Interval State Estimation Considering Randomness of Multiple Distributed Generations in Active Distribution Networks

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Abstract. The high-permeability Distributed Generation (DG) was connected to the power grid, so that the state estimation of the active distribution network(ADN) needs to consider the uncertainty of the DG output. In this paper, an interval state estimation method for active distribution network considering the randomness of Wind Turbine and PV output is proposed. The method uses the Extreme Learning Machine (ELM) to model the randomness of Wind Turbines and PV output in the form of interval numbers, and to perform ultra-short-term prediction on Wind Turbines and PV output interval, and use the output interval as pseudo measurement, based on the particle swarm optimization(PSO) State estimation of the ADN. The results of IEEE-33 system verification show that the state estimation results obtained by PSO algorithm are more accurate than the traditional weighted least square (WLS); the state estimation result presents an interval form, which can provide the dispatcher with a more intuitive system state quantity upper and lower bound information.

Introduction

The intermittent power generation of high-permeability DG makes it necessary to consider more uncertain factors. The accuracy of the estimation results obtained by traditional methods can not meet the dispatching requirements[1]. Therefore, it is worthwhile to model reasonably the uncertainty of DG output and increase accuracy of AND state estimation.

For the uncertain modeling of DG output, literature [2] regards DG output as the pseudo-measurement, ignoring the influence of DG output uncertainty. Document [3] treats DG as active power and reactive power injection nodes, but no specific physical model of DG is established. Literature [4] established a dynamic probability model of DG based on the difference in probability characteristics of DG at each time. However, the state estimation based on the probability distribution must obtain the detailed prior probability density function of each uncertainty in advance, carry out a large number of photovoltaic and wind power related data statistics, and make a prior assumption on the probability distribution of prediction errors, which results in a long time to solve the algorithm[5]. In addition, the probability density function of photovoltaic and wind power output is generally difficult to obtain, and it is only known in most cases. Upper and lower limits of power fluctuation [6]. Therefore, the interval number model can be used to describe the uncertainty problem in the state estimation model, so that it is not necessary to obtain the specific distribution of the parameters, and only need to pay attention to the upper and lower bounds of each uncertain variable, so the engineering application value is greater [7].

To solve these problems, an interval state estimation method considering the uncertainties of DG output is proposed in this paper. The example is verified by IEEE-33 system.

Uncertainty Modeling of DG Output

Photovoltaic Output Prediction Model

The main factors affecting photovoltaic output are: light intensity, ambient temperature, and weather type. The PV output prediction model is shown in Fig. 1. The input of the model is the light intensity, ambient temperature, and weather type. Therefore, the input layer node is set to 3; the output y_{max},

y_{min} are the upper and lower limits of the PV output prediction, so Set the output layer node to 2; the number of hidden layer nodes is set to 11.

Wind Turbine Output Prediction Model

The Wind Turbine output is mainly affected by the wind speed and the wind direction. The wind turbine output prediction model constructed by ELM is shown in Fig. 2. The input of the model is wind speed and wind direction. Therefore, the input layer node is set to 2; the output y_{max}, y_{min} are the upper and lower limits of the wind turbine output prediction, so the output layer node is set to 2, the number of hidden layer nodes is set to 12.
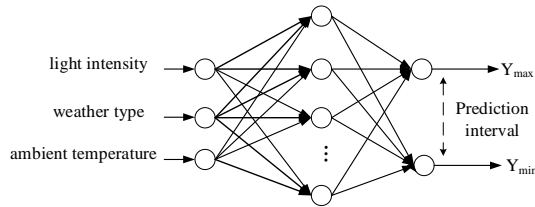

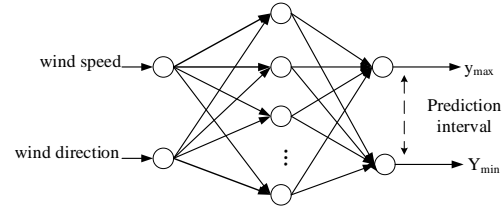Figure 1. Prediction model of photovoltaic output interval   Figure 2. Prediction model of fan output interval

ADN Interval State Estimation Model and Solution

Generally, In the actual distribution network the power measurement and current amplitude measuring device are installed only at the root or switch of the feeder [8], which will result in the insufficient number of real-time measurements.

