Research of Flow Characteristics Hybrid Model of Steam Turbine Stage based on the Improved PSO Algorithm

Zhao Ming¹, Yan Zhengbo¹, Zhou Liukun¹, Wang Huijie², Xu Xiaogang^{*2}

¹Yunnan Electric Power Test & Research Institute Group Co. Ltd. Electric Power Research Institute, Kunming 650217, Yunnan Province, PRC

²North China Electric Power University Baoding 071000, Hebei Province, PRC *Corresponding author, e-mail: hdxuxiaogang@163.com

Abstract

Power station steam turbine stage flow characteristics show the Corresponding relationship between pressure and flow rate, which is the important research foundation for analysis of steam turbine performance and the further optimization analysis of unit. Based on strict theory analysis, this article

obtained two important key characteristic coefficients such as the capacity of flow coefficient ψ_i and the

level of group critical pressure ratio \mathcal{E}_{sc} which mainly influenced the turbine characteristics. And then the secondary flow calculation model was imposed combining with the massive actual data, adapting the method of improved PSO algorithm. The practical results show that, the obtained model not only ensured good regularity and ductility, but also has higher calculation precision.

Keywords: steam turbine, unit, flow characteristics, hybrid model

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1. Introduction

Through-flow characteristics of the power plant steam turbines mainly reflect the pressure inside turbine at all levels (level group) with the corresponding through-flow. In case of variable conditions, the turbine flow of steam flow at all levels, the steam temperature of nozzle and rotor blades, the vapor pressure and humidity will deviate from the design values, which make the force of its parts, unit axial thrust, efficiency and output level group change significantly [1]. Therefore, the study of the characteristics of the steam turbine through flow is the basis of strength analysis, operational parameter optimization, unit efficiency and output changes.

Accurately describe the correspondence between all levels of pressure and flow unit performance analysis as well as a prerequisite for running state reconstruction and optimization of operating parameters. There is a strong coupling relationship among the parameters of the turbine level group. If use simple theoretical model analysis, as the analysis object mechanism and the actual complexity of the process, the equipment physical structure change is difficult to measure. As well as the variability of the operating conditions cause difficulty for the theoretical modeling of the flow characteristics of the turbine stage group is higher, and the accuracy of the model is not high.

With the continuous improvement of the level of power plant automation and control level, the unit stores vast amounts of actual operating data. If you rely solely on the information hidden in these data reflect performance of systems and related equipment, means of data analysis and are unable to profound analysis of the data behind the law, so inevitably cause hidden behind the data information and the law can not be deep understanding and effective use. Therefore, any single modeling method for the through-flow characteristics of the turbine stage group such as the study of complex problems, often difficult to work, and therefore produce the same complex object modeling tasks simultaneously using two or more modeling thinking. The use of two or more modeling method can complement each other, mutual support

and coordination to achieve the same goal of system modeling system modeling method called the mixed model.

In this paper, mechanism analysis of hybrid modeling method combined statistical identification research power plant steam turbines level group through-flow characteristics, which give full play to their respective advantages of the two methods. Modeling, the first rigorous theoretical analysis determine the structure of the model type and model of the basic structure, then use the improved particle swarm algorithm to identify the specific form of the model. Compared with traditional particle swarm optimization, an improved particle swarm algorithm has better global optimization capability, faster convergence speed and higher recognition accuracy.

In this paper, the theoretical analysis and data identification analysis hybrid approach is a modeling method of analysis based on the method of system identification mechanism. The analysis shows that this method is compared with a single theoretical analysis or statistical analysis method can greatly improve the modeling accuracy and modeling efficiency for the modeling of the actual unit.

2. Level Group Flow Capacity Characteristics Theoretical Analysis

Level group flow capacity characteristics of the key issues are the relationship between flow rate and pressure within the clear unit. When the level set of the series is infinitely more even level group critical pressure ratio approaches zero,

Stodola experience and experiment by running important conclusions of the flow rate and back pressure into an oval relationship [2, 3]. This conclusion is still steam turbine and gas turbine the basis of the theory of variable conditions. Friuli Siegel proved theoretically that in 1931, the elliptical relationship based on experimental and made famous Friuli Siegel formula for flow analysis level pressure.

$$\frac{D_{sc1}}{D_{sc}} = \sqrt{\frac{(p_{01}^0)^2 - (p_{21})^2}{(p_0^0)^2 - (p_2)^2}} \sqrt{\frac{T_0^0}{T_{01}^0}}$$
(1)

