A Novel Spinning Reserve Decision-Making Model for Power System with Considering Prediction Accuracy

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***Abstract*—the inherent factors, uncertainty and variability, are always existed in intermittent power resources such as wind and solar. Because of blind construction and lack of planning, the number of renewable generation plants are increasing dramatically, the transmission system could not afford such large capacity over such long distance. This paper proposes a novel spinning reserve decision-making model for power system with solar power integration. A new PV power generation forecasting model is established. The training target of neural network contains both accuracy section and maximum deviation section. In addition, Improved-Levenberg-Marquardt (ILM) algorithm is achieved for neural network training. A numerical study with practical data is presented and the result shows that new PV power generation forecasting model can reduce cost of construction of standby power plant with acceptable accuracy level. The proposed approach for spinning reserve decision-making with solar power integration power system is tested in a modified IEEE 9-bus 3-machine Benchmark Network.**

Keywords—solar power integration; neural network; spinning reserve; Improved-Levenberg-Marquardt (ILM) algorithm

I. Introduction

Solar energy is an important part of renewable energy, active development of solar power to improve the energy structure, promote energy conservation and emission reduction, improve the ecological environment is of great significance. However, due to the influence of natural factors, solar power has strong intermittency and random fluctuation, and the current prediction accuracy of solar power is not high. Large-scale solar power integration will have a great impact on the safe operation and economic dispatch of the power grid.

It is an important way to absorb large-scale solar power and reduce the risk of power grid operation to maintain sufficient rotating reserve of the system. Particularly, power regulation and reserve provided by conventional generations such as thermal and hydro are called in the minute to hour timeframes to complement the differences [1]. At the same time, the economy of power system dispatching must be considered, and the rotating reserve must be arranged reasonably. Many scholars have done a lot of research on the setting of rotating reserve and economic dispatching of power system with solar or wind power. A fast generation adjustment algorithm based on the base point and participation factors method is proposed in [2] to handle the fast fluctuations of loads and RESs. In [3], a reliability benefits quantification methodology from improved solar power forecasts was proposed, based on state-of-the-art solar power forecasts and a multi-timescale scheduling model. Instead of deterministic commands sent to wind farms, [4] proposed a robust wind power dispatch framework with minimum wind power curtailment and interval wind power schedule for wind farms with a set-point value-based schedule for the thermal units. A two-stage adaptive robust optimization model for the multi-period ED was proposed in [5], designed for a rolling-horizon operational framework to model the real time ED process. A hybrid computational framework based on quantum-inspired particle swarm optimization (QPSO) is proposed in [6] to achieve faster and better optimization performance for solving ED problems with considering carbon tax. A stochastic two-stage day-ahead unit commitment model and a rolling look-ahead economic dispatch model with the integration of concentrated solar power and wind resources was developed in [7] to assess the role of thermal energy storage and electric heater in the improvement of the system's operational flexibility. A Day-head solar Power Plant Forecasting Accuracy improvement on the hourly basis are proposed in [8]. The optimal mathematical formulation of regression model was provided. In addition, the paper gives the idea of empirical clasterization approach, providing significant improvement of prediction accuracy. Unlike conventional generation resources such as fossil fuels, large-scale integration of RES appears characteristics of intermittency and variability, imposing major challenges for power system operation. One is that the solar radiation is associated with solar panel output power, which is difficult to be accurately forecasted [9]. On the other hand, the output power generated by RES such as wind and solar possesses difficulties in precise controlling. To address the problem of predicting model accuracy and income inconsistency, [10] proposes a useful regularization method for neural network prediction.

The optimal reserve of the system is determined automatically through the interaction between the reserve cost and the risk cost, but the influence of the climbing constraint and the network constraint on the reserve is not considered. In addition, the above literature only considers the total amount of spare to meet the system requirements, but the accuracy and maximum deviation value, instead of a pure accuracy-based models should be considered as well. In this paper, both the accuracy and the maximum deviation value between the predicted value and the actual value are considered.

