Complete characteristic curve processing method based on improved backpropagation neural network and Logarithmic curve projection

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Abstract—The calculation of transient process is the basis of the design and construction of pumped storage power plant, which directly affects operation stability of pumped storage units. However, for satisfying the design of uniform and smooth flow in both directions, the complete characteristic curves of pumped turbine show a significant S feature, which brings difficulties to the interpolation calculation in the transient process as there are crossover and overlap phenomenon in pump and turbine working conditions. In this paper, a transformation method for complete characteristic curves based on logarithmic curve projection and improved backpropagation neural network is presented to solve the above problem. Furthermore, the feasibility and accuracy of the method are verified through the comparison of load rejection condition with on-site measurement, the results show that the proposed method overcomes the multi-value problem that exists in the original curve, in especial makes the small opening region well expressed. The simulation based on the transformed curve reaches a high similarity of transient process with the field test, both in the trend and extreme values, which provides great convenience for the calculation of transient process.

1. Introduction
Pumped storage power plant, as an effective solution to incorporate renewable energy and ensure the stability of power grid, has been vigorously developed for the past few years [1]. In the design of power plants, the primary thing is to conduct the calculation of transient processes for the purpose that the power plants can smoothly and safely convert between multiple working conditions. However, the analytical model of pump-turbine has not been obtained till now because of strong nonlinearity and time variation characteristics. Traditionally, the calculation of turbine adopts the complete characteristic curves given by the manufacturers, while there exist serious phenomena of crossover, aggregation, bending, and multi-values at both ends of the curves [2]. Specifically speaking, the pump-turbine has remarkable S characteristics where small changes in unit speed will cause sharp changes in the unit flow and unit torque. Hence, accurate calculation of the transient process of pumped storage power plants has become a great challenge to the economical and efficient operation of power plants.

Scholars have conducted fruitful research on the processing of complete characteristic curves. According to the dimensionless similar parameters of the pump, Suter et al. [3] proposed Suter transformation to deal with the complete characteristic curves of the pump-turbine, which effectively eliminated the multi-value phenomenon and brought convenience for interpolation calculation. Liu et al. [4] put forward an improved transformation method on the basis of Suter transformation, which effectively avoided the occurrence of serious crossover and overlap situations. Yang et al. [5]
constructed a B-spline space curved surface for the representation of the complete characteristics of pump-turbine, which effectively eliminated the multi-valued and non-corresponding problems existing in the plane curve representation. Chen et al. [6] presented an equal opening line method to better express the small opening characteristic and make a good connection between the zero opening characteristic and the finite opening characteristic. Nevertheless, there are still some defects in the existing treatment methods. The curves processed by the Suter transformation show uneven distribution under different opening degrees, and there are still serious aggregation and torsion at both ends of the curves. Several parameters have been added with the improved Suter transformation method, while there is no guidance for the selection of accurate parameters. The appropriate B-spline function is difficult to construct and the equal opening line method raises high requirements on the quantity of complete characteristic curves.

Based on the above discussion, a complete characteristic curve processing method based on improved backpropagation neural network and logarithmic curves projection (IBP-LCP) is proposed in this paper. The complete characteristic curves are first transformed by projection along the logarithmic curve, then the nonlinear relation of transformed curves is learned by introducing the improved BP neural network. The proposed method overcomes the multi-value of the original characteristic curves and makes the small opening region well expressed, which improved the calculation speed and precision of the transient process for pumped storage power plants.

The rest of this paper is organized as follows. In section 2, the proposed IBP-LCP processing method is elaborated in detail. The feasibility and accuracy of the proposed method are verified by the case of load rejection in a real pumped storage power plant in Section 3. Section 4 presents the conclusion of this study.

2. Processing method for complete characteristic curve

An accurate model of the pump-turbine is of great significance for the calculation of transient process. Nevertheless, the complete characteristic curves of pump-turbine have a significant S region, as shown in Fig.1, which got into trouble when conduct regulation guarantee calculation. In this paper, a novel processing method is proposed. The logarithmic curve projection is adopted to transform the complete characteristic curves in the first place, which overcome the multi-value problem without changing the continuity and smoothness of the original curves. Furthermore, the improved BP neural network is introduced to excavate the internal correlation of the transformed curves, thus the curves can be expanded reasonably.

(a) Flow characteristic curve  
(b) Torque characteristic curve

Fig.1 The complete characteristic curves of pump-turbine.

The Logarithmic curve projection takes \( x = \alpha t e^{\alpha t} \) as the abscissa to describe the characteristics of pump-turbine, the transformation formula is shown as follows:
\[
\alpha_i = x_{i1} / x_{11r} \\
v_i = Q_{i1} / Q_{11r} \\
x = \alpha_i / e^{v_i}
\]

(1) (2) (3)

Where, \(x_{i1}, Q_{i1}\) are unit rotational speed and unit flow, respectively. \(x_{11r}, Q_{11r}\) are the corresponding rated values. The transformed curves after LCP are shown in Fig.2. It is obvious that the transformed curve maintains the continuity and smoothness of the original curves and the curves are relatively uniform under different opening degrees. Compared with large opening degrees, there is no special point from small opening to zero opening degree, and there is no multi-value problem. Nevertheless, the transformed curves still have some shortcomings, as follows: (1) the abscissa of the curves is not aligned and the distribution of the data points in each curve is uneven. (2) the measured curves from the manufacturer are too few to meet the requirements of interpolation.

