The Fuzzy Control Technology Research of Pumped Storage Units Based on Dynamic Neural Network

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Keywords: Pumped storage units, Dynamic recursion fuzzy neural network, Dynamic back propagation algorithm.

Abstract. With the China's energy conservation and emissions reduction and energy structure adjustment working gradually thorough, the pumped storage power station has become an integral part of the grid. It has a crucial effect to the stable, safe and reliable operation of the power grid. According to the characteristics of the pumped storage units and the problems existing in the operation, using dynamic neural network method to accurately identify the dynamic characteristics of pumped storage unit in this paper. It becomes easy to realize the fuzzy inference function due to the introduction of product operation. The network is characterized by fewer parameters, faster convergence rate and the strong robustness. The simulation results also verify the effectiveness and accuracy of the proposed fuzzy neural network.

Introduction

In recent years, with the rapid development of China's economy, the continuous improvement of national awareness of environmental protection, energy saving and environmental protection has been put on the agenda. In accordance with the relevant requirements of China's energy development planning, in order to reduce the emission intensity of nitrogen oxides, fine particulate matter (PM2.5), reduce unit of GDP carbon dioxide emissions ratio, new energy power plants and nuclear power plants will be the direction of China's energy development. And pumped storage power station as the main facilities of improve grid absorption capacity, will also usher in the construction of high tide. By the end of 2015 the total installed capacity of the national pumped storage power plant is about 23 million kilowatts. By the end of 2020 total hydropower installed capacity will reach 380 million kilowatts, including conventional hydropower 340 million kilowatts, pumped storage 40 million kilowatts. It is expected that in 2025 the national hydropower installed capacity will reach 470 million kilowatts, including conventional hydropower 380 million kilowatts, pumped storage about 90 million kilowatts. To strengthen system integration optimization at the same time, focus on improving the capacity of power grid peak shaving, moderate speed up planning in construction of pumped storage power station. In our country and the world within the scope of pumped storage power generation technology with broad prospects for development.

In the maintenance of the safety of power grid at the same time, the pumped storage power plant itself sufficient to guarantee the safety of the operation for effective control of the unit has become a top issue for people. Compared with other conventional hydropower station, the working condition of pumped storage power station is much and complicated, so it is difficult to complete the accurate modeling on it. At present hydropower unit’s modeling problems more common in the study of conventional hydropower units [3]-[6]. In contrast, the research of pumped storage units is less. In pumped storage units modeling study,[7] discusses the development of a fuzzy inference system (FIS) based governor control for a pumped storage hydro-electric plant. [8]studied the modeling of regulating system of large pumped storage power station with long pipeline and parameters optimization in transient processes, as to simulate hydraulic vibration characters, BP neural network and RBF neural network are adopted in modeling of pump turbine. In essence, both the modeling research of hydropower units or pumped storage units, people still mainly use of the neural network.
approximation of nonlinear system characterization ability and adaptive learning function to solve the problem of system identification.

According to the characteristics of the pumped storage units and the problems existing in the operation, using dynamic neural network method to accurately identify the dynamic characteristics of pumped storage unit.

**The Dynamic Recursion Fuzzy Neural Network (DRFNN)**

![Dynamic Recurrent Fuzzy Neural Network Structure](image)

The topology of (SISO) DRFNN is shown in Figure 1. Network is composed of five layers: input layer, fuzzy layer, rule layer and de-fuzzy layer and output layer, In the rule layer to join a recursive by recursive neuron have internal feedback connection, as an internal memory in the form of automatic dynamic factors involved, is a kind of dynamic mapping, can capture the dynamic response of the system, and So this kind of network has stronger ability to deal with dynamic system, and can simplify the network model.

The first layer is the input layer, and the node of the layer is directly connected with the input vector, which plays the role of transferring the input value to the next layer.

The second layer is a fuzzy layer, each node represents a variable value language, such as S2, S1, CE, B1, B2, etc., its role is to calculate the amount of input membership functions belonging to the respective language variable valued fuzzy sets, according to the problem choose Gaussian function:

\[ \mu^j = \exp\left[-\frac{(x(k) - x_j)^2}{\delta_j}\right] \]

where, \( j = 1, 2, 3, \ldots, m \), \( m \) is the number of fuzzy division of \( x \), \( x_j \) and \( \delta_j \) represent the center and width of the membership function, \( x(k) \) is the input of the first time \( k \).

