Ultrashort-Term Scheduling of Interbasin Cascaded Hydropower Plants to Rapidly Balance the Load Demand

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ABSTRACT The short-term scheduling schemes of cascaded hydropower plants are based on day-ahead hydrological forecasting information. Affected by the accuracy of prediction, real-term hydrological information can considerably vary from previously forecasted values, especially for the power load and local inflows. As a result, short-term scheduling schemes are difficult to apply directly in real-time scheduling. To solve this problem, a rolling optimal hourly operation model for interbasin cascaded hydropower plants is proposed to rapidly balance the load demand. The model is deemed an ultrashort-term model, and it has a short-cycle schedule between short-term and real-time schemes. The basic strategy of solving the model is as follows. First, the day-ahead power load and local inflow information are corrected using a statistical method based on the most recent real-time information. Second, the water delay time, defined as the time between when water is released from upstream reservoirs and arrives at downstream reservoirs, is updated based on the most recent real-time information. Third, a heuristic method is proposed to dynamically update the short-term scheduling scheme over the next few hours. The objective is to minimize the maximum relative deviation between the actual water level of a reservoir at the end of 24 hours and the day-ahead forecasted value. This approach can keep the reservoir water level at the end of 24 hours close to the forecasted value and improve the accuracy of estimating the initial water level the next day. The developed method is applied to solve an ultrashort-term scheduling problem involving the cascaded hydropower plants located in Yunnan Province, China. The results indicate that the proposed model can achieve seamless coupling between short-term scheduling and real-time scheduling. The proposed method can provide a scientific basis for the real-time dispatching of large-scale hydropower plants and improve the practicality of short-term dispatching schemes.

INDEX TERMS Ultrashort term, water delay time, cascaded hydropower plants, real-time scheduling, optimal scheduling.

NOMENCLATURE The notations used in the mathematical model of hydropower operation are given as follows.

A. SETS

M Set of reservoirs or hydropower plants (HPs)
M₂ Set of HPs that can increase power generation
M₃ Set of HPs that can reduce their power generation

T Set of time periods
S Set of control sections
Sₘ Set of HPs that are directly connected to the control section s
α Sample series of local inflows between the period \( t^α_0 \) and the period \( t^α_A \)
β Sample series of local inflows between the period \( t^β_0 \) and the period \( t^β_A \)
D Number of local inflow sample series before the period \( t_{now} \)

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B. CONSTANTS

\( \Delta t \) Number of seconds in the \( t \)th period

\( T_{\text{before}} \) Number of time periods before \( t_{\text{now}} \)

\( A \) Length of the local inflow sample data sets

\( Z_{m,\text{max}}^T \) Maximum water level of the \( m \)th reservoir in period \( T \)

\( Z_{m,\text{min}}^T \) Minimum water level of the \( m \)th reservoir in period \( T \)

\( Z_F^T \) Day-ahead forecasted water level of the \( m \)th reservoir in period \( T \in m \)

\( T_{\text{before}} \) Number of time periods before \( t_{\text{now}} \)

\( P_s^T \) Maximum limiting transmission power in control section \( s \) in period \( t \) in MW

\( r_{s,m} \) Experience factor of plant \( m \) in control section \( s \) given by the dispatcher

\( \Delta N_m \) Maximum ramping capacity of the \( m \)th HP in period \( t \) in MW

\( V_{m,\text{min}}^t \) Minimum storage volume of the \( m \)th reservoir in period \( t \) in \( m^3 \)

\( V_{m,\text{max}}^t \) Maximum storage volume of the \( m \)th reservoir in period \( t \) in \( m^3 \)

\( q_{m,\text{min}}^t \) Minimum turbine discharge of the \( m \)th plant in period \( t \) in \( m^3/s \)

\( q_{m,\text{max}}^t \) Maximum turbine discharge of the \( m \)th plant in period \( t \) in \( m^3/s \)

\( N_{m,\text{min}}^t \) Minimum power generation of the \( m \)th plant in period \( t \) in MW

\( N_{m,\text{max}}^t \) Maximum power generation of the \( m \)th plant in period \( t \) in MW

\( B \) Length of the intersection of the sample series \( Q_m^{a-1,\text{release}} \) and \( Q_m^a \)

\( K \) Storage constant

\( x \) Weighting factor (reflecting the relative importance of inflows and releases in computing storage)

\( C_0 \) Coefficient of the Muskingum method

\( C_1 \) Coefficient of the Muskingum method

\( C_2 \) Coefficient of the Muskingum method

\( \varepsilon \) Computational accuracy

\( V_m^t \) Initial storage volume of the \( m \)th reservoir in period \( t \) in \( m^3 \)

\( V_m^{t+1} \) Final storage volume of the \( m \)th reservoir in period \( t \) in \( m^3 \)

\( Q_{m-1,\text{release}}^n \) Water release of the \( m-1 \)th reservoir in period \( n \)

\( Q_{m,\text{local}}^t \) Local inflow of the \( m \)th reservoir in period \( t \)

\( Q_{m,\text{delay}}^t \) Delay time inflow of the \( m \)th reservoir at time \( t \) from a water release of the \( m-1 \)th reservoir in period \( n \)

\( \tau_m^t \) Water delay time for the water traveling between reservoirs \( m-1 \) and \( m \) in hours

\( N_m^t \) Power generation of plant \( m \) in period \( t \) in MW

\( N_o^t \) Sum of the power generation of other types of plants in period \( t \) in MW

\( L_{\text{forecast}}^t \) Forecasted load demand of the UST scheme in period \( t \) in MW

