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Advanced Modelling of Full Characteristic Curve of Tubular Turbine Based on Back-Propagation Neural Network

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Abstract. For the comprehensive characteristics of hydro-turbine, it is generally grasped through the full characteristic curve map of hydro-turbine obtained from the experiment. However, due to the factors such as time cost, fund cost, experimental difficulty and safety, the experimental results cannot hold onto each working condition of hydro-turbine. And for the specific conditions of unknown working conditions, linear interpolation needs to be carried out through the existing experimental results, which will have a certain hidden danger to the safe and stable operation of the turbine. This paper uses the advantages of neural network to predict the overall operation space of hydro-turbine through back-propagation neural network under the condition of existing experimental points. The results show that the neural network method can effectively ensure the accuracy of the operation characteristics of the hydro-turbine, which can guide the safe and stable operation of the hydro-turbine more clearly, and ensure the efficient and stable operation of the hydro-turbine.

Keywords. Tubular turbine, neural network, grayscale analysis, gray relation analysis, intelligent operation

1. Introduction

Tubular turbine is a typical hydropower equipment used for low-head hydro-energy utilization [1]. The angle-adjustable guide vane and angle-adjustable runner blade are used to achieve desirable performance and good operation stability. The full characteristic curve map (FCCM) is usually used for hydropower plants. It describes the performance parameters such as head H, flow rate Q, power P and efficiency η in a unit form of unit flow rate Q_{11} and unit rotational speed n_{11} [2, 3]. Conventional FCCM is drawn based on hydrodynamic model test with discrete points and the two-dimensional continuous map can be generated by interpolation (see Figure 1). As adjustable blades and vanes are used, FCCM becomes very complex with too many parameters [4]. It

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increases the difficulty of selecting the operating point in actual applications because the relationship of these parameters is not fully built.

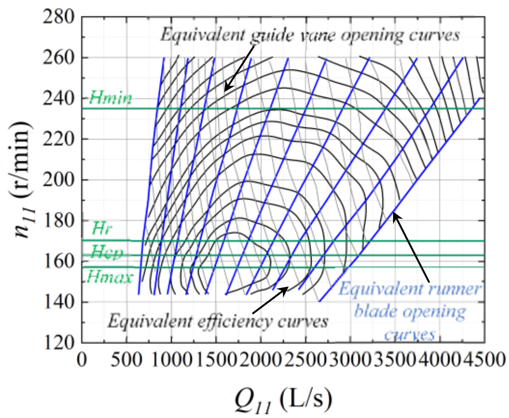

Figure 1. Conventional FCCM of tubular turbine.

Neural network is an algorithmic mathematical model that imitates the behavior characteristics of animal neural network and carries out distributed parallel information processing. This kind of network depends on the complexity of the system, and achieves the purpose of processing information by adjusting the interconnected relationship between a large number of internal nodes [5]. The advantages of neural network include following three main points. Firstly, it has the ability to learn and build models with nonlinear and complex relationships, which is very important for tubular turbine because the relationship between a large number of inputs and outputs is nonlinear and complex [6]. Secondly, neural network can be generalized. After learning from the initialization input and its relationship, it can also infer the unknown relationship between the unknown data, so that the model can be generalized and predict the unknown data [7, 8]. Thirdly, unlike many other prediction techniques, neural network does not impose any restrictions on input variables. In addition, many studies have shown that neural network can better simulate heteroscedasticity, that is, data with high volatility and unstable variance, because it has the ability to learn the hidden relationship in the data without imposing any fixed relationship in the data [9]. The back-propagation neural network is the most widely used form of neural network. It has the advantages of nonlinear mapping ability, self-learning and adaptive ability, generalization ability and fault tolerance ability [10, 11]. The disadvantages like local minimization problem and the contradiction between prediction ability and training ability does not exist in the tubular turbine case. Therefore, this research focuses on the application of the back-propagation neural network for building an advanced full characteristic curve of tubular turbine. It is of great significance to improve the intelligent optimal operation of the turbine unit.

