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Cross-year Optimal Scheduling Model of Large-scale cascade Hydropower Stations and its Benefits and Risks

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In terms of the instability of inflow and the year-end water level setting in cross-year long term optimal scheduling of large-scale hydropower cascade stations, the essay proposes the conception of the inflow at risk. In order to obtain the maximum generation benefit, the author establishes a mid-long term optimal scheduling model. The power generated, together with the water level of the reservoir in the first year, is regarded as basic statistics. The multi-scene scheduling scheme of the second year is regarded as a compensation for the relevant decisions of the first year. Therefore, the existing scheduling can be optimized. The conclusions are as follows: considering the benefit and risk of power generation, the model is designed as a unified scheduling model. The risk preference coefficient is introduced into the model. With Benders decomposition algorithm, the efficiency of the calculation is improved. The model can adjust the risk preference coefficient according to the expectation of the decision-maker to obtain balanced combinations of various returns and risks. At the same time, the model can reduce the risk resulted by the price fluctuation of water and electricity and the optimized model can adapt to different scenarios. The calculation results show that the proposed model can significantly improve the benefit of power generation of hydropower stations as well as reduce the wasted water of reservoirs.

1. Introduction

Compared to the thermal power generation, hydropower generation, with a more rational energy structure, is cleaner and can be recycled. Therefore, it contributes to sustainable development and brings obvious economic and environmental benefits. In order to meet the increasing demand for electricity, large-scale cascade hydropower stations are built all over the world. Based on spatial coupling model, this kind of hydropower station has many constraints, variables, and needs multi-period scheduling (Liang et al., 2009; Gil et al., 2003; Sasikala & Ramaswamy, 2010; Kumar & Naresh, 2007; Mandal & Chakraborty, 2008).

Many researches have been done on the generation optimization of water conservancy system. The focuses of the researches have switched from individual hydropower station to hydropower station group, from single factor to multiple factors and constraints, from conventional hydropower scheduling to optimal hydropower scheduling with multiple targets (Lu et al., 2010; Yuan et al., 2008; Mandal et al., 2008; Hota et al., 2009). The optimization methods include Lagrange optimization method, improved genetic algorithm, linear iteration method, neural network method, etc. (Brandão, 2010; Sumi, 2002; Keshtkar, 2017; Cabero et al., 2005; Yu et al., 2007; Mandal & Chakraborty, 2009). Scheduling cycles are mostly short. However, due to various uncertain factors, such as effects of different scenes and constraint conditions, researches on mid-long term scheduling of large-scale cascade reservoirs are few (Piantadosi et al., 2008; Li et al., 2007; Malekmohammadi et al., 2009).

In terms of uncertainties and year-end water level setting in cross-year long term optimal scheduling, this essay proposes the inflow at risk and establishes a long-term optimal scheduling model based on maximum benefit. On the basis of the power generation and reservoir water level in the first year, the decisions on multi-scene scheduling of the second year is regarded as a compensation for the relevant decisions of the first year. In this way, existing scheduling optimization can be achieved. The research results can provide theoretical references for long-term optimal scheduling of large-scale hydropower stations.

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2. Optimal scheduling model of cascade reservoirs power generation

2.1 Analysis on scheduling model

The long term scheduling of cascade hydropower station usually uses a month as a unit, and the scheduling period lasts many years. The objectives of scheduling are to achieve maximum power generation, maximum storage capacity or the minimum water waste. The optimal scheduling model of reservoir generation is shown in Fig. 1 and its period lasts 3 years. Through recording the inflow of the first year, the inflow of the second year can be predicted. The inflow of the second year can be used in the analysis of expected inflow of the third year. In this process, the information on reservoir displacement should be obtained in time. Thus, the assessments of the second year and the third year can comply with the relevant constraints of year-end reserved water level. In this way, the safety and economy of the scheduling can be enhanced. Efficient and comprehensive optimal scheduling can then be achieved (Namour et al., 2016; Osz & Hegyhat, 2018).

The reservoir inflow is continuous and unstable. When calculating, it can be regarded as a stochastic process in which discrete method is used. Thus, the problem can be simplified and the future distribution of inflows can be predicted based on existing statistical data. Some studies also used the independent distribution of several periods or the joint distribution of several adjacent periods to describe the correlation between reservoir water inflow and the time.