\( L_{\text{plan}}^t \) Planned load demand of the day-ahead plan in period \( t \) in MW

\( L_{\text{real}}^t \) Real load demand in period \( t \) in MW

\( \Delta L^t \) Power deviation between the power supply and power load in period \( t \) in MW

\( P_s^t \) Total transmission power in control section \( s \) in period \( t \) in MW

\( h \) Number of time periods

\( h^* \) Number of time periods when \( R(h^*) \) is a maximum

\( t_0^\alpha \) Start period of local inflow sample set \( \alpha \)

\( t_0^\beta \) Start period of local inflow sample set \( \beta \)

\( t_f^\alpha \) End period of local inflow sample set \( \alpha \)

\( t_f^\beta \) End period of local inflow sample set \( \beta \)

\( Q_{m,\text{local}}^\alpha \) Local inflow of sample set \( \alpha \) for the \( m \)th reservoir in period \( t \)

\( Q_{m,\text{local}}^\beta \) Local inflow of sample set \( \beta \) for the \( m \)th reservoir in period \( t \)

\( \bar{Q}_{m,\text{local}}^\alpha \) Mean of \( Q_{m,\text{local}}^\alpha \) from \( t_0^\alpha \) to \( t_f^\alpha \)

\( \bar{Q}_{m,\text{local}}^\beta \) Mean of \( Q_{m,\text{local}}^\beta \) from \( t_0^\beta \) to \( t_f^\beta \)

\( Q_{m,\text{local}}^d \) Local inflow of the \( m \)th reservoir in period \( t \) for the \( d \)th series

\( \bar{Q}_{m,\text{local}}^d \) Average local inflow of the \( m \)th reservoir for the \( d \)th series

\( Q_{m,\text{local}}^{D+1,hs} \) Forecasted value of the \( m \)th reservoir for the \( D+1 \)th series

\( \bar{Q}_{m,\text{local}}^{D+1,hs} \) Average local inflow of the \( m \)th reservoir for the \( D+1 \)th series

\( w_t \) Weight coefficient \( w_t \) in period \( t \) for the sample data

\( R_m^{t-1,m} \) Correlation coefficient

\( \Delta \alpha_m^t \) Power generation increment of the \( m \)th HP in period \( t \)

\( \Delta \alpha_m^{t,1} \) Idle capacity of the \( m \)th HP in period \( t \)

\( \Delta \alpha_m^{t,2} \) Maximum ramping capacity of the \( m \)th HP in period \( t \)
of real-time scheduling was minimizing turbine discharge and spills [14], achieving multipurpose reservoir flood control [15], maximizing reservoir storage at the end of a flood season [16], minimizing the total fuel cost of a hydrothermal system to meet the load demand [17], maximizing the energy production of 40 reservoirs [18], and maximizing hydropower system energy storage at the end of the scheduling period [19]. However, real-time scheduling remains difficult to optimize for a dispatcher. Practical scheduling scheme with long time horizons are needed to avoid large miscalculations, especially during the flood season, when the actual boundary conditions (such as the local inflow and power load) are significantly different from those for a typical forecast. In such cases, short-term scheduling schemes are difficult to directly apply, and the related boundary conditions must be adjusted. However, because of the large number of HPs and the strong hydraulic and electrical coupling, which is related to delay times [20]–[22], it is difficult for dispatchers to make scientific and reasonable revision decisions in a short time. In practice, dispatchers mainly rely on their experience to revise hydropower generation schedules. As a result, some serious problems can occur, such as the water level at the end of 24 hours failing to reach the day-ahead forecasted value, water spillage issues and excess local power generation due to transmission capacity limitations [23], [24].

This problem is also known as ultrashort-term (UST) scheduling, which is short-cycle scheduling with short-term and real-time components. For UST scheduling, previous studies focused on load forecasting [25]–[27], power generation adjustment strategies for AGC units based on load forecasting deviations [28]–[30], minimizing operation costs together with maximizing ability of accommodating wind power for wind-thermal-hydro power system [31], multi-time scale coordinated scheduling for minimizing wind power spillage [32], multi-time scale coordinated scheduling for multi-source generation systems to minimal operation cost of thermal units [33] and other tasks. In this paper, a rolling optimal hourly UST scheduling model for interbasin cascaded HPs is proposed to rapidly balance the load demands. The objective is to minimize the maximum relative deviation between the water level of the reservoir at the end of 24 hours and the day-ahead forecasted value under various hydraulic and electrical constraints. The innovation of this model is that it uses the latest local inflow and power load information to dynamically update the short-term scheduling scheme to effectively overcome the drawbacks of traditional short-term scheduling, which is difficult to apply in real-time scheduling and planning. The proposed method can achieve seamless coupling between short-term and real-time scheduling.