2. Basic Characteristics of FCCM and Tubular Turbine

According to the similarity theory of turbine, the unit flow rate Q_{11} and unit speed n_{11} of the same series of turbine under similar working conditions are equal respectively, and a certain value of Q_{11} and n_{11} determines a similar working condition. Therefore, Q_{11} and n_{11} can be used as parameter variables to represent the changes of efficiency η and runner blade opening a_0 and so on of the same series of turbines under different working conditions. In the rectangular coordinate system with n_{11} and Q_{11} as the ordinate and abscissa axes, draw the equivalent efficiency curves $\eta = f(Q_{11}, n_{11})$, the equivalent runner blade opening curves $a_0 = f(Q_{11}, n_{11})$, and the equivalent guide vane opening curves $\beta = f(Q_{11}, n_{11})$ for the adjustable-blade turbine. These isolines represent various main performances of the same series of turbines, so they are called the full characteristic curve map (FCCM) of the turbine. FCCM is generally obtained by the method of test of model hydro-turbine. Through the above expression method, the n_{11} and Q_{11} are used as parameter variables, so that the FCCM of each hydro-turbine are drawn with a unified scale, which eliminates the influence caused by the difference of geometric dimensions and working conditions of the hydro-turbine, and is convenient to investigate and compare the performance of the hydro-turbine.

In this study, the FCCM obtained from the model test of a tubular turbine is deeply analysed, and the influence and correlation of various parameters on the operation performance of the turbine in the FCCM are explored and excavated. The tubular turbine model in this study is shown in Figure 2 where z is usually used for the rotation axis.

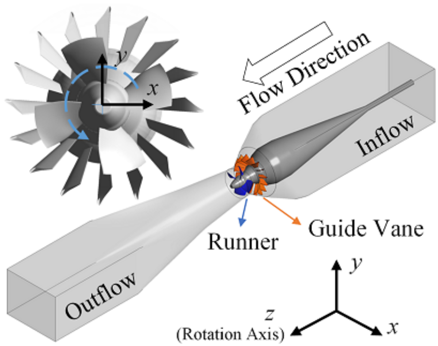

Figure 2. Tubular turbine and its components.

According to the similarity theory of hydro-turbine, the unit flow rate Q_{11} represents the flow rate through a given runner with a diameter of 1m when working under 1m head, and the flow rate through the turbine when working under similar conditions. The formula is defined as:

$$Q_{11} = \frac{Q}{D^2\sqrt{H}} \tag{1}$$

Where, D represents the diameter of the runner.

Unit speed n_{11} refers to the speed that a given runner with a diameter of 1m should have when working under 1m head and the turbine with similar geometry and working under similar working conditions. Its formula is defined as:

$$n_{11} = \frac{nD}{\sqrt{H}} \tag{2}$$

3. Pre-processing of the Model's Input

According to the FCCM in Figure 1, it can be seen that the selection of unknown working conditions in the FCCM in engineering and scientific research still depends on the linear interpolation and fitting of nearby known points. However, the flow characteristics of fluid and its impact on the energy characteristics of tubular turbine cannot be simply reflected by local linear interpolation, it is a complex nonlinear space. In terms of technical conditions, a comprehensive coverage of the whole space requires a lot of financial and material resources and a long-time test. Therefore, it is necessary to find a fast means to accurately reflect the overall picture of the comprehensive characteristic space of tubular turbine.

As a nonlinear and adaptive information processing system composed of a large number of processing units, artificial neural network has high adaptability to nonlinear, non-limited and unsteady high-dimensional complex space. Therefore, in order to comprehensively and carefully analyze the FCCM of tubular turbine, it is necessary to use artificial intelligence means to accurately study and predict the space composed of runner blade opening a_0, guide vane opening β and flow rate Q, head H, efficiency $\eta$and power P and the unit flow rate Q_{11} and unit rotation speed n_{11} converted by them. The specific strategies are as follows (Figure 3):

