A new method for calculating transition process based on full characteristic modeling of turbine

Xiao Liu¹, xiaoping jiang¹, yexiang xiao³.
¹Department of Electrical Engineering, China university of Mining and Technology (beijing, CN); ²School of Mechanical Electronic & Information Engineering China university of Mining and Technology; ³Department of Energy and Power Engineering, Tsinghua University.

Abstract: Hydropower units undertake the tasks of frequency modulation and peak load regulation, flood control and discharge in flood season. When the unit working condition changes greatly, the stability of unit output will be affected. Therefore, the study of the transient process is of great significance to maintain the stability of hydropower units. This paper introduces a calculation method of transition process based on comprehensive characteristic curve. Based on the data of the comprehensive characteristic curve of Chaijiaxia hydropower station, the full characteristic surface of the turbine is obtained by BP neural network algorithm. Finally, the differential algebraic equation of the transient process of the turbine is established, and the transient process is solved by combining with the full characteristics of the turbine.

keywords: Pumped storage, transition process, BP neural network, full characteristic curve

0. Introduction

Compared with conventional power stations, hydropower station stations have special functions such as peak regulation, frequency regulation, phase modulation and emergency backup. The stations need to set up or down frequently to satisfy these functions and need to respond quickly to ensure the flexibility and safety of the hydropower system. It has an irreplaceable role in UHV and smart grids. However, the flexibility of hydropower station must make the units start and stop frequently and the operating conditions change frequently, and the hydropower system cannot always be in a stable state of operation. Under loadshedding conditions, affected by the characteristics of zone S, its water hammer pressure and pulsating pressure are huge, which not only affects the stability of the unit operation, but also has a greater impact on the layout of the water pipeline system of the hydropower station. Therefore, the transition from one stable state to another frequently is an important research content in the construction and innovation process of hydropower station.

In the simulation calculation of the transient process of the hydropower unit, accurate modeling of the full characteristics of the hydraulic turbine can ensure the calculation accuracy. The internal water flow of the turbine is very complicated. The nonlinearity of the turbine and the time-delay characteristics of the water diversion pipeline determine the solution of the transition process. The calculation is a very complicated mathematical system. As a result, research on high-precision and efficient modeling and solving methods is an important part of the numerical simulation of the transition process.

In this paper, the comprehensive characteristic curve of the Chaijiaxia hydropower station is used, and the known data is processed through the BP neural network to obtain the full characteristic model of the turbine. Based on this, a differential algebraic equation of the transition process is established. The differential algebraic equation finally established is used to solve the transition process of the hydropower unit.

1. Fitting of comprehensive characteristic curve BP neural network

In this section, the comprehensive characteristic curve of the turbine will be used to obtain the full characteristic surface of the turbine. First, extract the required data from the turbine characteristic curve and
preprocess the data. Then use BP neural network training to obtain simulated flow characteristic surface. Finally, based on the flow characteristic surface, extend to the inefficient working condition area to obtain the full characteristic surface of the turbine.

1.1 Data processing

In the following, the comprehensive characteristic curve of the turbine of the Chaijiaxia Hydropower Station is taken as the research object. Firstly, import the comprehensive characteristic curve of the turbine's picture into the AutoCAD, and then draw the corresponding curves. Finally, load in the AutoLisp language to extract the coordinates. So that the working condition discrete points of the equal opening curve and of the equal efficiency curve are obtained on the comprehensive characteristic curve of its efficient working condition area.

\[
\begin{align*}
& \{a(n, Q) \\
& \eta(n, Q) \}
\end{align*}
\]

Flow: \(Q\), speed: \(n\), opening: \(a\), efficiency: \(\eta\).