The contributions of this research are summarized as follows: (1) Two types of runoff prediction models are proposed to forecast the local inflow of the first stage and the other stages of cascaded HP operation. (2) Two Types of discharge evolution models are proposed to forecast the inflow of downstream reservoirs from upstream reservoirs. (3) A heuristic method is proposed to dynamically update the power generation plan of each HP in the short term (over a

$$\Delta \alpha_{m,3}$$ Remaining deviation between the power load and power supply in period \(t\) when the power load exceeds the power supply

$$\Delta \beta_{m}$$ Power generation decrement of the \(m\)th HP in period \(t\)

$$\Delta \beta_{m,1}$$ Maximum power generation of the \(m\)th HP in period \(t\)

$$\Delta \beta_{m,3}$$ Remaining deviation between the power load and power supply in period \(t\) when the power supply exceeds the power load

$$\Delta \beta_{m,2}$$ Maximum ramping capacity of the \(m\)th HP in period \(t\)

$$\Delta \alpha_{m,2}$$ Remaining deviation between the power load and power supply in period \(t\) when the power supply exceeds the power load

$$\Delta Q_{\text{max,local}}^\text{ave}$$ Maximum error of local inflow forecasting in %

$$\Delta Q_{\text{max,local}}^\text{ave}$$ Average error of local inflow forecasting in %

$$Q_{\text{real,local}}^m$$ Real local inflow of the \(m\)th reservoir in period \(t\)

$$Q_{\text{local,release}}^m$$ Local inflow forecasting value of the \(m\)th reservoir for the rolling calculation (based on times) in period \(t\)

$$Q_{\text{local,release}}^m$$ Local inflow forecasting value of the \(m\)th reservoir for the rolling calculation (based on times) in period \(t\)

$$\alpha$$ Autocorrelation coefficient function between local inflow series \(\alpha\) and local inflow series \(\beta\)

$$\beta$$ Correlation function between the water releases of upstream reservoirs \(Q_{m-1,\text{release}}^m\) and the water inflows into downstream reservoirs \(Q_m^m\)

D. FUNCTIONS

$$R(h)$$ Autocorrelation coefficient function between local inflow series \(\alpha\) and local inflow series \(\beta\)

Correl(\(\ast\), \(\ast\)) Correlation function between the water releases of upstream reservoirs \(Q_{m-1,\text{release}}^m\) and the water inflows into downstream reservoirs \(Q_m^m\)

I. INTRODUCTION

In recent decades, with the unceasing expansion of the hydropower scale in fast-growing countries, such as China and Brazil, the problem of large-scale hydropower plant (HP) scheduling has become increasingly complicated. The most complex issues include short-term scheduling and real-time scheduling.

Many scholars have studied short-term scheduling and produced many innovative research results, such as peak-shaving scheduling [1]–[5], maximizing the total benefit [6]–[8], and minimizing the total fuel cost [9], [10]. However, due to the large number of HPs, useful forecasting information is limited, the forecasting accuracy is low, large and complex constraint sets are needed, and dimensionality issues can occur [11]–[13]; as a result, the current theoretical approach faces considerable challenges in terms of practicality, universality, and computational efficiency. There is still considerable difference between short-term scheduling schemes and the real scheduling process. The focus of most studies of real-time scheduling was minimizing turbine discharge

| \(\Delta \alpha_{m,3}\) | Remaining deviation between the power load and power supply in period \(t\) when the power load exceeds the power supply |
|---|---|
| \(\Delta \beta_{m}\) | Power generation decrement of the \(m\)th HP in period \(t\) |
| \(\Delta \beta_{m,1}\) | Maximum power generation of the \(m\)th HP in period \(t\) |
| \(\Delta \beta_{m,3}\) | Remaining deviation between the power load and power supply in period \(t\) when the power supply exceeds the power load |
| \(\Delta \beta_{m,2}\) | Maximum ramping capacity of the \(m\)th HP in period \(t\) |
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| \(\Delta Q_{\text{max,local}}^\text{ave}\) | Maximum error of local inflow forecasting in % |
| \(\Delta Q_{\text{max,local}}^\text{ave}\) | Average error of local inflow forecasting in % |
| \(Q_{\text{real,local}}^m\) | Real local inflow of the \(m\)th reservoir in period \(t\) |
| \(Q_{\text{local,release}}^m\) | Local inflow forecasting value of the \(m\)th reservoir for the rolling calculation (based on times) in period \(t\) |
| \(r(h)\) | Autocorrelation coefficient function between local inflow series \(\alpha\) and local inflow series \(\beta\) |
| Correl(\(\ast\), \(\ast\)) | Correlation function between the water releases of upstream reservoirs \(Q_{m-1,\text{release}}^m\) and the water inflows into downstream reservoirs \(Q_m^m\) |

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This problem is also known as ultrashort-term (UST) scheduling, which is short-cycle scheduling with short-term and real-time components. For UST scheduling, previous studies focused on load forecasting [25]–[27], power generation adjustment strategies for AGC units based on load forecasting deviations [28]–[30], minimizing operation costs together with maximizing ability of accommodating wind power for wind-thermal-hydro power system [31], multi-time scale coordinated scheduling for minimizing wind power spillage [32], multi-time scale coordinated scheduling for multi-source generation systems to minimal operation cost of thermal units [33] and other tasks. In this paper, a rolling optimal hourly UST scheduling model for interbasin cascaded HPs is proposed to rapidly balance the load demands. The objective is to minimize the maximum relative deviation between the water level of the reservoir at the end of 24 hours and the day-ahead forecasted value under various hydraulic and electrical constraints. The innovation of this model is that it uses the latest local inflow and power load information to dynamically update the short-term scheduling scheme to effectively overcome the drawbacks of traditional short-term scheduling, which is difficult to apply in real-time scheduling and planning. The proposed method can achieve seamless coupling between short-term and real-time scheduling.

The contributions of this research are summarized as follows: (1) Two types of runoff prediction models are proposed to forecast the local inflow of the first stage and the other stages of cascaded HP operation. (2) Two Types of discharge evolution models are proposed to forecast the inflow of downstream reservoirs from upstream reservoirs. (3) A heuristic method is proposed to dynamically update the power generation plan of each HP in the short term (over a
few hours). The developed method is applied to solve the UST scheduling problem for cascaded HPs located in Yunnan Province, China. The results show that the local inflow prediction method and the natural channel discharge evolution method can improve the accuracy of inflow forecasts without any data inputs from rainfall forecasts. The power generation updating method for cascaded HPs can control the water level of the reservoir at the end of 24 hours to achieve the forecasted value. The proposed model and method can improve the practicality of short-term dispatching schemes.