![Flow characteristic curve](image1)

![Torque characteristic curve](image2)

Fig.2 The complete characteristic curves of pump-turbine after logarithmic curve projection.

The BP neural network has strong nonlinear mapping ability and flexible network structure, which can be used to describe the nonlinear relationship of characteristic curves overcoming the above shortcomings [7]. For the problems that exist in traditional BP neural network, i.e. easy to form a local minimum but not the global optimal, many times of training, low learning efficiency, slow convergence, we adopt improvement strategies by adding dynamic parameter method and optimization of learning factors to solve. The dynamic parameters are expressed as follows:

\[
\Delta W(k+1) - \delta \Delta W(k) = a(1-\delta)E(k)/W(k)
\]

(4)

Where, \(\delta\) is an additional parameter, the range is \(0 \leq \delta \leq 1\). The essence of dynamic parameters is that, when the amount of correction is insufficient, the next amount of correction will be increased and vice versa. By adjusting the dynamic parameters, the oscillation trend in the learning process of the neural network can be reduced and the local minimum value can be avoided or reduced.

In order to reduce the number of iterations and speed up convergence, it is necessary to adjust the learning factor reasonably. Accordingly, the learning factor is modified by changing the step size according to the output error. The formula is as follows:

\[
a = a + \lambda \times \frac{E_r(n) - E_r(n-1)}{E_r(n)}
\]

(5)

Where, \(a\) is the learning rate, and \(\lambda\) is adjustment step size, which is usually between 0 and 1.
3. Model validation
To verify the performance and accuracy of the proposed processing method, a case study is conducted by implementing it in a real pumped storage power plant. When large electrical equipment failure or the power supply network outlet circuit breaker suddenly trip, the unit had to dump the load to maintain torque balance, while the huge residual energy causes the speed of the unit to rise quickly and the pressure of the water system to changes notably. Based on that, the load rejection condition, as the running tracks of unit span most of the characteristic curves back and forth, especially the hump domains and the S-shaped region, is implemented as the typical extreme transient process for comparison.

The IBP model, as shown in Fig.3, consists of double input $(x, y)$, double output $(Q, M)$, and double hidden layers taking account of the coupling relation between $Q$ and $M$. In the training process of the BP neural network, the maximum number of iterations is 300, the number of each hidden layer node is 15 which is selected by orthogonal test, the initial learning rate is 0.1, and the training objective error is $10^{-5}$. The hidden layer adopts the activation function of `tansig`, and the output layer adopts the linear activation function `purelin`. After the procedure of encryption and extension, the treated curves are shown in Fig.4, the results show that the inherent law of characteristic curves can be generalized from the existing data sequence which can be attributed to the strong self-learning and predictive ability of the IBP neural network.

Subsequently, the simulation of load rejection is performed in MATLAB. The default working condition is set to a complete load rejection, 733m water level in the upstream reservoir, and 181m water level in the downstream reservoir. The guide vane closes in 20s. other boundary conditions can be found in Ref. [8]. The transient process of key nodes, i.e. the process of rotational speed change, the pressure of volute, and the pressure of the draft tube are extracted for comparison with field test.

![Fig.3 The structure diagram of BP neural network.](image)

![Fig.4 The complete characteristic curves after IBP-LCP transformation](image)

(a) Flow characteristic curve  (b) Torque characteristic curve
As can be seen from Fig. 5, the simulation using the transformed complete curves shows an analogical transient process with field test. To be more specific, the occurrence time of the maximum relative rotational speed of the simulation model and the measured data are identical, same thing happens with the maximum water pressure of volute. Though for the rotational speed, volute, and draft tube, some deviation appears after 20 seconds of load rejection, the development trend of transient process achieves high similarity. In addition, IBP-LCP fits the nonlinear relationship of characteristic curves, the flow and torque characteristics could be obtained by just inputting the guide vane opening and unit speed, which greatly improves the calculation speed and accuracy of the transient process.

![Graphs](image)

(a) Rotational speed  
(b) Pressure of volute  
(c) Pressure of draft tube

Fig. 5 Comparison of transient process between the simulation model and the field test

4. Conclusion
In this paper, a complete characteristic curve processing method based on IBP-LCP is proposed. By using the treatment method, multi-value problem in complete characteristic curves of pump-turbine has been eliminated and reasonable expansion of the characteristic curve will not cause the omission of the original data with help of IBP. In addition, there is a good connection between the finite opening characteristic and the zero opening characteristic. Furthermore, without changing the continuity and smoothness of the original image, interpolation can be carried out, or the computer can be used for calculation. Compared with the measured data, the simulation based on the treated curves processed by the proposed method has a consistent transient process trend and extreme values with on-site measurement, which can serve as the basis for the calculation of transient processes.

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