For Limited series level group, calculation results of Friuli Nightingale formula, with the series of different and varying degrees of error. Literature [4] improved Friuli Siegel formula for this problem.

$$\frac{D_{s1}}{D_s} = \frac{p_{01}^0}{p_0^0} \sqrt{\frac{T_0^0}{T_{01}^0}} \sqrt{1 - \left(\frac{\varepsilon_{s1} - \varepsilon_{sc}}{1 - \varepsilon_{sc}}\right)^2} / \sqrt{1 - \left(\frac{\varepsilon_s - \varepsilon_{sc}}{1 - \varepsilon_{sc}}\right)^2}$$
(2)

 $\varepsilon_s = p_2 / p_0^0$ and $\varepsilon_{s1} = p_{21} / p_{01}^0$ are level pressure ratio before and after variable conditions. T_0^0 and T_{01}^0 are stagnation temperature before and after variable conditions. ε_{sc} is critical pressure ratio of level, if $\varepsilon_{sc} = 0$, By the above formula, Prototype of Friuli can be

critical pressure ratio of level, if sc, By the above formula, Prototype of Friuli can be obtained. Such as formula (2) shown below.

In addition, the literature [5] concluded that: The level of the critical pressure ratio is proportional to the thermodynamic temperature and the square root of stagnation in the flow and level with the critical level. And in the actual variable conditions, the change of the square root of the thermodynamic temperature before level stagnation is very small. Therefore, the level of critical pressure ratio only have relation with level structure size and turbine speed. For fixed speed steam turbine, the critical pressure of the class is constant related with the level of structural dimensions. Further extended Limited to the multi-level, the same level group of the critical pressure ratio is constant related to the geometry level group levels.

The actual data analysis showed that improved Friuli Siegel formula, when only one Friuli Nightingale formula calculation error; when design conditions level group pressure is relatively small, the error is larger; amplitude of conditions is larger, the calculation error is increased. Improved Friuli Siegel formula for different series in different operating conditions has high accuracy.

Adoption of improved Friuli Siegel formula calculated for the through-flow characteristics theory has higher precision. Combined with improved Friuli Nightingale formula, Consider at all

levels of the group's overall flow coefficient μ_i and the average flow area F_i levels group flow can be expressed as:

$$D_{si} = \mu_i F_i \frac{p_{0i}^0}{\sqrt{T_{0i}^0}} \sqrt{1 - \left(\frac{\varepsilon_s - \varepsilon_{sc}}{1 - \varepsilon_{sc}}\right)^2}$$
(3)

For different level group of the turbine, due to the series at all levels within the group, flow area, vane type, even scaling and the degree of deformation, and other equipment inherent differences in the structure, Therefore, the flow capacity of the group at all levels must be different. For a certain class group, the geometric parameters are constants determined and the

actual speed of the steam turbine is essentially the same, the critical pressure \mathcal{E}_{sc} of the group at all levels will not change with the change of the actual operating conditions and changes.

Meanwhile, the level group of the flow coefficient μ_i is related with the dynamic viscosity of the working fluid, steam dryness (only low-level group for the last few levels in the wet steam), the geometric structure of the surface, roughness of the channel as well as higher [2]. For determined unit, the geometric structure and surface roughness is certain, and in the actual range of normal operating conditions, the amount of change of the dynamic viscosity of the working fluid with the degree of dryness in the same one of the group can be ignored.

Therefore, the flow coefficient μ_i and the flow area F_i of a group can be regarded as a constant.

Meanwhile, the amount of steam turbine inner leakage is also an important factor to affect the level group through-flow performance. Considering the actual level group shaft seal leakage have closed relation with the balance steam leakage inner leakage amount and Level

group pressure, defined level group of the inner leakage total amount of steam as ΔD_i , Analog of formula (3) given by the flow rate calculation model, similarly, using the form above.

$$\Delta D_{i} = \mu_{i}^{l} F_{i}^{l} \frac{p_{0i}^{0}}{\sqrt{T_{0i}^{0}}} \sqrt{1 - \left(\frac{\varepsilon_{s} - \varepsilon_{sc}}{1 - \varepsilon_{sc}}\right)^{2}}$$

$$\tag{4}$$

 μ_i^l and F_i^l are seals and peace leak of hole at flow coefficient and the leakage area. For a certain class group, the structural parameters of the total area of its shaft seal structure, the seal, number teeth, as well as balance of holes gap, of Are inherent properties of the device. Therefore, the leakage area F_i^l is a constant. The flow coefficient μ_i is related to many factors.