The remainder of this paper is organized as follows. The details of the objective function and constraints are given in Section II. The solution methods are introduced in Section III. The proposed method is used to address a hydropower system consisting of 23 HPs in Section IV. Finally, the conclusions are given.

II. PROBLEM FORMULATIONS

A. OBJECTIVE FUNCTION

In this paper, the short-term scheduling scheme starts at 0:00 and ends at 24:00. The time scale is 1 hour. A complex problem faced daily by power grid companies in operating real-world hydropower systems in China is getting the water level of reservoirs 24 hours in advance as close to the day-ahead forecasted value as possible [34]. The forecasted value is used as the initial water level of the reservoir to develop the short-term scheduling scheme for the next day. Therefore, the objective is to minimize the maximum deviation between the water level of the reservoir at the end of 24 hours and the day-ahead forecasted value. In addition, it should be noted that there is a large difference in the reservoir storage levels of different reservoirs; hence, the relative deviation should be used in the objective function, which can be expressed as follows [35]:

\[
\min \left[ F^T = \max_{1 \leq m \leq M} \frac{Z^T_m - ZF^T_m}{Z^T_{m,\max} - Z^T_{m,\min}} \right] \quad (1)
\]

where \( F^T \) is the maximum relative deviation of the water level in period \( T \). \( T = 24 \) is the set of time periods, with index \( t \in T \). \( M \) is the set of reservoirs or HPs, with index \( m \in M \). \( Z^T_{m,\max} \) and \( Z^T_{m,\min} \) are the maximum and minimum water levels of the \( m \)th reservoir in period \( T \), respectively. \( Z^T_m \) and \( ZF^T_m \) are the water level and the day-ahead forecasted value of the \( m \)th reservoir in period \( T \), respectively. The horizon of UST scheduling is the time between \( t_{\text{now}} \) and \( T \). This horizon is shown in Fig. 1.

B. CONSTRAINTS

1) THE WATER BALANCE EQUATION OF RESERVOIRS

\[
V^t_m = V^t_m + \left( Q^{t}_m - q^{t}_m - S^{t}_m \right) \times \Delta t, \quad m \in M, \ t \in [t_{\text{now}}, T]
\]  

where \( t_{\text{now}} \) is the current time and start time of the simulation calculation; \( Q^{t}_m \), \( q^{t}_m \), and \( S^{t}_m \) are the inflow, turbine discharge and spillage rate of water for the \( m \)th reservoir in period \( t \) in \( \text{m}^3/\text{s} \), respectively; \( V^t_m \) and \( V^{t+1}_m \) are the initial and final storage volumes of the \( m \)th reservoir in period \( t \) in \( \text{m}^3 \) and \( \Delta t \) is the number of seconds in period \( t \).

2) WATER DELAY TIME OF THE UPSTREAM RESERVOIR RELEASE

It takes time for water to flow from an upstream reservoir to a downstream reservoir. This travel time is called the water delay time, and it can be expressed by the following formula. The expression is established based on the assumption that
the water delay time is an integer value. A detailed analysis will be given in Section III.B.

\[
Q_m^l = Q_{m,\text{local}} + \sum_{n=1}^{t} Q_{m,\text{delay}}^{n,}\quad n \in [t - T_{\text{before}}, t], \quad t \in [t_{\text{now}}, T] \\
Q_{m,\text{delay}}^{n} = \begin{cases} 
Q_{m-1,\text{release}}^{n}, & n + \tau_m^{n-1} = t \\
0, & n + \tau_m^{n-1} \neq t 
\end{cases}
\]

where \(Q_{m,\text{local}}^{l}\) is the local inflow of the mth reservoir in period t; \(Q_{m,\text{delay}}^{n}\) is the delay time of the inflow of the mth reservoir in period t from the upstream reservoir m-1 due to the release \(Q_{m-1,\text{release}}^{n}\) in period n; and \(\tau_m^{n-1}\) is the water delay time for the water flow between reservoirs m-1 and m in hours. A schematic diagram of the final constraint is shown in Fig. 2 [22].

![Reservoir release routing effect between reservoirs m-1 and m. In this example, the minimum and maximum water delay times are 1 h and 3 h, respectively.](image)

**FIGURE 2. Reservoir release routing effect between reservoirs m-1 and m. In this example, the minimum and maximum water delay times are 1 h and 3 h, respectively.**

3) THE POWER BALANCE CONSTRAINTS FOR THE POWER GRID [35]

\[
\sum_{m=1}^{M} N_m^l + N_0^l = L_{\text{forecast}}^l \\
L_{\text{forecast}}^l = L_{\text{plan}}^l + \max\left(L_{\text{real}}^l - L_{\text{plan}}^l, 0\right)
\]

where \(N_m^l\) is the power generation of plant \(m\) in period t in MW; \(N_0^l\) is the sum of the power generation from other types of plants in period t in MW, such as thermal plants, wind plants and photovoltaic plants; \(L_{\text{forecast}}\) and \(L_{\text{plan}}\) are the UST forecasted load demand and the day-ahead planned load demand in period t in MW; \(L_{\text{real}}\) is the real load demand in period t in MW; \(T_{\text{before}} = 8(8)\) h is the number of time periods before \(t_{\text{now}}\); and \(T_{\text{before}}\) is an experience value given by the dispatchers that work for grid companies.