Interval Number

The interval number can be represented an uncertainty that fluctuates within a certain range [9]:

$$A = [\underline{a}, \overline{a}] = \{a \in R, |\underline{a} \le x \le \overline{a}\}. \tag{1}$$

Where, $\underline{a}$ is the lower bound of the uncertainty of the uncertainty; $\overline{a}$ is the upper bound of the uncertainty of the uncertainty.

Objective Function

The measurement equation is:

$$z = h(x) + v. \tag{2}$$

Then the objective function of the state estimation is:

$$J(x) = [z - h(x)]^T R^{-1} [z - h(x)] \tag{3}$$

Consider the uncertainty interval of the state variable at the measurement device. The objective function of interval state estimation is established by using interval number theory. The original nonlinear measurement equation (2) becomes equation (4).

$$\begin{cases} \overline{z} = h(\overline{x}) + v \\ \underline{z} = h(\underline{x}) + v \end{cases}. \tag{4}$$

The objective function of such state estimation is changed from equation (3) to equation (5):

$$\begin{cases} J(\overline{x}) = [\overline{z} - h(\overline{x})]^T R^{-1} [\overline{z} - h(\overline{x})] \\ J(\underline{x}) = [\underline{z} - h(\underline{x})]^T R^{-1} [\underline{z} - h(\underline{x})] \end{cases}. \tag{5}$$

z is the measurement, $h(x)$ is the measurement function, v is the measurement error, x is the state variable, and R^{-1} is the measurement weight.

PSO for State Estimation Model

PSO does not require the objective function to be micro and continuous, so the particle swarm algorithm is used here to solve the state estimation.

In this paper, the phase angle Delta and the amplitude V of the node voltage are taken as state variables to solve the state estimation objective function formula (5).

Analysis of Examples

In this paper, the IEEE-33 system of distribution network is used to analyze the state estimation. In the IEEE-33 system, nodes 9, 15, 23, and 30 are DG access nodes. Nodes 15 and 23 are connected to PV with rated capacity of 400 kW, and nodes 9 and 30 are connected to Wind Turbine with a rated capacity of 500 kW. These nodes are all nodes without measuring devices.

PV Output Interval Prediction Simulation

The light intensity, ambient temperature, weather conditions and corresponding PV output of a PV station for one month are selected. Here, a PV station with a capacity of 400 kW is taken as an example. Fig. 3 shows the PV output prediction interval obtained by using the ELM PV prediction model.

Wind Power Output Interval Prediction and Simulation

Take a Wind Turbine with a capacity of 500kW as an example. The data of wind speed, direction and output of wind turbines for three months in a certain area are selected. In the prediction process, the measurement interval is 15 min. Fig. 4 shows the wind power output prediction interval obtained by using the ELM wind power prediction model.
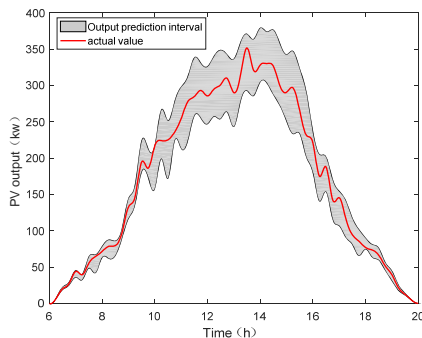