There is the functional relationship between turbine torque \(M\) and flow, speed, and efficiency:

\[
M = k \frac{\eta Q}{n} = (Q, n)
\]

The dynamic characteristics of the turbine are expressed by the torque characteristics and flow characteristics of the turbine:

\[
\begin{align*}
& Q = f_Q(n, a, H) \\
& M = f_M(n, a, H)
\end{align*}
\]

Then normalize the data in order to facilitate BP neural network training process.

\[
\begin{align*}
& q_0 = f_Q(a_0, n_0) \\
& m_0 = f_M(a_0, n_0)
\end{align*}
\]

\([q_0]\) and \([m_0]\) are used as learning samples of the flow and torque characteristics of the BP neural network model. The flow characteristic and torque characteristic have same function variables, so the same BP neural network model can be used for their training. As a result, only the flow characteristics will be studied later. In order to obtain the dynamic regulation characteristics of the hydraulic turbine in the whole working condition area, it is necessary to use the data sets \([q_0]\) and \([m_0]\) to be predicted by the BP neural network and extend predicted data to the inefficient working condition area. The flow characteristic surface can be regarded as composed of several spline curves \(L(X)\) in the range of \(0 \leq x \leq 1\) after normalization.
extracting \( L(x) \) series of flow characteristic data from the non-linear spline curve \( A \) to form the value point matrix \( K[k_0, k_1, \cdots, k_n], k_n = L(x_n), 0 \leq x \leq 1 \), and the points in the definition domain of the matrix form the spline curve value point parameter constraint matrix. The optimization of the combination of value points of the spline curve can be transformed into the optimization of the combination of vertices of the control polygon. The optimal value point matrix sequence is represented by the distribution density of the control polygon vertices distributed in proportional intervals in \( 0 \leq x \leq 1 \), the expression is:

\[
x_i = \frac{|p_{i+1} - p_i|}{|p_0| + |p_1| + \cdots + |p_n|}, i = 1, 2, \cdots, n - 1
\]

\( p_i \) is the vertex of the control polygon corresponding to the value point \( k_i \).

\( x_i \) is composed of two parts: standard value \( x_{ie} \) and error correction value \( \varepsilon \), among which,

\[
x_{ie} = \frac{p_i - p_{i-1}}{p_n - p_0}, i = 1, 2, \cdots, n - 1
\]

\[
\varepsilon = \int_0^x [(L'(x) - L(x))dx]
\]

Calculating the spline curve \( L(X) \) at proportional intervals, and all the value points obtained from that calculation form a linear matrix \([M]\). The flow characteristic curve of efficient working condition area is trained through the BP neural network to obtain the value point matrix \([M]\). And then the flow characteristic curve can be extended through the tangential extension method, thereby it's possible to get the full flow characteristic surface based on the extended flow characteristic curve.

1.2 Obtain the full characteristic surface of the turbine

Establish a three-layer BP neural network structure. The input of the input layer contains the sample matrix \((a_0, n_0)\) of the guide vane opening and rotation speed, so two neurons are set. The hidden layers adopt gradient descent operation and hyperbolic tangent S-gaussian nonlinear function with 10 neurons. Using the Simulink module in Matlab to compile the BP neural network model (picture), Besides, write a function to learn and train the weights and thresholds set in the established BP network model automatically through the
proportional interval characteristic-points fitting algorithm. The output of the output layer is flow, and 1 neuron is set.

The full flow characteristic surface is obtained after the training of BP neural network by simulation.

The full flow characteristic surface is obtained after the training of BP neural network by simulation.

2. Differentiation of Transition Process—Construction of Algebraic Equations

2.1 Nonlinear Modeling of Hydropower units

The construction of the full-featured mathematical model for the mixed-flow turbine of the Hydropower units has been completed. It is also necessary to establish a mathematical model for the water diversion system, generator and actuator.
2.1 Water diversion system

During the transition process, the water movement of the diversion system is a pressured non-constant flow. Referring to the two-port model of the single-tube single-machine water diversion system with a surge tank under the S domain, the mathematical model of each section is established.

Surge model:

\[ F_T \frac{d \Delta H_T}{dt} = 2T_q \left| Q_T \right| \frac{dQ_T}{dt} + Q_T \]

\( F_T \) is the cross-sectional area of the surge tank, and \( \Delta H_T \) is the head deviation.

The time constant of the surge well flow is \( T_q = \frac{1}{2g\zeta^2 f_c} F_T \) (\( f_c \) is the impedance hole area and \( \zeta \) is the flow coefficient).