4) THE TRANSMISSION CONTROL CONSTRAINT [35–36]

In general, small and medium-sized HPs are located at the end of the grid and have low voltage levels. It is necessary to use step-by-stage grid-connected power to transmit electric energy to far-away areas. However, if several HPs crowd limited transmission channels at the same time, the total transmission power may exceed the static stability limit of a given section, so the total power generation of grid-connected HPs must be limited in period t. Generally, a system contains several primary control sections and HPs, and each primary control section can contain several two-stage control sections. A schematic of this constraint is shown in Fig. 3. Mathematically, \(P_s^l\) is given by the dispatcher.

\[
\begin{cases} 
P_s^l = \sum_{m=1}^{s_m} (r_{s,m} \times N_m^l) + P_{s-1}^l \\
P_s^l \leq P_S^l, \quad s = 1, 2 \ldots S
\end{cases}
\]

where S is the set of control sections, with index \(s \in S\); \(s_m\) is the number of HPs that are directly connected to the control section \(s\); \(P_s^l\) and \(P_S^l\) are the total transmission power and maximum limiting transmission power in control section \(s\) in period t in MW, respectively; and \(r_{s,m}\) is the experience factor of plant \(m\) in control section \(s\), which is given by the dispatcher.

5) THE MAXIMUM RAMPING CAPACITY CONSTRAINT

\[
|N_{m-1}^l - N_m^l| \leq \Delta N_m
\]

where \(\Delta N_m\) is the maximum ramping capacity of the mth HP in period t in MW.

6) OTHER CONSTRAINTS

To ensure that all the reservoir and plant variables are within the feasible ranges, some constraints should be considered in the model [37–39]. Mathematically,

\[
V_{m}^{l,\min} \leq V_m^l \leq V_{m}^{l,\max}
\]

\[
q_{m}^{l,\min} \leq q_m^l \leq q_{m}^{l,\max}
\]

\[
N_{m}^{l,\min} \leq N_m^l \leq N_{m}^{l,\max}
\]

where \(V_m^{l,\min}\) and \(V_m^{l,\max}\) are the minimum and maximum storage volumes of the mth reservoir in period t, respectively; \(q_m^{l,\min}\) and \(q_m^{l,\max}\) are the minimum and maximum turbine
discharge values of the mth plant in period t, respectively; and
\( N_{m,\min}^t \) and \( N_{m,\max}^t \) are the minimum and maximum power
generation levels of the mth plant in period t, respectively.

III. SOLUTION METHODOLOGIES
To address the complex practical problem of UST scheduling,
this paper develops a UST model for determining the optimal
time real-time power generation plan. The UST model consists of three submodels: a runoff forecasting model, which is
developed to predict the local inflow of cascaded HPs; an upstream reservoir release forecasting model, which is
developed to predict the downstream reservoir inflows from the water released by upstream reservoirs; and a real-time optimization scheduling model, which is developed to update the power generation plan of each HP when the power supply is not equal to the power load in the UST scheduling horizon. An overall solution strategy is shown in Fig. 4.

FIGURE 4. The overall solution strategy.

A. FORECASTING LOCAL INFLOWS
Currently, most models, including the black-box model, require the input of forecasting information, such as rainfall information, the runoff yield and concentration information, to predict runoff. Most HPs are located in remote mountainous areas, and several or even dozens of HPs can only shared a hydrological station. Rainfall forecasting information is almost useless for UST scheduling because the forecasting scale (such as 8 hours or 12 hours) is too large. In this case, it is necessary to study the local inflow forecasting method of UST without forecasting information inputs. According to the position of the HP in the cascaded HP system, the HPs can be divided into first-stage HPs and nonfirst-stage HPs, as shown in Fig. 5.

1) FORECASTING THE LOCAL INFLOW OF THE FIRST-STAGE CASCADED HPs
The local inflow of the first-stage cascaded HPs mainly comes from antecedent precipitation and tributaries. In general, the inflow from antecedent precipitation will not suddenly change at the hourly scale. However, the inflow from tributaries can vary significantly within hours. There are many reasons for these sudden changes. One of the main reasons is the influence of human activities, such as the operation of many small HPs. Although these small HPs have poor regulation capacities, they are still capable of providing regulation for several hours and disrupting the regular tributary flows. In this case, the key to the local inflow forecasting of the nonfirst-stage cascaded HPs is to fully understand the runoff response trends of the tributaries. We can solve this practical problem with the data mining concept. Specifically, when large quantities of historical data are available, we can develop a reasonable prediction model by analyzing the historical trends. Then, the prediction accuracy of the model can be assessed with actual data. For example, a historical local inflow of W HP in Yunnan Province is shown in Fig. 6(a). We note that the hourly local inflow of the W HP varies greatly due to the interference of small HPs located on the tributaries. It is very difficult to directly use statistical models to forecast the local inflow. A longer history of the local inflow of the W HP is shown in Fig. 6(b). The hourly local inflow also varies greatly, but it fluctuates with a few hours into the future can be forecasted by the stationary
time series method based on the actual local inflow in the
previous few hours. Mathematically,

\[
Q_{m-1, \text{local}}^{t} = \frac{1}{T_{\text{before}}} \sum_{t=t-1}^{T} Q_{m-1, \text{local}}^{t}, \quad t \in [t_{\text{now}}, T]
\]  

(10)

where \( T_{\text{before}} \) is the number of time periods before \( t_{\text{now}} \) (see Fig. 1).