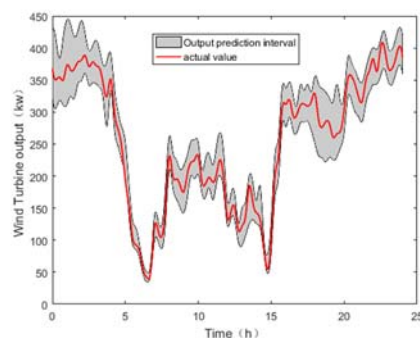Figure 3. Prediction curve of photovoltaic output interval

Figure 4. Prediction curve of fan output interval

Analysis of State Estimation Results

In order to reflect the results, the PV output interval [225.6-347.1] kW and the wind power output interval [171.2-198.4] kW were selected as the research objects in the time section (15:15). The state estimation results are shown in Fig 5a and Fig 5b. The true value of the system in the figure is the power flow calculation result of the IEEE-33 system connected to the DG.

It can be seen from the Fig. 5a and Fig. 5b that at any node of the network, the amplitude and phase angle of the node voltage also fluctuate within a certain range due to the interval fluctuation of DG output.
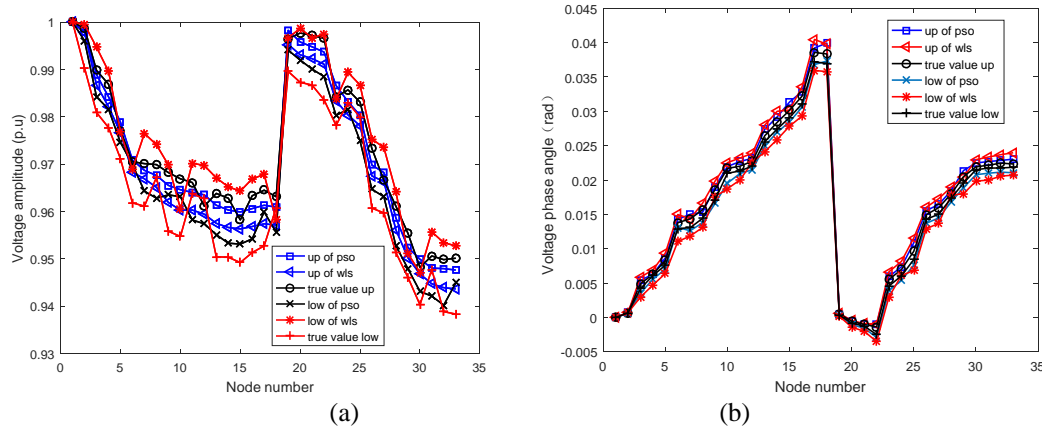
(a) (b)

Figure 5. (a) Voltage Amplitude State Estimation; (b) Voltage Phase Angle State Estimation

The interval results were evaluated by the average interval width.

Node voltage amplitude average interval width:

$$\psi_{Vare} = \frac{1}{n}\sum_{1}^{n}(\overline{V} - \underline{V})$$

(6)

Node voltage phase angle average interval width:

$$\psi_{\delta are} = \frac{1}{n}\sum_{1}^{n}(\overline{\delta} - \underline{\delta})$$

(7)

The state estimation average interval width obtained by the two algorithms is shown in Table 1.

Table 1. Average interval width of state estimation results under different algorithms

State estimation algorithm	Average interval width	
	ψ_{Vare}	$\psi_{\delta are}$
PSO	0.0307	0.0093
WLS	0.0491	0.0116

It can be seen from Table 1 that the interval of the state estimation results solved by the PSO is narrower than the interval width obtained by the WLS, which indicates that the accuracy of the estimation results based on the PSO is higher.

Conclusion

The following conclusions are drawn:

1) The state estimation results obtained by the PSO are more accurate than the WLS;

2) After describing the randomness of the wind turbine and the PV output in the form of interval numbers, the state estimation results also show the interval form.

The interval state estimation method proposed in this paper can provide dispatchers with more intuitive information about upper and lower bounds of system state variables, and provide corresponding reference for actual system scheduling and system decision-making.

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