Generalized Load Modeling Considering Inverter Capacity Limitation

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Abstract. This paper aims at the problem of the generalized modeling considering the capacity limitation of inverter. Firstly, how the inverter capacity limitation can influence the generalized load fault response of the grid-connected point was analyzed. Then, the idea of fitting the piecewise function was proposed and applied to the training process of the generalized load artificial with neural network class model. To be clearer, fault samples were jointly trained at the same time to learn different segmentation characteristics. The modeling and simulation results show that the proposed method can improve the generalization ability and stability of the artificial neural network class model in generalized load modeling.

1. Introduction

In recent years, the penetration rate of the Distributed Generation (DG) in the distribution network has gradually increased, so its dynamic characteristics in the traditional load model needs further consideration. [1] and [2] show dynamic equivalents in the active distribution network which contains direct drive fans and doubly-fed fans. [3] shows the generalized load model containing fuel cells. As the composition of the distribution network gets more complex, more model parameters [4] need to be identified, which will undoubtedly increase the difficulty of model identification. In addition, the inverter capacity limitation and reactive power support were not considered in the literature above [5], and so the fault response of the actual inverter such as low voltage ride-through cannot be described well. Moreover, the difficulty of model identification will further increase after considering the inverter capacity limitation. In contrast, the non-mechanism model can have a good equivalent effect without increasing the complexity of the model even when the composition of the distribution network is complex, to which the mechanism model is not applicable.

In a non-mechanism load model, the Artificial Neural Network (ANN) model (the feedforward network, cyclic network, etc., are collectively referred to as the Artificial Neural `Network model in this paper, and the feedforward network is used in the example) has the best modeling effect [6], but currently its application in the generalized load modeling is still rarely discussed [7].

On this basis, this paper first studied the relevant issues of ANN in generalized load modeling; and secondly analyzed the influence mechanism of inverter capacity limitation on the load dynamic response in generalized load modeling, thereby, it is proposed that the issue of generalized load
modeling considering the inverter capacity limitation can be made equivalent to the issue of fitting the piecewise function, and further, the joint training of different fault samples was carried out to improve the generalization ability of the model. The simulation results show that the neural network model still has a strong fitting ability in generalized load modeling, but the generalization ability gets worse after the inverter capacity limitation is considered while the joint training with multiple fault samples in this paper improved the generalization ability of the ANN greatly.

2. ANN-based Generalized Load Modeling

2.1. Nonlinear Load Dynamic Model

Generally, the PQ decoupling non-mechanism model without considering the frequency effect in the dynamic load modeling can be expressed as:

\[
P(k) = f_P(P(k-1), P(k-2), \ldots, P(k-N_P),
U(k), U(k-1), \ldots, U(k-N_U))
\]

\[
Q(k) = f_Q(Q(k-1), Q(k-2), \ldots, Q(k-N_Q),
U(k), U(k-1), \ldots, U(k-N_U))
\]

Where, NP and NQ are the order of active power and the reactive power, respectively. NP=NQ=N. The general idea of load modeling is to approximate the functions \(f_P\) and \(f_Q\) with equivalent function to approximate the actual load model by using the equivalent function for calculation when the system is transient stable. ANN has been proved to have the arbitrary-precision function approximation ability [8], therefore, the ANN has a strong fitting ability as well in theory. Although the ANN fitting ability may be enhanced by increasing the number of neurons and the order of the model, it will increase the training time and the transient stability calculation time accordingly. In the practical application, therefore, it is necessary to select the number of neurons and the order of the model reasonably. In addition, the training algorithm and selection of its parameters as well as the structure of the neural network are also the key factors to be considered.

2.2. BP Algorithm and L-M Algorithm

The BP algorithm is an algorithm for obtaining the gradient of the network weight to the error function in the feedforward network training, and it is essentially the application of the chain rule of the function partial derivative. Generally, the "BP Neural Network" refers to upgrading the weight with the gradient descent method after the partial derivative of the weight to the error function is obtained with the BP algorithm in the feedforward network training process. Therefore, what is common in various current feedforward network training methods is that they all use the BP algorithm to obtain the partial derivative of the network weight to the error function in the first stage, and what is different among them is how to update the weight after the partial derivative is obtained in the second stage, which purely involves the issue of optimization.