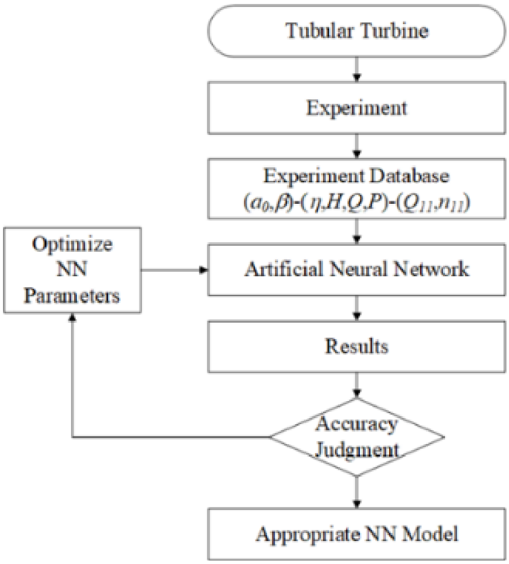

Figure 3. Neural network model strategy.

In this research, the back-propagation neural network is used to learn and predict the experimental points of the FCCM, and the parameters of the neural network are adjusted according to the accuracy of the model. Finally, the neural network model suitable for the tubular turbine in this study is obtained.

Combined with the FCCM of the tubular turbine and according to the actual operation of the turbine, the independent variables in the system are selected as the input parameters of the neural network, mainly the runner blade opening a_0 and guide vane opening β of the turbine. These two parameters are adjusted according to the actual operation conditions during the operation of the turbine. The range of runner blade opening a_0 is -18°-16°, and the range of guide vane opening β is 40°-78°. Similarly, the dependent variables in the system are selected as the output parameters of the neural network, which are mainly reflected in the FCCM of the model, namely efficiency η, head H and power P. Finally, the unit flow rate Q_{11} and unit rotation speed n_{11} of tubular turbine are calculated through the obtained output parameters and the conversion formula above.

In the neural network of this research, Levenberg-Marquardt algorithm is used for training, which can provide a good numerical solution. According to the number of samples, continuously adjust and select the number of training and verification samples, and finally select 30% of the samples as the training samples, 35% of the samples as the validation samples, and 35% of the samples to ensure the accuracy of the neural network model. Meanwhile, the number of hidden layers n_{hl} in the neural network has obvious impact on the prediction effect. Therefore, the formula recommended is used to ensure the rationality of the number of hidden layers n_{hl} [12]:

$$n_{hl} = \sqrt{n_{in} + n_{out}} + C_{epr} \tag{3}$$

where, n_{in} is the number of input layers, in this research, it has two layers; n_{out} is the number of output layers, in this research, it has four layers; C_{epr} is the empirical coefficient which can be recommended as 1-10. So the range of n_{hl} is between 3 and 13. Therefore, the number of hidden layers is chosen as 10 in this research.

According to the above settings, the neural network model suitable for the FCCM of tubular turbine in this study is finally obtained.

4. Results and Analysis

In the figure of FCCM, since unit flow rate Q_{11} and unit rotation speed n_{11} are parameter variables, they represent the change of efficiency η of the same series of turbines under different working conditions. However, in the actual operation process and experimental operation of the hydro-turbine, the conditions are adjusted through the runner blade opening a_0 and guide vane opening β. Therefore, the comparative analysis between the experimental results of the FCCM and the neural network results in this research will be carried out based on Q_{11}-n_{11} and a_0-β.

Q_{11} - n_{11} -η contour map has been drawn according to the experimental results and neural network results, and the accuracy of the neural network model obtained above by comparing the similarity of the graphics can be analyzed. Among them, the two-dimensional contour map obtained by linear interpolation according to the experimental results is shown in Figure 4a and the color in the figure indicates the efficiency of the hydro-turbine. Similarly, a two-dimensional contour map is drawn according to the results of the neural network model, as shown in Figure 4b.