According to the mass balance, level group flow can be expressed as:

$$D_i = D_{si} + \Delta D_i \tag{5}$$

(3), (4) into the Equation (5), and is defined as the level group overall flow capacity coefficient:

$$D_{i} = \psi_{i} \frac{p_{0i}^{0}}{\sqrt{T_{0i}^{0}}} \sqrt{1 - \left(\frac{\varepsilon_{s} - \varepsilon_{sc}}{1 - \varepsilon_{sc}}\right)^{2}}$$
(6)

Therefore, for a defined level group, flow capacity factor and class groups critical pressure ratio are constants determined by the inherent. Its specific value of actual operation

data is obtained by identifying. (6) establish the basic framework of the hybrid model, the level set of initial pressure p_{0i}^0 , initial temperature T_{0i}^0 , level group pressure ratio \mathcal{E}_s as the main parameters of the flow of analytical grade group, Ψ_i and \mathcal{E}_{sc} are coefficient and the characteristics of the unit, and for determined level group, the two parameters determine are constants.

3. Improved Particle Swarm Algorithm and the Application of Level Group through-flow Characteristics Parameter Identification

Particle swarm optimization is a swarm intelligence optimization algorithm [6]. At the beginning, it simulates birds flying foraging behavior to achieve the purpose of optimizing collaboration between birds; particles according to the individual's own serious cognitive and social groups continue to modify the direction of flight, and eventually the entire group to food, that is, the optimal solution is close to.

The mutation is introduced in the adaptive mutation particle swarm optimization algorithm on the basis of the traditional particle swarm algorithm, and a percentage of particles are initialized in every generation [7]. The operation of mutation expands the population search space of each generation and reduces the possibility of which falling into local minimum. The proportion of the variant in the variant should be a right value for that the algorithm convergence speed will increase if the proportion is too high. Contrary, if the proportion is too low, the population search space can not be expanded, and the risk of local minimum can't be avoided.

Ten pressure stage groups between the governing stage and low pressure cylinder vent of the steam turbine were taken as the object in order to analyze the actual modeling. Combining the above theory model structure, this paper apply the adaptive mutation particle swarm optimization algorithm to parameter identification and data regression analysis according to the actual operation data within the scope of 40~100% load, finally, the flow calculation model of stage group can be obtained.

When we use the adaptive mutation particle swarm optimization algorithm to model the flow characteristics of stage group, adaptive function is shown as follows.

$$f = \min \sum_{j=1}^{m} \left[y - pop(i,1) \frac{p_{0i}^{0}}{\sqrt{T_{0i}^{0}}} \sqrt{1 - \left(\frac{\varepsilon_{s} - pop(i,2)}{1 - pop(i,2)}\right)^{2}} \right]^{2}$$
(7)

Where, pop(i,1) and pop(i,2) are identification parameters Ψ_i and \mathcal{E}_{sc} ; i is the population size; m is the length of training sample.

The optimization process of adaptive mutation particle swarm optimization algorithm is as follows:

- 1) Divide the training dataset of the samples into k free subsets according to k cross-validation requirements.
- 2) Contract a value range of optimization parameter C and $^{\mathcal{E}_{sc}}$, and encode the position vector of each particle with two-dimensional coding to create an initial particle population.
- Select training set for each particle corresponds to the parameters for cross-validation, and choose the accuracy rate of the forecast model as the objective function value corresponds to the particle.
- 4) Iterate the particles in the particle swarm as follows:

$$v_{i}^{k+1} = \omega v_{i}^{k} + c_{1} r_{1} \left(p_{i}^{k} - x_{i}^{k} \right) + c_{2} r_{2} \left(p_{g}^{k} - x_{i}^{k} \right), i = 1, 2, \cdots$$

$$(8)$$

$$x_{i}^{k+1} = x_{i}^{k} + v_{i}^{k+1}, i = 1, 2, \cdots$$

$$(9)$$

Where, V_i^{k+1} is the flight speed of the *i* particle in the k+1 generation, x_i^{k+1} is the flight speed of the *i* particle in the k+1 generation, p_i^k is the position of the *i* particle from the first generation to the k generation, P_g^k is the best position of particles from the first generation to the k generation, $p_i^k - x_i^k$ is the individual cognition, $p_g^k - x_i^k$ is the social cognition, $^{(D)}$ is the inertia factor expressed the degree that one trust oneself, C_1 , C_2 is normal number known as the acceleration factor, r_1 , r_2 is a random number of (0,1).