II. PV POWER GENERATION FORECASTING

A. Proposed Neural Network Based Forecasting Model

In traditional PV power generation forecasting models, accuracy is the only pursued target in PV power generation forecasting models. In general, a better accuracy will lead to better decision making. Actually, when the actual PV power generation is less than the predicted PV power generation, the standby power plant will be dispatched to generate electricity (such as coal-fired power plants) to compensate for the deviation power. Therefore, the maximum deviation between the predicted value and the actual value will affect construction scale and cost of the standby power plant. Thus, pure accuracy model may not bring optimal construction cost of standby power plant. In this case, a new PV power generation forecasting model is required to take into account both accuracy and maximum deviation value, instead of a pure accuracy models. In this paper, both the accuracy and the maximum deviation value between the predicted value and the actual value are considered. Equation (1) is the objective function for model training.

$$\min: obj = Err + \mu \cdot Max(err) \tag{1}$$

Where Err is a term to reflect the differences between the predicted value of PV power generation and the actual value of PV power generation. "$Max(err)$"is the maximum deviation between the predicted value of PV power generation and the actual value of PV power generation. "μ" is the maximum deviation coefficient, which represents the weight of maximum deviation.

When the actual PV power generation is less than the predicted PV power generation, the standby power plant will be dispatched to generate electricity (such as coal-fired power plants) to compensate for the deviation power. The construction scale of the standby power plant depends on "$Max(err)$". The larger the maximum deviation is, the greater the construction cost of standby power plant is, which is not conducive to economic benefits.

If the term "Err" is removed, the accuracy of the forecasting model cannot be guaranteed. When the accuracy is too low, the integration of PV power generation into the main grid will pose a huge risk. For this reason, "Err", "$Max(err)$" and "μ"are combined into the objective function to djust training relationship between accuracy and maximum deviation.

With strict accuracy requirement, decision make may decrease the "μ" so that a more accurate solution can be obtained. Oppositely, decision maker may increase the "μ" to obtain less construction cost of standby power plant. Different decision maker will have different error acceptance and have different minimum accuracy requirements.

- Objective Function Transformation

In this paper, back-propagation training is selected as the training process of neural network. In back-propagation model, the objective function is shown in (2) below.

$$\min: \begin{cases} obj = Err + \mu \cdot Max(err) \\ \quad\;\; = mean(Acc^2) + Max(Acc) \\ Acc = Y - T \end{cases} \tag{2}$$

In Equation (2), Y is a P×N matrix representing the output of neural network, which is the predicted value of PV power generation. T is a P×N matrix representing the training target, which is the actual value of PV power generation.

"$mean(Acc^2)$" is the mathematical expression of "Err", which represents accuracy of the forecasting model. It is the average deviation square of the predicted value and the actual value. "$Max(err)$"is the mathematical expression of "$\mu \cdot Max(err)$", which represents the maximum deviation between the predicted value of PV power generation and the actual value of PV power generation. It should be noted that "$Max(err)$"is not considered in traditional feed-forward neural network.

- Converting Non-derivable Functions into Derivable Functions

Back-propagation is a derivation based optimization method. But "$Max(err)$" is not derivable, therefore a substitute function in (3) can be used instead of "$Max(err)$".

$$Max(Acc) \approx \varepsilon(Acc) \cdot \ln(sum(e^{Acc})) \tag{3}$$

" $\varepsilon(Acc)$ " is a step function, which ensures that " $\varepsilon(Acc)$ " is one when predicted value is larger than the actual value. Otherwise, " $\varepsilon(Acc)$ " is zero. But step function is not derivable, therefore a substitute function in (4) can be used instead of " $\varepsilon(Acc)$ ".

$$\begin{cases} \varepsilon(Acc) \approx \dfrac{(\tanh(\alpha \cdot Acc)+1)}{2}, \alpha > 0 \\ \tanh(Acc) = \dfrac{e^{Acc} - e^{-Acc}}{e^{Acc} + e^{-Acc}} \end{cases} \tag{4}$$

The substitute function is similar to the activation function for neurons in feed-forward neural network. Fig.1 shows the function output with α =0.3、0.9、1.5 and positive infinity. It can be seen that the larger α value is, the closer " $\varepsilon(Acc)$ " is to the step function, which can ensure that the construction cost of the standby power plant will not be affected when predicted value of PV power generation is less than actual value of PV power generation.