The third layer is a layer of rules, each node represents one fuzzy rule, it is to match the antecedent of fuzzy rules to calculate the degree of activation of each rule \( w_j(k) \):

\[ w_j(k) = \prod_{i=1}^{m} w_{ci}(k)w_{ji}^j\exp[-\frac{(x(k)-x_j)^2}{\delta_j}] \]

In formula(2), \( W_{ji} \) is the connection weights that from the \( j \)th node of recursive layer to the \( i \)th node of rule layer, \( w_{ci}(k) \) is the activation degree of \( i \)th node of recursive layer:

\[ w_{ci}(k) = w_{ci}(k-1) \quad i = 1, 2, \ldots, j \ldots, m \]

Thus, the network activation \( w_j(k) \) of each rule at the \( k \) time not only includes the activation value \( \mu^j \) calculated by the current input, but also includes the contribution of the previous moment of each activation value.
Therefore, the introduction of the recursive layer is to strengthen the accuracy of the network identification, so that the static network has dynamic characteristics. The most important is that this paper uses the method of product operation in the rule layer, which can effectively guarantee the activation degree $0 < w_j(k) \leq 1$, also facilitate the realization of the fuzzy inference function.

The fourth layer is de-fuzzy layer, where fuzzy conclusions can be calculated by de-fuzzy operation. The activation degree of each node in this layer is:

$$\phi = \frac{1}{\sum_{i=1}^{m} w_i(k)}$$  \hspace{1cm} (4)

The output of the $j$th node of this layer is:

$$w_j(k) = \phi \cdot w_j(k)$$  \hspace{1cm} (5)

The fifth layer is the output layer, and the fuzzy strategy (COG) is adopted. The output of the network at $k$ time is:

$$y(k) = \tilde{y}_j(k) \cdot \tilde{w}_j(k) = \sum_{i=1}^{m} \tilde{y}_i(k) w_i(k) \Big/ \sum_{i=1}^{m} w_i(k)$$  \hspace{1cm} (6)

where, $\tilde{y}_i(k)$ is the first fuzzy rule conclusion at $k$ time.

**DRFNN Learning Algorithm**

The number of fuzzy division has been determined, you need to learn there are four network parameters. They are the connection weights $W_{ji}$ of the recursive layer to the rule layer, the center $x_j$ and the width $\delta_j$ of the membership function of the input variables, and the connection weights $\tilde{y}_i$ of the hidden layer to the output layer (that is, the rule conclusion).

Using the MSE (Mean Square Error) defines the objective function:

$$MSE = \frac{1}{N} \sum_{k=1}^{N} \sum_{p} E_p(k)$$  \hspace{1cm} (7)

where, $N$ is number of samples, $E_p(k)$ is error objective function for each iteration, that is:

$$E_p(k) = \frac{1}{2} \| y_p(k) - y(k) \|^2$$  \hspace{1cm} (8)

In formula (8), $y_d(k)$ and $y(k)$ are actual sample output and DRFNN output of the object are identified at the $k$ time. By the formula (1)-(3) found:

$$w_{cj}(k) = w_{cj}(k-1) = [\prod_{i=1}^{m} w_{ci}(k-1) W_{pj}] \exp[-(\frac{x_j(k-1)-x_j}{\delta_j})^2]$$  \hspace{1cm} (9)

Formula (9) shows that $w_{cj}(k)$ is dependent on the right of connection at different times in the past, or is a dynamic recursive process, so the corresponding BP algorithm called dynamic BP algorithm.

All parameters are adjusted by using the gradient descent method to find the parameter vector that minimizes the objective function $E_p$. The specific parameter adjustment learning algorithm is described as follows:

(1) The adjustment of the weights $W_{pi}$ of the recursive layer to the rule layer:
\[ W_p(k+1) = W_p(k) - \eta_p \frac{\partial E_p}{\partial W_p} \]  

where, \( \eta_p \) is Learning rate coefficient, The greater the learning rate coefficient, the faster the convergence rate of the algorithm, but it is easy to generate oscillation. So the choice principle should be determined according to the actual situation. Use the chain rule for derivative:

\[
\frac{\partial E_p}{\partial W_p} = \frac{\partial E_p}{\partial y(k)} \frac{\partial y(k)}{\partial w_j(k)} \frac{\partial w_j(k)}{\partial W_p} 
\]

(11)

(2) The adjustment of the center \( \delta_j \) of the membership function of the input:

\[ x_j(k+1) = x(k) - \eta_x \frac{\partial E_p}{\partial x_j} \]  

(12)

(3) The adjustment of the width \( \delta_j \) of the membership function of the input:

\[ \delta_j(k+1) = \delta_j(k) - \eta_\delta \frac{\partial E_p}{\partial \delta_j} \]  