2) FORECASTING THE LOCAL INFLOW OF THE NONFIRST-STAGE CASCADED HPs
The local inflow of the nonfirst-stage cascaded HPs mainly comes from antecedent precipitation and tributaries. In general, the local inflow from antecedent precipitation will not suddenly change at the hourly scale. However, the local inflow from tributaries can vary significantly within hours. There are many reasons for these sudden changes. One of the main reasons is the influence of human activities, such as the operation of many small HPs. Although these small HPs have poor regulation capacities, they are still capable of providing regulation for several hours and disrupting the regular tributary flows. In this case, the key to the local inflow forecasting of the nonfirst-stage cascaded HPs is to fully understand the runoff response trends of the tributaries. We can solve this practical problem with the data mining concept. Specifically, when large quantities of historical data are available, we can develop a reasonable prediction model by analyzing the historical trends. Then, the prediction accuracy of the model can be assessed with actual data. For example, a historical local inflow of W HP in Yunnan Province is shown in Fig. 6(a). We note that the hourly local inflow of the W HP varies greatly due to the interference of small HPs located on the tributaries. It is very difficult to directly use statistical models to forecast the local inflow. A longer history of the local inflow of the W HP is shown in Fig. 6(b). The hourly local inflow also varies greatly, but it fluctuates with a
certain cycle, and the daily average local inflow varies little. This is important information for forecasting the local inflow. Therefore, a time series method was developed at a given time scale to eliminate the interference of small HP scheduling.

(1) Identify the trends in the local inflow sample data

First, we must determine whether the local inflow sample data before \( t_{\text{now}} \) display a specific frequency fluctuation. This problem can be addressed by using the autocorrelation coefficient in statistics, as given by formula (11), as shown at the end of the next page.

where \( A \) is the length of the local inflow sample set; \( t_A^\alpha \) and \( t_0^\beta \) are the start periods of local inflow sample sets \( \alpha \) and \( \beta \), respectively, as shown in Fig. 6(a); \( t_A^\alpha \) and \( t_0^\beta \) are the end periods of local inflow sample sets \( \alpha \) and \( \beta \), respectively; \( h \) is the number of time periods; \( R(h) \) is the autocorrelation coefficient between local inflows \( \alpha \) and \( \beta \); \( h^* \) is the number of periods when \( R(h) \) is at a maximum; \( Q_{m,\text{local}}^{\alpha,\beta} \) is the average of \( Q_{m,\text{local}}^{\alpha} \) from \( t_0^\alpha \) to \( t_A^\alpha \), and \( Q_{m,\text{local}}^{\beta} \) is the average of \( Q_{m,\text{local}}^{\beta} \) from \( t_0^\beta \) to \( t_A^\beta \). If \( R(h) \) is large, the local inflow is highly regular.

(2) Calculating the average local inflow of the sample data

\[
\bar{Q}_{m,\text{local}}^{d,\text{HR}} = \frac{1}{h^*} \sum_{t=1}^{h^*} Q_{m,\text{local}}^{d,t}, \quad d \in D
\]

where \( Q_{m,\text{local}}^{d,t} \) is the local inflow of the \( m \)th reservoir in period \( t \) for the \( d \)th series; \( Q_{m,\text{local}}^{d,\text{HR}} \) is the average local inflow of the \( m \)th reservoir for the \( d \)th series; and \( D \) is the number of local inflow sample series before period \( t_{\text{now}} \), with index \( d \in D \).

(3) Forecasting the average value of the \( d \)th series

An AR model can be established to predict the average local inflow of the \( d \)th series as given by formula (13).

\[
\bar{Q}_{m,\text{local}}^{d+1,\text{HR}} = b_1 \bar{Q}_{m,\text{local}}^{d,\text{HR}} + \ldots + b_D \bar{Q}_{m,\text{local}}^{d,\text{HR}} + \ldots + b_D \bar{Q}_{m,\text{local}}^{d,\text{HR}}
\]

where \( \bar{Q}_{m,\text{local}}^{d+1,\text{HR}} \) is the forecasted value of the \( m \)th reservoir for the \( D+1 \)th series and \( b_1, b_2, \ldots, b_D \) are autoregressive coefficients that are calculated using the least square method.

(4) Calculate the weight coefficient \( w_t \) in period \( t \) for the sample data

\[
w_t = \frac{\sum_{d=1}^{D} \bar{Q}_{m,\text{local}}^{d,t}}{\sum_{d=1}^{D} \sum_{t=1}^{T} \bar{Q}_{m,\text{local}}^{d,t}}
\]

(5) Decompose the \( d \)th average local inflow series at the hourly scale

\[
Q_{m,\text{local}}^{d,t} = (\bar{Q}_{m,\text{local}}^{d,\text{HR}} \times T) \times w_t
\]

where \( Q_{m,\text{local}}^{d,t} \) is the forecasted value of local inflow for the \( m \)th reservoir in period \( t \).