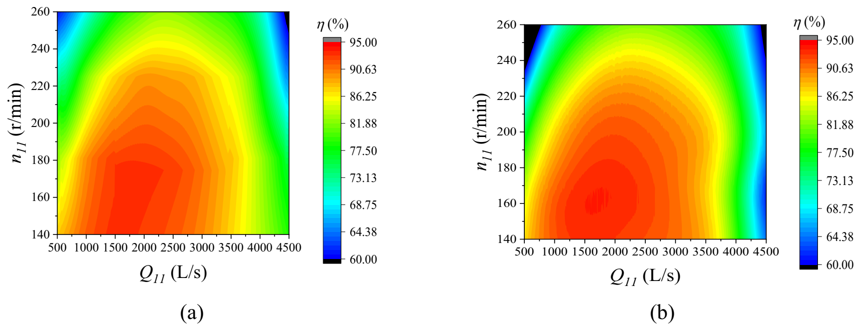

Figure 4. Q_{11}-n_{11}-η contour maps obtained by different methods. (a): Q_{11}-n_{11}-η contour maps obtained by experiment; (b): Q_{11}-n_{11}-η contour maps obtained by neural network.

In order to compare the similarity of the two images, the gray level difference is carried out after the graying of the two images. The image obtained after the difference is shown in Figure 5. The darker the color, the lower the difference between the two pictures, the more similar the two pictures are, and the brighter the color, the greater the difference between the two pictures. It can be seen from Figures 4a and 4b that in the overall picture comparison, the FCCM obtained by experimental linear interpolation is similar to that obtained by neural network. Only the extremely obvious highlight area appears in the upper left corner with little experimental data. However, due to the requirements of safety and stability of hydro-turbine during operation, it will hardly operate to this area, so it has little impact on practice. In the main operation area, that is, the high-efficiency area, the linear interpolation shows obvious edges and corners, which is difficult to appear in the real flow, but the prediction map of neural network can be accurately and smoothly expressed, indicating that the prediction of neural network can more accurately reflect the changes of the high-efficiency area of tubular turbine with unit flow rate Q_{11} and unit rotation speed n_{11}.

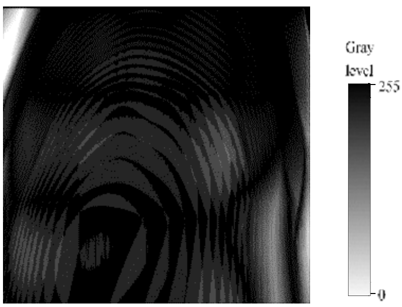

Figure 5. Q_{11}-n_{11}-η gray level difference map of experiment and neural network.

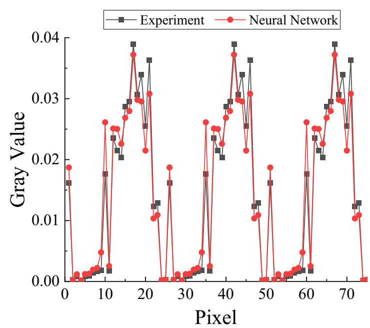

Figure 6. Grayscale value difference map of 25 small areas.

In order to further scientifically display the similarity between the two groups of pictures and facilitate observation and reduce the amount of data, 0-255 in the grayscale map is divided into 25 small areas, and then Euclidean Distance and Cosine Similarity are used to accurately reflect the similarity of pictures, that is, the accuracy between the neural network results and the real experimental results and their linear interpolation.

Figure 6 reflects the difference of grayscale between the experimental interpolation grayscale map and neural network grayscale map in each region of the picture. It can be seen from the figure that the overall color scale distribution between the two pictures has been the same, and there is only a small gap in grayscale level at individual points. It can be seen that the similarity of brightness pictures is very high.

Euclidean Distance is the most common distance measure, which is used to measure the distance of individuals in space. It measures the actual distance between two points in N-dimensional space. The smaller its value, the more similar the two pictures are. The formula is as follows:

$$A=(a_1,a_2,\ldots a_n),B=(b_1,b_2,\ldots,b_n),\ d(A,B)=\sqrt{\left[\sum(a_i-b_i)^2\right]}(i=1,2,\ldots,n) \quad (4)$$