(13)

(4) The adjustment of the connection weights \( y_i \) of the hidden layer to the output layer:

\[ y_i(k+1) = y_i(k) - \eta_y \frac{\partial E_p}{\partial y_i} \]  

(14)

**Dynamic Fuzzy Neural Network Modeling of Pumped Storage Units**

A pumped storage power plant is a pure pumped storage power station, power house at dam toe, Pump/turbine type is HLN80−LJ−553, The design head is 71.6m, Maximum flow rate of hydraulic turbine is 147m³/s, The maximum flow rate of the pump is 120m³/s, The rated speed of the turbine is 125rpm, Motor/generator type is MV820/240/42-48, rated power of generator is 91MVA, rated power of motor is 90.2MW/59.7MW, the moment of inertia of the unit GD2=164715N.m², when the relative opening of the guide vane is 0.85, the coefficient of the unit is shown in Table 1.

<table>
<thead>
<tr>
<th>param</th>
<th>( e_{q_r} ) (p.u)</th>
<th>( e_{q} ) (p.u)</th>
<th>( e_{r} ) (p.u)</th>
<th>( e_{q_h} ) (p.u)</th>
<th>( e_{s} ) (p.u)</th>
<th>( T_a ) (s)</th>
<th>( e_{g} ) (p.u)</th>
<th>( T_w ) (s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>value</td>
<td>0.65</td>
<td>1.40</td>
<td>0.60</td>
<td>0.45</td>
<td>-0.95</td>
<td>7.9</td>
<td>1.50</td>
<td>1.59</td>
</tr>
</tbody>
</table>

According to the parameters in the above table, the transfer function of the pumped storage unit can be expressed as:

\[
G(s) = \frac{0.245(1-6.678s)}{(1+0.716s)(1+3.224s)} 
\]

(15)

Discrete continuous model, and the sampling period is 0.1 seconds, In order to improve the sampling precision, the first order holder is adopted. The difference equation is obtained from (15) as follows:

\[
y(k) = 1.839y(k-1) - 0.8431y(k-2) - 0.03333u(k) + 0.002503u(k-1) + 0.0318u(k-2) 
\]

(16)

Simulation is used to verify the effectiveness of the DRFNN method. From (16) to collect 240 samples data. Among them, 120 as training data, 120 as the test data. Due to the unit under different condition of model parameters change is very big, only under the working condition of a certain data
to train the model adaptability is very poor, under other conditions the error will be very big, so choose samples is very important, should choose typical data as the training sample under different working conditions.

Choose \( W_j \) and \( \tilde{y}_j \) are \([0,1]\) respectively, uniformly distributed random numbers. After 25 iterations, the mean square error converges to a small value, as shown in Figure 2.

Figure 3 is a unit speed and error curve. Figure 3 (a) shows that the learning process is stable. Figure 3 (b) shows the estimated error curve of 120 pairs of test samples. As can be seen from Figure 3, the DRFNN method can well approximate and reflect the dynamic characteristics of the system.

As can be seen from Figure 3. After training, when we identify the characteristics of the pumped storage units online, according to the controlled quantity \( u(k) \) and output \( y(k) \) can accurately identify the output of the turbine unit \( y(k+1) \), identification error can be up to \( 10^{-4} \). The results show that the proposed DRFNN network has good identification ability. As can be seen from the Figure 3 changes in working conditions, the identification error will increase, generally within the allowable error range. In practice, if you want to get a more accurate mathematical model, it is needed to train the network in real time, so as to adapt to various working conditions.

The error of the training process is shown in Figure 2. It can be seen that the training convergence is very fast, and the training can reach a high accuracy for the 25 time.

![Figure 2. The error of DRFNN training process.](image)

![Figure 3. The unit speed and error curve.](image)

**Conclusion**

By using fuzzy neural network method can accurately identify input and output characteristics of pumped storage units, has good capability of nonlinear approximation, DRFNN has both the reasoning function of fuzzy inference system, and the training and learning function of neural network. Thus DRFNN can the advantages of both fuzzy inference system and neural network combining, overcome the pure neural network black box features, has a certain transparency. Through a lot of experiments, it is proved that the DRFNN network training is fast, the training times are few, and the problem of local optimum is overcome. So the DRFNN network can be used to establish a more accurate model of the input and output of the pumped storage unit, which can solve the nonlinear and time-varying problem of the pumped storage unit in the actual operation.

**Acknowledgement**

This research was financially supported by Jilin Province Science Foundation (20130206080SF )

**References**