For the algorithms used in the second stage, the most common ones are the gradient-based gradient descent algorithm and its variants (such as the inertial gradient descent algorithm, and the variable learning rate gradient descent algorithm) as well as the Jacobian matrix-based L-M (Levenberg-Marquardt) algorithm and the BFGS Quasi-Newton algorithm, etc. As far as the present situation is concerned, using the L-M algorithm to update the weight in the lightweight neural network model (the number of weight parameters is several hundred or less) is usually much superior to the gradient descent algorithm and its variants in terms of the training speed, and it has been proved to be the best training algorithm for the lightweight neural network. Since it has been proved that the ANN-based dynamic load modeling can achieve a good fitting without too many neurons [8], therefore the L-M algorithm was used to train the neural network in this paper. Its weight update formula is [9]:

\[
\Delta \theta = J_m^T J_m + \mu_m I_m \Delta \theta = J_m^T e_m
\]

Where, \(J_m\) is the Jacobian matrix of the error function to the weighted partial derivative; \(e_m\) is the error vector; \(\mu_m\) is the control coefficient, the increase of which can result in that this algorithm more...
approximates the gradient descent algorithm, and the decrease of which can result in that this algorithm more approximates the Gauss Newton iteration algorithm; $I_m$ is a unit matrix, which can effectively avoid matrix singularity, causing that the inverse matrix cannot be solved.

3. ANN-based Generalized Load Modeling

3.1. Inverter Decoupling Control Mechanism

Generally, grid-connected distributed generation is required to be controllable, and the overall control strategy of its inverter system is shown in Figure 1[10]. In the inverter control modeling, the active control part and the reactive control part should mainly be considered. In addition, the amplitude limiting part is required to be additionally added due to capacity limitation.

![Figure 1. Inverter Control Block Diagram](image)

The active control part achieves power tracking via the power outer loop PI control, as shown in Formula (3).

$$i_{d,ref} = (k_{pp} + \frac{k_{pp}}{s})(P_{ref} - P_m)$$  (3)

Where, $i_{d,ref}$ is the d-axis reference current of the active outer loop output, $P_{ref}$ is the active reference value, $P_m$ is the active measurement value, and $k_{pp}$ and $k_{ip}$ are the controller ratio and the integral parameter.

For the reactive control part, the low voltage ride-through ability of the inverter was mainly considered, that is, the reactive output is normally 0; and the reactive current support is provided according to the ratio of voltage drop when voltage drop happened; and the control strategy is as shown in Formula (4):

$$i_{q,ref} = \begin{cases} 
0 & U_{AC,m} \geq U_{lim0} \\
 k_q \left( U_{AC,m} - U_{lim0} \right) & U_{AC,m} < U_{lim0}
\end{cases}$$  (4)

Where, $i_{q,ref}$ is the q-axis reference current; $U_{AC,m}$ is the measured AC bus voltage; $U_{lim0}$ is the voltage threshold, the reactive power support will be provided once the voltage drop below this threshold which is generally 90% of rated voltage; $k_q$ is the proportion coefficient of reactive power support.

Since the inverter power output is as shown in Formula (5),

$$\begin{cases} 
P = v_d i_d + v_q i_q \\
Q = v_d i_q - v_q i_d
\end{cases}$$  (5)

If $v_q=0$ is taken, then $P = v_d i_d$ and $Q = -v_q i_q$, thus achieving the control of the active $P$ by controlling $i_d$, and the control of the PQ decoupling of the reactive $Q$ by controlling $i_q$[10]. Since the current control inner loop is very short [1], it can be considered that $i_d=i_{d,ref}$ and $i_q=i_{q,ref}$. When the inverter capacity limitation is considered, therefore, setting amplitude limiting links to $i_{d,ref}$ and $i_{q,ref}$ is equivalent to considering the capacity limitation, namely, the limitation expression is as shown in Formula (6).
3.2. Inverter Dynamic Process Analysis Considering Capacity Limitation

In the research of generalized load modeling containing the distributed generation, [1] proposed that the inverter control link may be simplified as the active and reactive outer loop. Through in-depth research, it is found that the above equivalent is only reasonable under certain conditions.

First, a complete photovoltaic model was established in the DIgSILENT platform to analyze the dynamic response process of the inverter. With the photovoltaics with rated capacity $P_e$ as an example, when the initial output was 40% $P_e$, the fault responses under different voltage drop amplitudes were simulated respectively. The results are as shown in Figure 2 to Figure 5.

The results in Figure 2 to Figure 5 are analyzed as follows. Since $P = P_{d1}$ under the decoupling control, when the initial PV output was 40% $P_e$, $i_{d,ref} = 0.4$. As the voltage $v$ (i.e. $v_d$) suddenly dropped, resulting in a sudden drop of $P$, the active power PI controller generated a difference value $P_{ref} - P_m$ at that time, causing the increase of $i_{d,ref}$ (i.e. $i_d$) to maintain $P$ as constant as possible. However, when the voltage drop was too large (more than 40%), the inverter delivered massive reactive power as required by the low voltage ride-through. In this case, $i_{q,ref}$ was greatly increased according to Formula (4), so that $|i_{d,ref}| + |i_{q,ref}|$ met the limitation conditions in Formula (6). While the priority of $i_{q,ref}$ is higher than $i_{d,ref}$, so the inverter provides the sufficient reactive power support under the capacity limitation through the sacrifice of the active output.