Cosine Similarity measures the difference between two individuals by using the cosine value of the angle between two vectors in vector space. The more similar the two vectors are, the smaller the included angle is, and the closer the cosine value is to 1. Compared with distance measurement, Cosine Similarity pays more attention to the difference of two vectors in direction than distance or length. The formula is as follows:

$$A=(a_1,a_2,\ldots a_n),B=(b_1,b_2,\ldots,b_n),\ \cos\theta=\frac{\sum_1^n(a_i\times b_i)}{\sqrt{\sum_1^n a_i^2}\times\sqrt{\sum_i^n b_i^2}} \quad (5)$$

Thus, the similarity between the neural network results and the experimental results can be obtained. Through the Euclidean Distance, its value is calculated as 0.026. Through the Cosine Similarity, the cosine value is 0.999 and the included angle is 1.67°. It can be seen that the consistency between the neural network model and the actual data is very high. Therefore, the results of the neural network model can be used to replace the real data for analysis, so as to explore the complex influence of different operating conditions of the hydro-turbine.

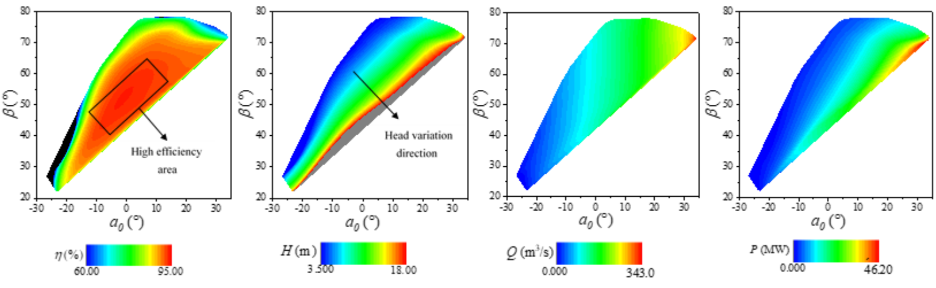

Figure 7. Contour maps of energy characteristics of hydro-turbine under the joint influence of a_0 and β. (a): contour of a_0-β-η; (b): contour of a_0-β-H; (c): contour of a_0-β-Q; (d): contour of a_0-β-P.

According to the neural network model obtained above, since the adjustment of the working condition of the hydro-turbine is carried out through the runner blade opening a_0 and the guide vane opening β in the actual operation and experiment, we focus on the relationship and influence between a_0-β space and the real external characteristics of the hydro-turbine, mainly including the efficiency η, head H, flow rate Q and power P. a_0-β-η, a_0-β-H, a_0-β-Q and a_0-β-P can be drawn. A total of four pictures are shown as Figures 7a-7d.

It can be seen from Figure 7a that the high-efficiency area of tubular turbine is very wide. Within the range of runner blade opening a_0 and guide vane opening β, the efficiency of turbine can almost reach more than 85%. Only when a few angles are combined in the edge area of the picture, the turbine shows extremely low efficiency. It can be seen that in order to ensure the operation of the hydro-turbine in the high-efficiency area, it is necessary to ensure that the runner blade opening a_0 of the hydro-turbine is between -10° and 10° and the guide vane opening β is between 40° and 60°. It can be seen from Figure 7b that the head H of the turbine increases from top left to bottom right as a whole (i.e., in the direction of the black arrow in the figure), and the change of H is jointly affected by the runner blade opening a_0 and the guide vane opening β. Figure 7c reflects the influence of the flow rate Q of tubular turbine with the change of runner blade opening a_0 and guide vane opening β. The change of flow rate Q is directly proportional to the runner blade opening a_0 and guide vane opening β as a whole. The larger the runner blade opening a_0 is, the larger the guide vane opening β is, the larger the flow rate in the turbine is. Within the high-efficiency area of the turbine, the flow rate range of the turbine is in the middle of the overall operation range, it shows that there is no obvious correlation between flow rate and efficiency. Figure 7d reflects the power change of the tubular turbine. The power of the turbine is closely related to its power generation. The high-power area of the tubular turbine is concentrated in the upper right corner of the overall changing working conditions, that is, the area with runner blade opening a_0 is, the larger the guide vane opening β. However, for the safety and stability of the turbine, the operation of turbine cannot blindly consider the power generation. Under the real long-term operation condition, its power is relatively much lower.