Paragraph A:

\[
\begin{align*}
  h_T(s) &= -2h_w_thth(T_{ts}^s + f_i)q_i(s) \\
  q_A(s) &= \frac{q_i(s)}{ch(T_{ts}^s + f_i)} \tag{2.1}
\end{align*}
\]

Paragraph B:
Paragraph C:

\[
\begin{align*}
    h_f(s) &= \frac{h_f(s)}{ch(T_{r2}s/2 + f_2)} - 2h_{w2}th(T_{r2}s/2 + f_2)q_1(s) \\
    q_A(s) &= \frac{h_f(s)th(T_{r2}s/2 + f_2) + q_1(s)}{2h_{w2}} + \frac{h_f(s)th(T_{r2}s/2 + f_2)}{ch(T_{r2}s/2 + f_2)}
\end{align*}
\]  

(2.2)

In the formula, \(T_{r1}, T_{r2}, T_{r3}, h_{w1}, h_{w2}, h_{w3}, f_1, f_2\) and \(f_3\) are the water hammer constructive characteristics, pipeline characteristic coefficient, and hydraulic friction coefficient of the diversion pipes in the three sections.

\[
T_{a} \frac{dx}{dt} = m_i - m_x - e_n x
\]

Do the inverse Lagrangian transformations of (2.1)(2.2)(2.3), and simultaneous surge tank equations to obtain the water diversion system model:

\[
\begin{align*}
    h_f(t) + e^{-2f_2}h_f(t - T_{r2}) &= 2e^{-2f_2}h_f(t - T_{r2}) - 2h_{w2}q_2(t) + 2h_{w2}e^{-2f_2}q_1(t - T_{r2}) \\
    h_f(t) + e^{-2f_3}h_f(t - T_{r3}) &= 2h_{w3}q_3(t) - 2h_{w3}e^{-2f_3}q_1(t - T_{r3}) \\
    q_2(t) + e^{-2f_2}q_2(t - T_{r2}) &= \frac{1}{2h_{w2}}[h_f(t) - e^{-2f_2}q_1(t - T_{r2})] + e^{-2f_2}q_1(t - T_{r2}) \\
    h_f(t) + e^{-2f_3}h_f(t - T_{r1}) &= -2h_{w1}[q_2(t) + q_f(t) - e^{-2f_3}q_1(t - T_{r1}) - e^{-2f_3}q_1(t - T_{r1})]
\end{align*}
\]  

(2.4)

2.1.2 Generators and actuators

Generator rotor motion equation:
\[ T_a \frac{dx}{dt} = m_r - m_g - e_n x \]  

(2.5)

Among them, \( x \) is the relative value of the speed deviation, \( T_a \) is the unit inertia time constant, \( m_r \) is the relative value of active torque, \( m_g \) is the relative value of load torque, and \( e_n \) is the unit's comprehensive self-adjusting coefficient.

Ignore the nonlinear link of the actuator and establish its first-order model:

\[ \dot{y} = \frac{1}{T_y} y + \frac{1}{T_y} u \]  

(2.6)

\( T_y \) is the time constant of the relay, \( y \) is the relative value of the guide vane opening, and \( u \) is the governor output.

2.2 Establish Differential-Algebraic Equations

Unified time units, simultaneous (2.4) (2.5) and (2.6), get the differential of the transition process algebraic equation:

\[
\begin{align*}
q(t) &= f_q(n(t), y(t)) \\
m(t) &= f_m(n(t), y(t)) \\
F_r \frac{d \omega H_r}{dt} &= 2T_y \left| Q_r \right| \frac{dQ_r}{dt} + Q_r \\
\dot{y}(t) &= \frac{1}{T_y} y(t) + \frac{1}{T_y} u(t) \\
h_1(t) + h_1(t - T_{r2}) - 2h_1(t - \frac{T_{r2}}{2}) + 2h_{r2}q_1(t) - 2h_{r2}q_1(t - T_{r2}) &= 0 \\
h_2(t) + h_2(t - T_{r3}) - 2h_{r2}q_2(t) + 2h_{r2}q_2(t - T_{r3}) &= 0 \\
q_2(t) + q_2(t - T_{r2}) - \frac{1}{2h_{r2}} [h_2 - q_1(t - T_{r2})] - q_1(t - \frac{T_{r2}}{2}) &= 0 \\
h_2(t) + h_2(t - T_{r1}) + 2h_{r1}[q_2(t) + q_2(t - T_{r1}) - q_1(t - T_{r1}) - q_1(t - T_{r1})] &= 0 
\end{align*}
\]  

(2.7)

3. Numerical solution and case analysis of transition process

For the target transition process, substitute the flow or torque in the full characteristic curve at that process, and use the ODE converter to solve the discretization numerical value directly of equation (2.7).