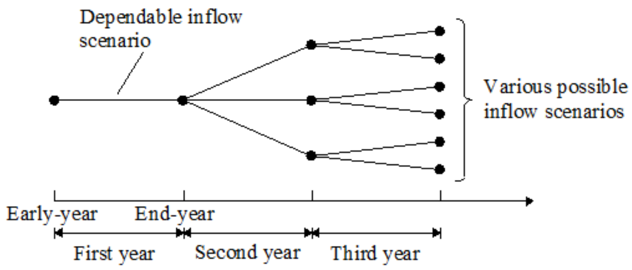


Figure 1: Illustration of Biennial stochastic scheduling

Inflow at risk (IaR) is used to predict the inflow of the hydropower station, which refers to the maximum prediction error of the inflow. The monthly inflow is the difference between the prediction inflow of the first year and the IaR. The calculation formula is as follows:

$$P(e-\mu_e \geq z_\alpha \sigma_e)=\frac{\alpha}{100} \tag{1}$$

$$\tilde{e}=\mu_e+z_\alpha\sigma_e \tag{2}$$

$$P\left(\frac{e-\mu_e}{\sigma_e}\leq z_\alpha\right)=P\left(e<\tilde{e}\right)=(100-\alpha)\% \tag{3}$$

Ideally, the prediction error complies with normal distribution. In general, the formula is set as 4:

$$P(e-\mu_e \geq k\sigma_e)=\frac{1}{k^2+1} \tag{4}$$

$$\tilde{e}=\mu_e+k\sigma_e \tag{5}$$

e is the predicted error, μ_e is the mean value of predicted error, σ_e is mean square error, z_a is independent variables under the normal distribution, and k is relevant parameter.

2.2 Establishing a scheduling model for cascade reservoirs

The stochastic scheduling model for cascade hydropower station takes advantage of phased linear programming method. The scheduling method of the first year is set as the first phase. The compensation scheduling in the same scene for the second year is set as the second phase and things are the same for the latter years (the number of the years is represented by N). The decisions made for the second or the latter years should comply with the constraints of the algorithm. In the algorithm, the water energy and the electric energy are processed with linear method, and the modeling function is as follows:

$$\max \psi = \sum_{h=1}^{H} \left(\sum_{t=1}^{T} Q_{h,,t} P_t + \sum_{\omega \in \Omega} P^{\omega} \sum_{t=T+1}^{N} Q_{h,t}^{\omega} P_t^{\omega} \right) \tag{6}$$

The total benefits of the model consists the power generation benefit of the first year and the expected benefit of the second year. In the first year, power generation efficiency is improved by optimizing the scheduling plan, and the plan of the second year should be made according to multiple scenarios.
The relation of water energy and electric energy is as follows

$$Q_{h,t} = A_h q_{h,t} W_{h,t} \Delta t \tag{7}$$

A_h is the output power coefficient of hydropower stations, $W_{h,t}$ is average water head, Pt is the real-time electricity price, $Q_{h,t}$ is power generation, h is the number of hydropower station, and H is the number of hydropower stations. The corresponding constraints are as follows
The constraints on reservoir water balance

$$v_{h,t}^{\omega} = v_{h,t-1}^{\omega} + \left[-q_{h,t}^{\omega} - s_{h,t}^{\omega} + R_{h,t}^{\omega} + \sum_{m \in U_h} \left(q_{m,t}^{\omega} + s_{m,t}^{\omega} \right) \right] \Delta t \tag{8}$$