- 5) Evaluate all particles with the objective function values. And when the currently assessing value is superior to its historical evaluation, treat it as the best historical evaluation to inform the current optimal position vector of the particle.
- 6) Seek the global optimal solutions, and update it if its value is better than the current history.
- 7) Update the speed and position, and carry on the mutation of some particles to form a new generation of particles.
- 8) Repeat the step 4) 7).
- 9) Stop searching when the program reach a termination criterion, and output the optimal parameters.

The optimal particle variation ratio of the model is 2% according to the test results. The optimal identification results of the Ψ_i and \mathcal{E}_{sc} are shown in Table 1.

	Table 1. The Calculation Results of Ψ_i and ε_{sc} of each Stage Group									
Stage group	1	2	3	4	5	6	7	8	9	10
\mathcal{E}_{sc}	0.2401	0.2295	0.2648	0.3556	0.2161	0.1230	0.1471	0.2394	0.1280	0.2653
ψ_i	1197	2143	2042	3615	2884	2727	5093	11796	69313	68518

The change of extraction temperature is small in the actual operation process, therefore, $\sqrt{\Delta T_0^0} \approx 0$. $D_i = f(p_0^0, \varepsilon_s)$.



Figure 1. The Relationship among the Inlet Pressure P_0^{\dagger} , Pressure Ratio \mathcal{E}_s and the Flow of the No. 1 Stage Group

The No. 1 stage group consists of seven stages from governing stage to the first level extraction in series. The characteristic relation of flow, stage group pressure ratio and inlet pressure is shown in Figure 1. When the stage group pressure ratio maintain invariant, the relationship between the flow and inlet pressure is linear. The flow of stage group will increase if

the inlet pressure increase. That is, if $\varepsilon_s = const$, then $D_i = a \cdot p_0^0$.

If the inlet pressure is kept constant, the flow of stage group will decrease with the

increase of pressure ratio. From Table 1, we can find out that the critical pressure ratio ξ_{sc} of each stage group is not the same by the regression analysis, due to the progression and geometric structure of each stage group. With the volume flow of the steam increasing gradually in steam turbine, the flow area of each stage group increases gradually, and flow ability

coefficient Ψ_i of each stage group increases gradually. The laws reflected by the model are consistent with the conclusion of theoretical analysis.

This paper takes the actual operation data as the known conditions, including the inlet pressure, temperature and pressure after the stage group. Then, we can calculate flow rate of the stage group under different working conditions according to the established model, comparing to the actual flow calculated according to the energy conservation of heating system. The flow calculation results of the No. 1 stage group and the No. 9 stage group are shown in Figure 2-Figure 5.



Figure 2. The Comparation Chart of Flow Calculation Results of the No. 1 Stage Group



Figure 3. The Error Analysis of the Model of the No. 1 Stage Group



Figure 4. The Comparation Chart of Flow Calculation Results of the No. 9 Stage Group



Figure 5. The Error Analysis of the Model of the No. 9 Stage Group

5. Conclusion

Compared with the traditional particle swarm optimization algorithm, the adaptive mutation particle swarm optimization algorithm has better global optimization characteristics, faster convergence speed and higher identification precision in the process of building the

Research of Flow Characteristics Hybrid Model of Steam Turbine Stage... (Zhao Ming)

model of flow characteristics. According to the parameter identification of such actual problem, the method used in this paper has obvious advantages.

The curved surface calculated by the model basically conforms to the results of the Stodola flow test. The hybrid model has higher degree of agreement to the actual value and higher calculation accuracy for the No. 1 stage group worked in the high pressure. However, for the No.9 stage group worked in the low pressure and partly in the wet steam zone, certain error exists in high load zone (maximum error is 8%), and the calculation error is reduced with the decrease of the load and the increase of the steam dryness.

The research of this paper suggests that the hybrid modeling method used in the flow characteristics research of the actual unit has high precision and very good regularity and extensionality. Meanwhile, the improved particle swarm optimization algorithm used to identify the parameters has good recognition effect.

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