Calculation results of load rejection transition process:
4. Conclusion

a) The data extracted from the comprehensive characteristic curve of the turbine are normalized, then the flow and torque equations are established with variable turbine speed and opening. So the multi-valued comprehensive characteristic curve of a turbine can be transformed into a spatial characteristic surface determined by two independent variables.

b) The BP neural network is used to automatically learn and train the flow sample to generate the flow characteristic surface in the high efficiency working condition area, so as to realize the numerical processing of the comprehensive characteristic curve of the hydraulic turbine. Based on the proportional interval characteristic-points fitting algorithm, the full flow characteristic surface is generated, which can directly reflect the dynamic regulation characteristics of hydraulic turbine in the whole working condition area.

c) As an important boundary condition of the transient process, the full characteristics of the turbine are combined with the time delay equation of the water diversion system, the motion equation of the actuator and the first-order inertia link of the generator to complete the modeling of the nonlinear differential algebraic equations of the transient process. At the same time, the DAE equation is established to realize the calculation of the transient process.

d) The transient process calculation based on the full characteristic surface of turbine can simulate the dynamic parameter changes of turbine in the transient process.

References:

[1] Sun Yusong, Sun Yuanzhang, Lu Qiang. Research on nonlinear controller for hydro generator sets[J]. Proceedings of the CSEE. 2001, 21(2): 56-65.

[2] R. Blanc-Coquand, S. Lavigne, H. Deniau. Experiential and Numerical Study of Pressure Fluctuation in High Head Pump Turbine[C]. Hydraulic Machinery and Systems 20th IAHR Symposium, 2000.

[3] Tiller, W. Rational B-splines for curve and surface representation [C]. IEEE Computer Graphics and its Application, 1983, 3: 61-69.

[4] Olimstad G, Nielsen T, Borresen B. Dependency on Runner Geometry for Reversible-Pump Turbine Characteristics in Turbine Mode of Operation[J]. Journal of Fluids Engineering, 134(12): 102-121

[5] Wylie E B, Streeter V L. Fluid Transients[M]. New York: McGraw Hill Book Co, 1978.

[6] T Yokoyama, K Shimmei. Dynamics Characteristics of Reversible Pump Turbines in Pump Storage Plants[C]. In Proceedings of the USDE and EPRI Symposium, Boston, Massachusetts, 1984
[7] Z Yao, H L Bi. Analysis on influence of guide vanes closure laws of pump turbine on load rejection transient process[C]. 6th International Conference on Pumps and Fans with Compressors and Wind Turbines, 2013, 52: 104-106.

[8] Spalart P, Allmaras S. Aone-equation turbulence model for aerodynamic flows[J]. Recherche A erospatiale, 1994, 1(1): 5-21.

[9] Li Qing, Zhang Weijie, Chen Jing. Comparison and optimization of numerical fitting methods for fingerprint curves[J]. Modern Electronics Technique, 2015, 38(24): 27-30, 35.

[10] Menter F R. Two-equation eddy-viscosity turbulence models for engineering applications[J]. A iaa Journal, 1994, 32(8): 1598-1605.

[11] V L Streeter, E B Wylie. Fluid Transient in systems[J]. Upper Saddle River: Prentice-Hall Company, 1993(08): 1-20.

[12] Nielsen G M. Seattered data modeling[C]. IEEE Computer Graphiesand Application, 1993, 13(1): 60-70.

[13] Girimaji S S, Jeong E, Srinivasan R. Partially Averaged Navier-Stokes Method for Turbulence: Fixed Point Analysis and Comparison With Unsteady Partially Averaged Navier-Stokes[J]. Journal of Applied Mechanics, 2006, 73(3): 422-4292.