B. FORECASTING THE UPSTREAM RESERVOIR RELEASE

Different fields used different definitions of the water delay time. In terms of hydraulics, researchers generally agree that water flows in rivers in the form of gravitational waves of different phases. The water release rate or flow rate (\( m^3/s \)) and the water travel speed (\( m/s \)) in different cross-sections are variables that are closely related to the water depth in the river, slope and roughness. Accurately predicting water flow patterns requires solving the complex Saint-Venant equations [20], [21]. In terms of hydrology, almost all scholars treat the water delay time as a constant[4], [40], [41] or a piecewise linear function closely related to the water outflow of the upstream reservoir [3], [42], [43]. The definition used in hydraulics seems to be more scientific than that in hydrology. However, it is very difficult to obtain exact water delay time expressions with hydraulic methods for an optimal hydropower scheduling problem. Therefore, researchers [22] proposed a pricewise linear function with different probabilities as weights to solve the water delay time problem. Historical data were used to fit general functions with different weighting coefficients. However, this process was very complicated, and it can be difficult to fit the general weight coefficients when the hydrologic conditions of HPs are constantly changing.

In this article, we use statistical methods to obtain the water delay time. Thus, the delay time is not a constant or a value derived from a general piecewise linear function. Notably, the delay time varies based on real-time hydrological information. The problem can be divided into two subproblems according to the correlation relationship between the water releases of upstream reservoirs \( Q_{m-1,\text{release}} \) and the water inflows that enter downstream reservoirs \( Q_{m}^{\text{HR}} \). These flows are...
closely correlated and weakly correlated to the delay time, respectively, and are described in detail below.

1) CLOSE CORRELATION

For example, Fig. 7(a) shows 10 days of sample data for $Q^t_{m-1,\text{release}}$ and $Q^t_m$. When the $Q^t_m$ curve was kept stationary and the $Q^t_{m-1,\text{release}}$ curve was shifted to the right at different times (water delay time), the correlation coefficient between $Q^t_{m-1,\text{release}}$ and $Q^t_m$ was determined, as shown in Fig. 7(b). The results show that for the water delay time $\tau^m_{n-1} = t - n = 6(h)$, the correlation coefficient reaches the maximum value of 0.97. Thus, the optimal water delay time is 6 h in period $t$. Based on this principle, a function of the water delay time $\tau^m_{n-1}$ and correlation coefficient $R_{m-1,m}^{n,t}$ with $Q^t_{m-1,\text{release}}$ and $Q^t_m$ as parameters is proposed in formula (16).

$$\begin{align*}
\max R_{m-1,m}^{n,t} = \text{Correl}(Q^n_{m-1,\text{release}}, Q^m_n) \\
\tau^m_{n-1} = t - n
\end{align*}$$

where

$$0 \leq n \leq t$$

$$B - \tau^m_{n-1} \leq t \leq 24$$

$$12(h) \leq B \leq 24(h)$$

(16)

where Correl(, ) is the correlation function and $B$ is the length of the intersection of the sample series $Q^t_{m-1,\text{release}}$ and $Q^t_m$. According to data analysis, the following relation is generally appropriate $12(h) \leq B \leq 24(h)$. If $B$ is less than 12 h, the similarity probability of the two smaller data sets will greatly increase, but that does not suggest that there is similarity between the two data sets. In contrast, if $B$ is larger than 24 h, the similarity probability of the two data sets is greatly reduced, and it is difficult to find an appropriate water delay time. Other variables are shown in (3). There are many methods that can be used to solve formula (16), such as the traversing method or bisection method. Before performing simulations for each time period $t$, the optimal water delay time $\tau^m_{n-1}$ can be determined by formula (16). Therefore, it the delay time is a variable value based on real-time hydrological information.

2) WEAK CORRELATION

If $R_{m-1,m}^{n,t} \leq 0.75$, the correlation relationship between the water releases of upstream reservoirs and the water inflows into downstream reservoirs is very weak, and it is difficult to obtain exact water delay time expressions $\tau^m_{n-1}$. In this case, the Muskingum method can be used to calculate the downstream inflow $Q^t_m,\text{delay}$ from the upstream reservoir release...
information. Formula (3) can be expressed as follows:

\[ Q_m' = Q_{m,\text{local}}' + Q_{m,\text{delay}}' \]
\[ Q_{m,\text{delay}}' = C_0 Q_{m-1,\text{release}}' + C_1 Q_{m-1,\text{release}}' + C_2 Q_{m,\text{delay}}' \]

where \( \Delta t \) is the number of seconds in period \( t \); \( K \) is a storage constant; and \( x \) is a weighting factor (reflecting the relative importance of inflows and releases in storage computations). The coefficients \( C_0, C_1 \) and \( C_2 \) are computed from the \( K, x \) and \( \Delta t \) inputs. We use a hypothesis and trial-and-error algorithm to obtain the optimal \( K \) and \( x \) values according to sample data for the releases from the upstream reservoir and inflows to the downstream reservoir. The value of \( x \) that produces a plot that approaches a straight line is considered to be the correct value for the reach [44].

C. CHECKING THE WATER BALANCE EQUATION

In general, after applying the methods introduced in Section III A and B to forecast the latest inflow, the original water balance equation (Formula 2) for cascaded HPs is disrupted and needs to be corrected. Corrected results may have little effect on an HP with a good regulatation capacity (such as one associated with annual or multiyear regulation storage reservoirs), but they can considerably influence HPs with a poor regulation capacity (such as those associated with weekly or daily regulation storage reservoirs). In this paper, a standard method is used to determine the most recent discharge according to the water balance equation under the assumption that power generation does not change. If the forecasted inflow is large, the reservoir may experience water spillage under the original power generation plan. The HP needs to gradually increase power generation to avoid spillage in a later scheduling period. In contrast, if the forecasted inflow is small, the water level of the reservoir may drop below the minimum level given in the original power generation plan. The HP needs to gradually decrease power generation to raise the water level in later scheduling periods.