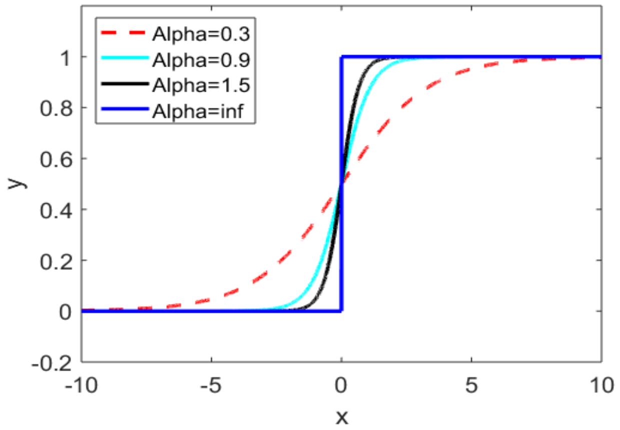


Figure.1 Function output with different α

" $\ln(sum(e^{Acc}))$ " is a derivable function which approximates the maximum value of Acc. Function *sum*() receives a P×N exponent matrix with base e. The index is Acc which is the deviation between the predicted value and the actual value, calculates the logarithm of the sum of all the matrix elements. Illumination data of 10,20,30,40,50 and 60 days were randomly selected and the maximum value within the sample days was calculated by using this approximation function. Table I shows maximum value obtained by the approximate function method, actual maximum value and deviation between them.

TABLE Ⅰ RELEVANT DATA OF SAMPLE DAYS

Days	Approximate Method Maximum (LUX)	Actual Maximum (LUX)	Deviation (LUX)
10	613.0556	613	0.556
20	636.6992	636	0.6992
30	690.0009	690	0.0009
40	690.0009	690	0.0009
50	690.0009	690	0.0009
60	690.0009	690	0.0009

As can be seen from the table, the maximum relative deviation between the maximum value obtained by the approximate function method and the actual maximum value is 0.11%, and this small deviation does not affect the training performance. Therefore, it is feasible to use derivable approximate function to get the maximum value.

- Variable Constrains of Objective Function

In combination with (2), (3) and (4), feed-forward neural network structure is adopted in training. For practical requirements, neural network output should be non-negative as PV power generation is always non-negative. At the same time, in order to ensure the minimum accuracy of the prediction model, it is necessary to add precision constraints. Thus, solution selection range should satisfy requirements in (5).

$$\begin{cases} Y > 0 \\ mean(\dfrac{|Acc|}{T}) \le K \end{cases} \tag{5}$$

Where K is the coefficient to limit prediction error set by neural network user. Function *mean*() receives a P × N matrix of the percentage deviation of predicted value from actual value, and calculates the average of all the matrix elements.

B. Improved-Levenberg-Marquardt Algorithm

Levenberg-Marquardt algorithm is used to solve non-linear squares problems. But objective function in (1) is not pure least square problem because of the maximum deviation part. Thus, this paper introduced an Improved-Levenberg-Marquardt (ILM) algorithm for neural network training. Fig.2 is ILM flow chart for feed-forward neural network.