Therefore, [1] used a simplified PQ outer loop to make the inverter fault process equivalent is reasonable only under certain conditions, and such equivalence can neither describe the inverter response under the inverter capacity limitation, nor show the characteristic that the inverter provides massive reactive power support under low voltage ride-through, which is manifested as the poor generalization ability of the model.

According to the analysis above, the fault responses of the inverter can be divided into the response under a small amplitude voltage drop when the capacity limitation is not reached and the response under a large voltage drop when the inverter has been saturated. Therefore, the generalized load model described by Formula (1) is actually a two-segment function with respect to the voltage $U$. When $U$ is in different intervals, $f_{0}$ and $f_{0}$ will change. In order to improve the generalization ability of the model, the model is needed to get the function characteristics of the two segments at the same time, so the problem is further abstracted into the issue of fitting the piecewise function.
4. Multi-fault Sample Joint Training

To illustrate how the ANN fits the piecewise function, the piecewise function shown in Formula (7) is taken as an example.

\[ y = \begin{cases} 5x & x > 0 \\ 3x^3 & x < 0 \end{cases} \]

(7)

Generally, we can get multiple fault samples with different voltage drops. Obtaining a unified model based on multiple fault samples, is called “Load Synthesis”. [11] achieved the synthesis of load modeling by obtaining the "center of gravity" of multiple fault curves and then identifying the "center of gravity". Some literature performed the load synthesis by identifying each fault, and then obtained the weight-average of the identified parameters. Through research, however, the above methods are not effective in the case of considering the inverter capacity limitation discussed in this paper.

From the above analysis, this paper proposes that the load synthesis should be carried out based on the idea of fitting the piecewise function when the inverter capacity limitation is considered. That is, each fault sample is regarded as the sample of the generalized load model in different voltage intervals, and a joint training is carried out on such samples. From Formula (1), let \( N = 1 \), then a fault sample can be expressed as \([x, y]\), where \( x = [x(1), x(2), \ldots, x(k)]^T \), \( y(k) = [y(k-1), u(k), u(k-1)]^T \);
$y = [y(1), y(2), …, y(k)]^T$, $y$ is P or Q. Next, we integrate the fault sample $[x_1, y_1]$ and the fault sample $[x_2, y_2]$ to form a unified fault sample matrix $[[x_1^T, x_2^T]^T, [y_1^T, y_2^T]^T]$ for training.

5. Multi-fault Sample Joint Training

A simulation system shown in Figure 6 was established in the DIgSILENT platform, where ZIP denotes the ZIP load, IM denotes the induction motor load, PV indicates the photovoltaic, and PMSG refers to the direct drive fan. To simplify the research in this paper, the simulation analysis was carried out for certain fixed scenario (new energy output was 40% of the capacity), and the other scenarios were analyzed in the same way; in addition, to distinguish it from the traditional load modeling and highlight the influence of DG fault response on the grid connection point, the DG output was set to be greater than the load. When the set fault was 0.2s, the US voltage dropped, and when the former was 0.4s, the voltage returned to the normal state. Part of the key parameters of the system are shown in Table 1.

![Figure 6. Structural diagram of system](image)

| Parameter | Value | Parameter | Value |
|-----------|-------|-----------|-------|
| ZIP 1/2/3/4 Active Output/MW | 0.1   | ZIP 1/2/3/4 Reactive Output/Var | 0.0   |
| IM 1/2/3/4 Capacity/MW | 0.3   | IM 1/2/3/4 Output/MW | 5.0   |
| PV 1/2 Capacity/MW | 1.0   | PV 1/2 Output/MW | 0.1   |
| PMSG 1/2 Capacity/MW | 0.5   | PMSG 1/2 Output/MW | 0.4   |
| PV Reactive/Var | 0.0   | PMSG Reactive/Var | 0.2   |
| ZIP active constant resistance coefficient | 0.6   | ZIP active constant current coefficient | 0.2   |
| ZIP reactive constant resistance coefficient | 0.6   | ZIP reactive constant current coefficient | 0.2   |

Table 1. System key parameters

Through several times of simulation, it is found that the first-order nonlinear difference equation has had a good fitting ability, and the enhancement of the training effect by increasing the model order did not match the complexity of the added model, so the first-order model was selected in this paper; and a good fitting ability can be achieved when the number of neurons was just taken as 10. To analyze the generalization ability of the model, the training error is defined as below:

$$err = \frac{1}{k} \sum_{i=1}^{k} (y_{target} - y_{ANN})^2$$

(8)
Where, \( k \) is the number of rows of the fault sample matrix. In this paper, the ANN convergence condition was set as: \( \text{err} \leq 0.001 \). Besides, all the results were averaged after multiple times of calculation, which was to reduce the impact of random initialization of the weight of the ANN model.