In order to further explore the influence degree and intensity of the operating parameters on the external characteristics of the turbine, the gray relation analysis is selected as the statistical analysis method. Gray relation analysis through the grey system analysis of the correlation degree between the index in the system and several factors affecting it, we can get which factors this index is more related to.

Table 1. Gray relation analysis table of influence factors on turbine performance.

Influencing factors	***η***		***H***		***Q***		***P***	
	CD	CO	CD	CO	CD	CO	CD	CO
a_0	0.61	2	0.69	2	0.68	2	0.77	2
β	0.73	1	0.77	1	0.83	1	0.86	1

Note: CD: correlation degree; CO: correlation order.

Since a_0-β are important factors affecting the external characteristics of hydro-turbine, gray relation analysis is carried out for these factors to find out the strength of the factors affecting the external characteristics of hydro-turbine.

It can be seen from Table 1 that in the real operation of tubular turbine, the correlation degree of turbine energy characteristics is $\eta < H < Q < P$ from low to high. It can be seen that the influence of runner blade opening a_0 and guide vane opening β has the highest correlation degree on turbine power and the lowest correlation degree on efficiency. The influence of runner blade opening a_0 and guide vane opening β on the energy characteristics of hydro-turbine is relatively high, both of which are above 0.6, reaching the correlation degree of “strong correlation”. Among the influence correlation degrees of some energy characteristics, they are above 0.8, which is the correlation degree of “very strong correlation”.

The influencing factors can be ranked according to their correlation degree: $\beta > a_0$. In the table, the influence degree of runner blade opening a_0 and guide vane opening β on the energy characteristics of hydro-turbine is obviously consistent, which shows that the correlation degree of guide vane opening β is higher. This conclusion is also reasonable. Because the change of guide vane opening β will more obviously affect the flow area of guide vane components, that is, it can more effectively control the flow rate in the turbine. There is a certain conversion relationship between energy characteristics, the change of flow rate will greatly affect other energy characteristics of the turbine. The runner blade opening a_0 changes the angle of attack of the flow into the runner components in the turbine, which affects more detailed problems such as the optimal efficiency and cavitation performance of the turbine.

Finally, taking the head H and power P of the turbine as the base and the efficiency η as the index, another form of FCCM can be obtained, that is, the operating characteristic curve, as shown in Figure 8.

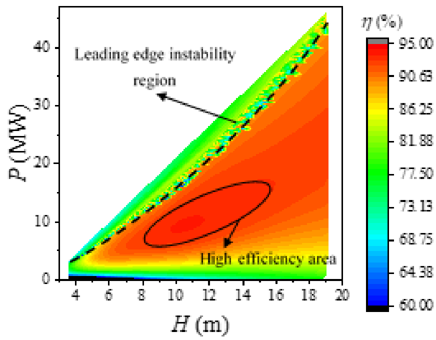

Figure 8. Contour map of the operating characteristic curve.

From the operating characteristic curve, the overall operation range of tubular turbine is in the triangular area at the lower right, and its maximum high- efficiency area is in the narrow area with head of 9-12 m and power of 5-10 MW. Near the high-efficiency area, the increase and decrease of power and the decrease of head will lead to the sharp decline of efficiency. In the leading edge area of the middle area of the picture, the dotted line in the picture, there is a very obvious area of large efficiency oscillation, which shows that the internal flow of the turbine is complex and the flow changes extremely violently, which is very harmful to the stability of power generation. In order to ensure the safe and stable operation of the turbine, the operation of the turbine must avoid this narrow and long area.

5. Conclusions

In the FCCM of hydro-turbine, due to the limitations of experimental and real operating conditions, only the real situation of a few characteristic operating points can be obtained.

For unknown operating conditions and the overall operation of hydro-turbine, it can only be obtained through the linear interpolation of known points. In this research, taking the constant flow turbine as an example, it establishes the neural network model and predicts the unknown working conditions by using the advantages and characteristics of neural network. The results show that the neural network method can effectively ensure the accuracy of FCCM, and the results can more clearly guide the safe and stable operation of hydro-turbine and ensure the efficient and stable power of plant.

Acknowledgments

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