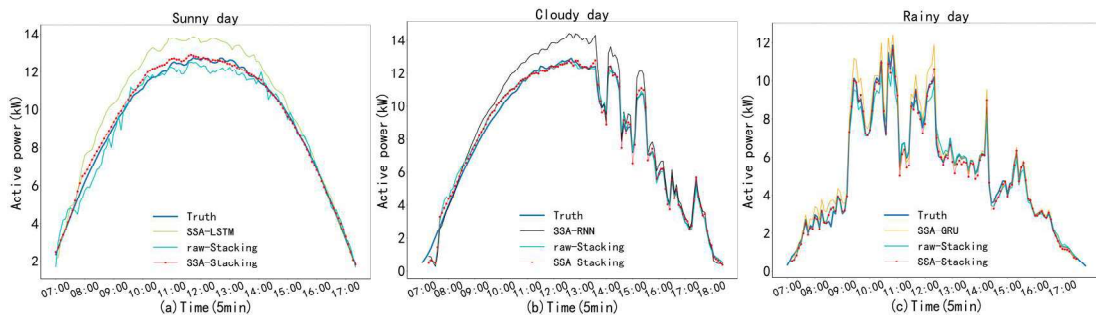

FIGURE 4 Illustration of forecasts by different models

TABLE 1. The forecasting error of different models

Weather	Method	MAPE(%)	RMS(kW)	MAE(kW)
Sunny day	SSA-LSTM	11.12	0.90	0.75
	SSA-GRU	11.41	0.86	0.75
	SSA-RNN	11.45	1.01	0.87
	raw-Stacking	6.92	0.42	0.34
	SSA-Stacking	**3.74**	**0.22**	**0.17**
Cloudy day	SSA-LSTM	13.66	1.05	0.92
	SSA-GRU	12.42	0.96	0.83
	SSA-RNN	11.14	0.91	0.74
	raw-Stacking	7.03	0.35	0.26
	SSA-Stacking	**6.16**	**0.33**	**0.25**
Rainy day	SSA-LSTM	9.64	0.41	0.33
	SSA-GRU	8.07	0.47	0.34
	SSA-RNN	11.57	0.5	0.4
	raw-Stacking	6.7	0.35	0.24
	SSA-Stacking	**5.74**	**0.22**	**0.17**

ACKNOWLEDGEMENTS

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