5.1. Research on the Extrapolation Ability

We established the model for ANN by taking the data from 20% voltage drop. The results are shown in Figure 7 to Figure 8.

\[\text{Figure 7. Active power of 20\% voltage drop}\]

\[\text{Figure 8. Reactive power of 20\% voltage drop}\]

The results of Figure 7 show that if the model fits small amplitude voltage drop well, the extrapolation of the active model can basically fit the large voltage drop response, but there is still a certain generalization error, which, as analyzed easily, is because the inverter capacity limitation is not considered under the small-amplitude voltage drop. As the result, the generalization ability under the large voltage drop gets worse.

The results in Figure 8 and the corresponding calculations show that the generalization of the reactive power is generally better than that of the active power. As analyzed easily, this is because the reactive power has a higher priority than the active power in the fault response, while the active power is first restrained by the capacity limitation in the fault response. However, it is found through multiple experiments that the reactive ANN model sometimes gets involved in the local optimal solution, with a quite unstable generalization ability, and frequently has a large generalization error. This may be caused by the defects (parameter random initialization and over-fitting, etc.) of the ANN model itself on the one hand; and on the other hand, the reactive fluctuation is more sensitive to voltage (namely, the fluctuation range is larger), and it will present a larger generalization error after getting involved in the local optimal solution.

5.2. Interpolation Ability

We established the model of ANN with 70% voltage drop, and observed the interpolation ability of the established model under 20% voltage drop. The results are shown in Figure 9 to Figure 12.
Figure 9. Active power of 70% voltage drop

Figure 10. Active power of 20% voltage drop

Figure 11. Reactive power of 70% voltage drop

Figure 12. Reactive power of 20% voltage drop

The results in Figure 11 and 12 show that the reactive power interpolation was very poor at this time. It can be seen from the figures that the actual reactive power support was more than the estimated reactive power support of the model (when the reactive power is negative, it indicates that
DG provides the reactive power support). This is likely because the reactive power support of the inverter was saturated at 70% voltage drop, so this model would underestimate the reactive power support ability under low voltage drop.

5.3. Research on Interpolation and Extrapolation Abilities of Joint Training

To research the enhancement effect of the model’s generalization ability resulted by joint training of multiple fault samples, the generalization abilities of the active and reactive models in the 20% voltage drop model, the 70% voltage drop model, the “gravity method” integrated model [11] and the joint training model discussed in this paper were compared in Figure 13 and 14.

As can be seen from Figure 13, the active extrapolation ability of the ANN model was relatively poor. For the model established by 20% voltage drop fault sample, the extrapolation error increased rapidly with the increase of the degree of the voltage drop; while the interpolation ability of the model established by 70% voltage drop was better. The gravity method resulted a larger error relative to the model established by 70% voltage drop, which was because the 20% and 70% fault samples were both considered in this model, therefore the error was between the two. For the joint training method with the fault sample, the two samples were combined into one fault sample, and the load model was trained based on the idea of the piecewise function, and the overall error was reduced indeed.

In a similar way, according to Figure 14, the reactive power interpolation ability of the ANN model was very poor, and the reactive extrapolation ability would rapidly get poor under the high amplitude voltage drop. Similarly, the error in the center of gravity method was between those of the 20% and 70% models and did not perform better than a single model. However, after the joint training was carried out on the 20% and 70% voltage drop fault samples, the ANN did get the generalized load characteristics of the two segments very well at the same time, thus greatly reducing the generalization error under each voltage drop. Besides, the results of multiple times of calculation show that the model receiving the joint training was quite stable.
In summary, the model segmentation characteristics brought by the inverter capacity limitation is better considered with a joint training on different fault samples during generalized load modeling compared to the traditional integrated method. Although it is sometimes difficult to accurately explain the specific reasons for the case that the generalization ability of the model gets worse in different scenarios, both the active power and reactive power generalization errors are well reduced after the joint training is carried out. In addition, the robustness on the model gets stronger. The model can be less susceptible to initial values and over-fitting as well.

6. Conclusion
Aiming at the poor generalization ability of the generalized load model when the inverter capacity limitation is considered, the influence of inverter decoupling control mechanism and capacity limitation on the generalized load dynamic process was analyzed; the idea of dividing the inverter dynamic responses into the pre-saturation part and post-saturation part was proposed; and the analogy between the generalized load modeling and the piecewise function fitting issues was carried out, that is, the joint training was carried out on the fault samples under different voltage drop.

The simulation results show that the joint training of fault samples can improve the generalization ability of active power and reactive power models at the same time, thus increasing the robustness of the models, and reducing the influence of random initialization and over-fitting of parameters.

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