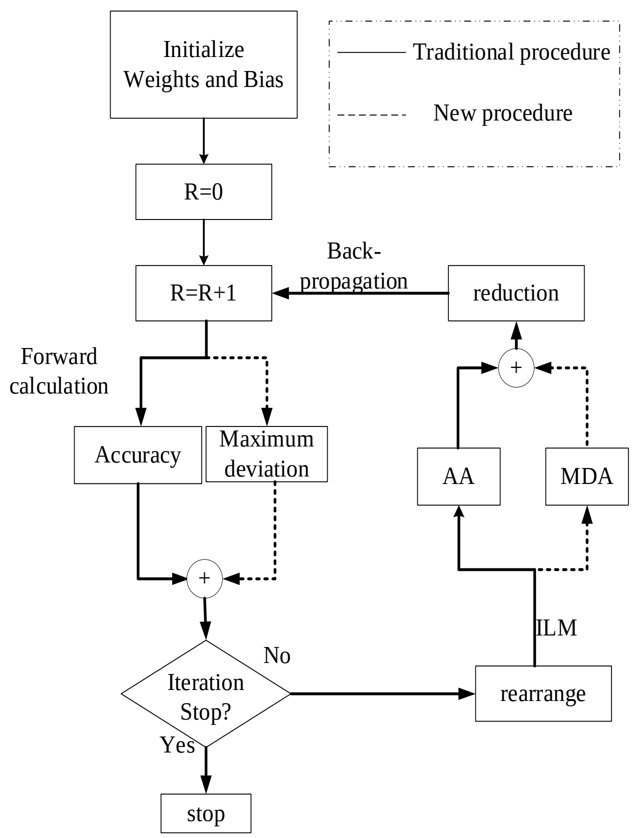


Figure.2 ILM flow chart for feed-forward neural network

As can be seen from Fig.2, this structure is quite different from traditional feed-forward neural network. There are two components in the process of back propagation. The first component is the accuracy adjustment (AA) of weight and bias. The second component is the maximum deviation adjustment (MDA) of weight and bias, which is different from traditional feed-forward neural network. Using the same forward calculation with traditional Levenberg-Marquardt algorithm represents that network operation after training ignores the maximum deviation between the predicted value and the actual value.

There are 4 steps to complete the arguments variation in back-propagation in ILM.

Step 1. Objective function transformation

The accuracy and maximum deviation of the objective function (1) are decomposed into (6).

$$\begin{cases} \min : obj = Err + \mu \cdot Max(err) \\ = \dfrac{\sum_{q=1}^{Q}(e_q^2)}{Q} + \varepsilon(e_q) \times \ln(\sum_{q=1}^{Q}(e^{e_q})) \end{cases} \tag{6}$$

Where e_q is the q_{th} element in vector Acc. Equation (6) shows that objective function of ILM is not least square problem, which is different from traditional Levenberg-Marquardt algorithm.

Step 2. Gradient computation

According to (6), the gradient of objective function and relative parameters are shown in (7).

$$\begin{cases} \nabla obj = \dfrac{2}{Q} \cdot J^T \times E + \mu \cdot J^T \times \Psi_1 \\ \Psi_1 = \varepsilon'(e_q) \times \ln(E_q) + \varepsilon(e_q) \times \dfrac{e^{e_q}}{E_q} \\ E_q = \sum_{q=1}^{Q}(e^{e_q}) \end{cases} \tag{7}$$

A new term constructed with Ψ_1 is introduced for maximum deviation representation.

Step 3. Hessian computation

Hessian matrix is derived from (7) as shown in (8).

$$\begin{cases} Hess = \dfrac{2}{Q}(J'^T \times E + J^T \times J) + \mu \cdot \Psi_2 \\ \Psi_2 = (J'^T \times \Psi_1 + J^T \times J \times e^{e_q} \times \Psi_3) \\ \Psi_3 = \dfrac{\varepsilon''(e_q) \times \ln(E_q)}{e^{e_q}} + \dfrac{2\varepsilon'(e_q) + \varepsilon(e_q)}{E_q} + \dfrac{e^{e_q} \times \varepsilon(e_q)}{E_q^2} \end{cases} \tag{8}$$

Compared with the traditional Levenberg-Marquardt algorithm, Hessian matrix in ILM is transformed into (8). In Equation (8), two new term Ψ_2 and Ψ_3 are introduced, which are related to the maximum deviation.