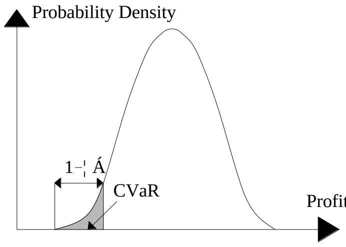


Figure 3: Probability curve of the profit function

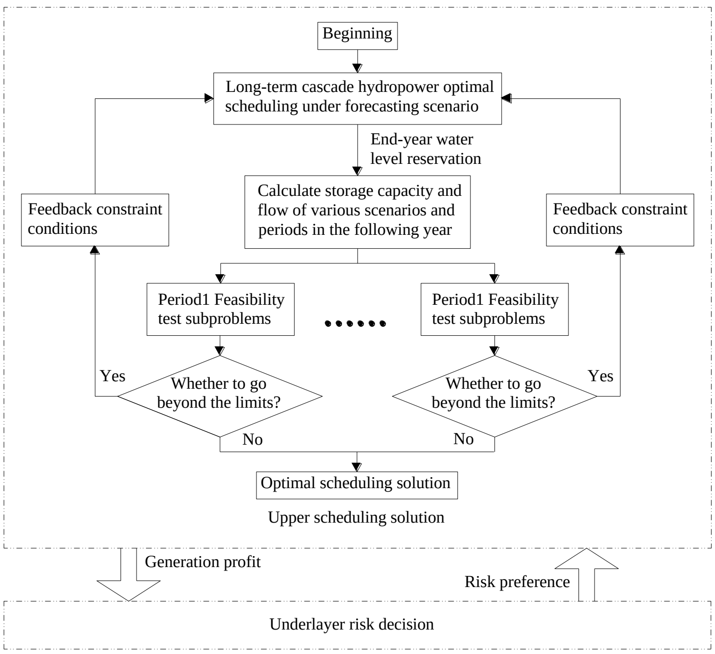


Figure 4: Solving procedure of the transformation model

The curve of probability density function for the benefit of the model is shown in Fig. 3.
The hydropower scheduling scheme is transferred from the upper part of the model to the lower part. The lower part measures the risk and calculates the relevant coefficient of the hydropower system. The results are then transferred to the upper model. The upper and lower models mutually influence each other.
θ and δ in formula 23 are Lagrange correlation factors. With different risk preference coefficients β, the optimal scheduling model is transformed into a linear programming model, and the final transformation process is shown in Figur 4. According to the mid-long term scheduling model of cascade reservoir power generation, the capacity and outflow of the second year and the third year under various scenarios can be calculated. The feasibility of sub-problems in different periods (the number of the periods is represented by T) can also be verified. In this way, the overall optimal scheduling scheme can be achieved. The risk decision of the lower part can be made by the power generation benefit and the risk preference coefficient.

3. Examples for optimal model

The water inflow and power generation during years are recorded as raw data and are used to verify the algorithm in this paper. The inflow can be divided into low flow, normal flow and high flow, so that the simulation will be more comprehensive. Table 1 shows the predicted values, mean values and standard variances of the three kinds of inflows in the first year. The table shows statistics from March to Dec. The confidence interval is set as 95%. The simulation of the latter years is based on Monte Carlo method. The computing environment is CPU 2.60GHz with 16GB built-in storage. The calculating software is GAMS. The traditional prediction model was compared with the algorithm in this essay. According to the calculation results, with this method, the power generation benefit in a calendar year can increase by 3.14% compared with the predicted value. The total wasted water decreased by 13.5%. The effect of the optimization is obvious.

Table 1: Statistical specification of inflows of representative wet, average and dry years

Period	Wet Year			Average Year			Dry Year		
	Predictive Value/ (m^3/s)	Average Value/ (m^3/s)	Standard Deviation/ (m^3/s)	Predictive Value/ (m^3/s)	Average Value/ (m^3/s)	Standard Deviation/ (m^3/s)	Predictive Value/ (m^3/s)	Average Value/ (m^3/s)	Standard Deviation/ (m^3/s)
3	471	465	25.47	441	450	55.43	454	470	25.47
4	644	631	41.12	542	538	86.76	480	492	12.69
5	902	911	31.14	977	969	125.49	866	873	147.28
6	2613	2624	35.55	2050	2117	641.51	1388	1394	227.15
7	5244	5310	25.17	3780	3765	846.28	2342	2351	650.47
8	4775	4761	40.78	3311	3307	677.27	2391	2386	211.21
9	3780	3765	31.65	3318	3321	433.74	2536	2544	352.66
10	2843	2822	42.94	2045	2036	305.26	1675	1579	188.64
11	1305	1289	45.81	1086	1114	101.15	949	878	35.55
12	817	823	38.05	713	722	45.09	581	575	23.94