Step 4. Argument updated

According to (7) and (8), the parameter $X^{(r+1)}$ can be updates in (9).

$$X^{(r+1)} = X^{(r)} - [Hess^{(r)} + \lambda I]^{-1} \times \nabla obj^{(r)} \tag{9}$$

The update of weights and bias variation can be obtained from the corresponding elements from $X^{(r+1)}$.

III. Case Study And Discussion

The proposed approach in this paper for establishing spinning reserve decision-making model is tested in a modified IEEE 9-bus 3-machine Benchmark Network, shown in Figure 5. A 50MW Photovoltaic generation system is connected with Bus 9. The mathematical model for simulating the network is established in PowerFactory DIgSILENT Version 15.1, and the proposed algorithm is implemented with DIgSIELNT Programming Language (DPL) in the software package. In order to present realistic scenarios, 24 hours 93 days practical data of an individual solar farm and load data was applied into the system to calculate the required capacity for restraining fluctuation brought by intermittent power, such as wind and solar. OPF tool box with Interior Point method in DIgSILENT was used to simulate the scenarios. Generator fuel cost functions are stated in Table II.

TABLE II GENERATOR FUEL COST FUNCTIONS

Generator	Fuel Cost Function
G01	$0.11P^2+5P+150$
G02	$0.085P^2+1.2P+600$
G03	$0.1225P^2+1P+335$

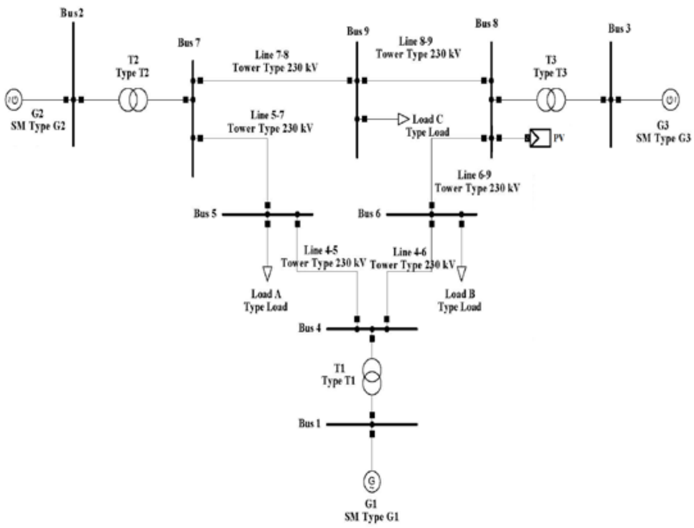
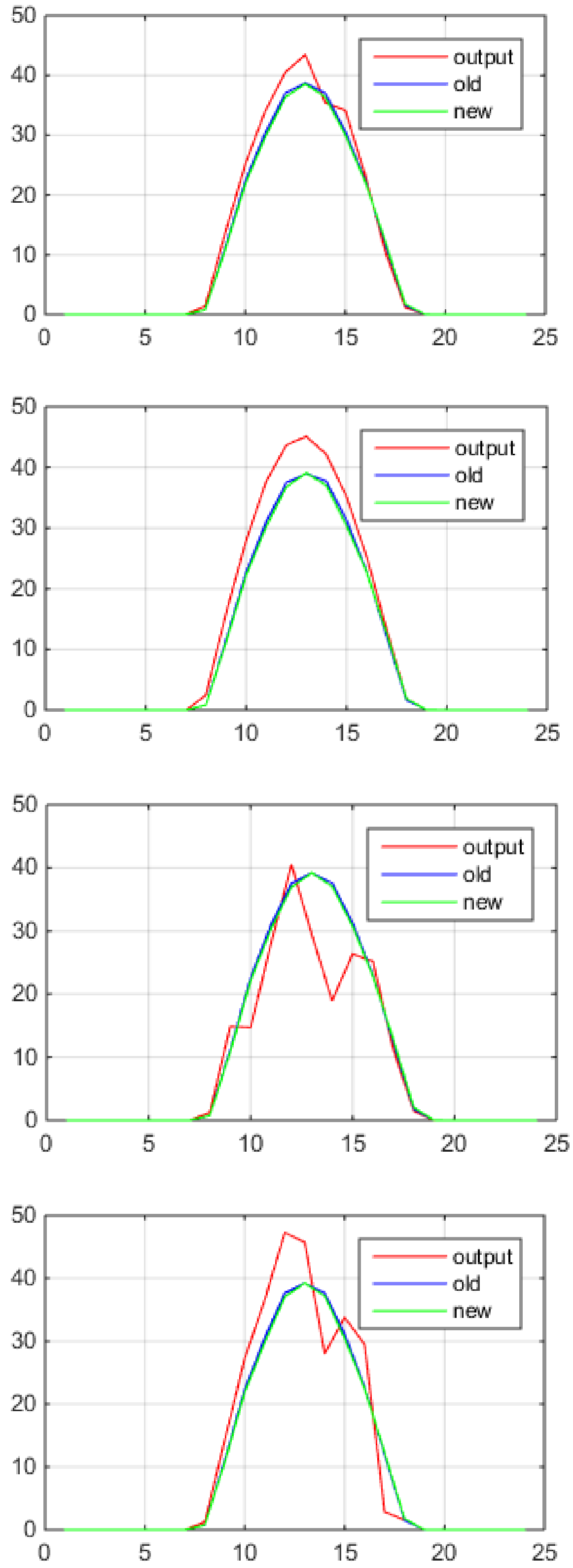


Figure.3 Modified IEEE 9-bus 3-machine Benchmark Network

As can be seen in Fig.4, predicted solar output power with the proposed new model are compared with that of old model and the real output power. In traditional neural network forecasting models, accuracy nearly becomes the only pursued target for PV power generation forecasting models. However, this may not reduce the scale and cost of construction of standby power plant. While in the proposed model, the training target of neural network contains both accuracy section and maximum deviation section.



(a)

(b)

(c)

(d)

Figure.4 Predicted solar power output with new and old models and real power output

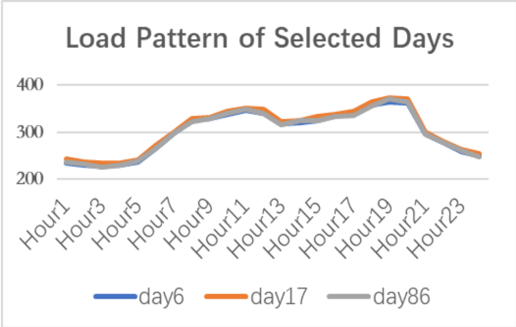


Figure.5 Load pattern of selected days

By the load pattern shown in Fig,5, the result can be obtained by optimal power flow calculation. Three evaluation indices are applied to analyze the performance of the model. Obviously, old model has large average error rather than that of the proposed model. More power and extra fuel cost are required to maintain the total power system operation.

TABLE III GENERATOR FUEL COST FUNCTIONS

	Ave Error	Extra power requirement/hour	Extra Fuel Cost/hour
Old Model	2.067	19.82	22.23
New Model	1.962	16.33	18.5595

IV. CONCLUSIONS

Uncertainty and variability are the inherent factors of intermittent power re-sources such as wind and solar. In traditional neural network forecasting models, accuracy nearly becomes the only pursued target for PV power generation forecasting models. However, this may not reduce the scale and cost of construction of standby power plant. To solve the problem, this paper proposes a new PV power generation forecasting model. The training target of neural network contains both accuracy section and maximum deviation section. Also, this paper establishes an Improved-Levenberg-Marquardt (ILM) algorithm for neural network training. A numerical study with practical data is presented and the result shows that new PV power generation forecasting model can reduce cost of construction of standby power plant with acceptable accuracy level. However, this paper only gives the power capacity requirement from traditional power plant like coal-fire plants and hydro power plants. Fluctuation from load variation and load forecasting error are not taken into account. In the future work, load variation and network topology change due to planning will be considered in the model to give a better result.

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