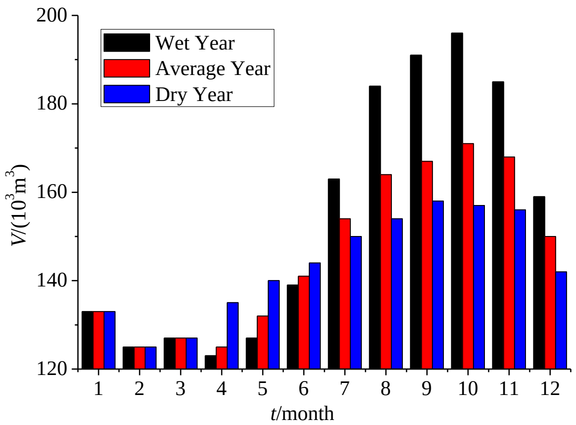
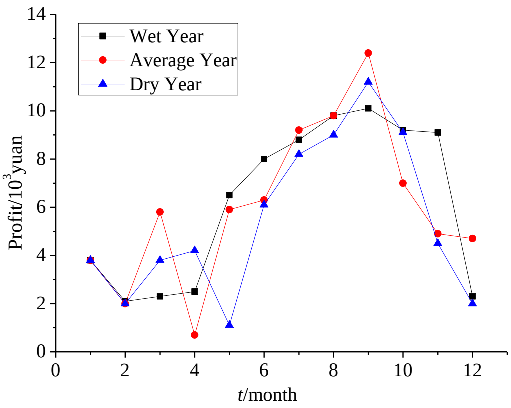


Figure 5: Reservoir storage solutions of different scenarios

Take a hydropower station as an example, the original reserve water level of the reservoir is 170m. After modeling and calculation, the number is adjusted to 172m. According to the actual operation of the hydropower station, the annual power generation benefit increased by about 3.8%. Fig. 5 shows the data on water storage of the selected hydropower station in low flow year, normal flow year and high flow year. The year-end reserved water level is obtained by decomposition algorithm. In this way, the maximum power generation benefit can be achieved in the next year and the risk resistance of all the hydropower stations can be improved.
Curves in Fig. 6 show the benefits comparison of the power stations in the three scenarios with different inflows. According to the figure, the changes of the three kinds of scenarios within a year are roughly the same. After calculation, the volatility of each month decreased, showing that this algorithm can effectively reduce the risk of hydropower stations.



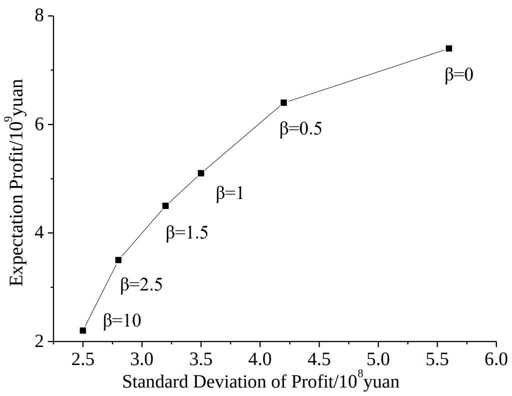


Figure 6: Revenue comparison for representative scenarios

Figure 7: Expected profit versus profit standard deviation

The curves in Fig. 7 show the comparison between the risk benefit coefficient and the expected benefit of the hydropower station. The greater the β is, the lower the expected benefit is. Moreover, the corresponding risk is lower. It can be seen that high yields are accompanied by high risks. β depends on the risk tolerance of the decision maker. Compared with the traditional decomposition method, the optimal scheduling decomposition method can reduce the time of calculation by nearly 45% and thus meet the real-time requirement in practice.

4. Conclusions

In terms of the instability of inflow and the year-end water level setting in cross-year long term optimal scheduling of large-scale hydropower cascade stations, the essay proposes the conception of the inflow at risk. In order to obtain the maximum generation benefit, the author establishes a mid-long term optimal scheduling model. The power generated, together with the water level of the reservoir in the first year, is regarded as basic statistics. The multi-scene scheduling scheme of the second year is regarded as a compensation for the relevant decisions of the first year. Therefore, the existing scheduling can be optimized. The model is compared to the traditional hydropower scheduling model, and the conclusions are as follows:
(1) Considering the benefit and the risk of power generation, the model is designed as a unified scheduling model. The risk preference coefficient is introduced into the model. With Benders decomposition algorithm, the efficiency of the calculation is improved.
(2) The model can adjust the risk preference coefficient according to the expectation of the decision-maker to obtain balanced combinations of various returns and risks. At the same time, the model can reduce the risk caused by the price fluctuation of water and electricity and the optimized model can adapt to different scenarios.
(3) The calculation results show that the proposed model can significantly improve the benefit of power generation of hydropower stations as well as reduce the wasted water of reservoirs.

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