D. CHECKING THE BALANCE OF THE POWER SUPPLY AND POWER LOAD [31]

After checking the water balance equation, the power generation plan of some HPs may change. Additionally, due to the random fluctuations in the power load, the real-time load \( L_{\text{real}}' \) and day-ahead forecasted load \( L_{\text{plan}}' \) are generally not exactly the same, and they can considerably vary. These two reasons directly lead to an imbalance between the future power supply and power load. Therefore, the power balance equation for UST scheduling needs to be checked again.

\[ \Delta L' = L_{\text{forecast}}' - N_o' - \sum_{m=1}^{M} N_m' \]  

where \( L_{\text{forecast}}' \) is the UST load predicted by formula (4) and \( \Delta L' \) is the power deviation between the power supply and power load in period \( t \). When \( \Delta L' > \epsilon \), the power generation of HPs must be increased to balance the power load. When \( \Delta L' < -\epsilon \), the power generation of HPs must be reduced to meet the power load demand. When \( |\Delta L'| \leq \epsilon \), the power supply and power load are balanced. The computational accuracy \( \epsilon = 0.001 \text{ MW} \), and the other variables are those defined in formula (4).

E. UPDATING THE POWER GENERATION SCHEDULE OF CASCADED HPs

When \( |\Delta L'| > \epsilon \), it is necessary to update the power generation plan of HPs to achieve a balance between the power supply and power load. However, it is difficult for dispatchers to make scientific and reasonable revision decisions in a short time. There are many difficulties that must be overcome, such as determining which HPs should have modified generation plans, HP ranks, and the variation range of power generation for each HP. These problems are usually addressed according to the experience of dispatchers in practical projects. In this paper, a heuristic method is proposed to solve the problem of updating the short-term generation plan in UST scheduling. An overall solution strategy is given as follows.

1) WHEN \( \Delta L' > \epsilon \), THE POWER LOAD EXCEEDS THE POWER SUPPLY

Some HPs may need to increase their power generation to meet the power load demand. In this case, the solution method is as follows. ① Select HPs. The HPs without idle capacity are eliminated for period \( t \). \( M_2 \) is the set of HPs that can increase their power generation capacity. ② \( M_2 \) HPs are ranked. The relative deviation \( F_m' \) between the actual water level and forecasted value at the end of \( T \) is calculated for the \( m \)th HP. Then, the \( F_m' \) values are ranked from large to small, which can be expressed as follows:

\[ F_m'^T = \frac{Z_m'^T - Z_{m,\text{min}}'^T}{Z_{m,\text{max}}'^T - Z_{m,\text{min}}'^T}, \quad 1 \leq m \leq M_2 \]

The HPs at the top of the list are given priority for increasing their power generation. Notably, the water level of the HP at the top of the list is higher than the forecasted value. Increasing power generation can reduce the water level in period \( T \) and gradually approximate the forecasted water level. ③ The power generation increment \( \Delta \alpha_m'^T \) of the \( m \)th HP in period \( t \) can be expressed as follows:

\[ \begin{align*}
\Delta \alpha_m'^T & = \min (\Delta \alpha_{m,1}', \Delta \alpha_{m,2}', \Delta \alpha_{m,3}') \\
\Delta \alpha_{m,1}' & = N_m' - N_m'^T \\
\Delta \alpha_{m,2}' & = \Delta N_m \\
\Delta \alpha_{m,3}' & = \Delta L' - \sum_{m_0 \in M_2, m_0=1}^{m-1} \Delta \alpha_{m_0}' 
\end{align*} \]
where $\Delta \alpha'_{m,1}$ is the idle capacity of the $m$th HP in period $t$; $\Delta \alpha'_{m,2}$ is the maximum ramping capacity of the $m$th HP in period $t$, which is shown in formula (6); and $\Delta \alpha'_{m,3}$ is the remaining deviation between the power load and power supply in period $t$.

2) WHEN $\Delta L^t < -\varepsilon$, THE POWER SUPPLY EXCEEDS THE POWER LOAD

Some HPs need to reduce their power generation to meet the power load demand. In this case, the solution method is as follows. ① Select HPs. The HPs with power generation levels smaller than the minimum value and no spillage issues are eliminated in period $t$. $M_3$ is the set of HPs for which power generation can be reduced. ② $M_3$ HPs are ranked. Obtain the relative deviation $F^T_m$ between the actual water level and the forecasted value for the $m$th HP at the end of $T$. Then, the $F^T_m$ values are ranked from small to large. The HPs at the top of the list are given priority for reducing their power generation. Notably, the water levels of the HPs at the top of the list are lower than the forecasted values. Reducing the corresponding power generation will raise the water level at the end of $T$ and gradually approximate the forecasted value. ③ The power generation decrement $\Delta \beta^l_m$ of the $m$th HP in period $t$ can be expressed as follows:

$$
\begin{align*}
\Delta \beta^l_m &= \min\{\Delta \beta^l_{m,1}, \Delta \beta^l_{m,2}, \Delta \beta^l_{m,3}\} \\
\Delta \beta^l_{m,1} &= N^l_m - N^t_m \\
\Delta \beta^l_{m,2} &= \Delta N^t_m \\
\Delta \beta^l_{m,3} &= |\Delta L^t| + \sum_{m_0 \in M_3} \Delta \beta^l_{m_0}
\end{align*}
$$

where $\Delta \beta^l_{m,1}$ is the maximum power generation of the $m$th HP in period $t$ that can be reduced; $\Delta \beta^l_{m,2}$ is equal to $\Delta \alpha'_{m,2}$, which is the maximum ramping capacity of the $m$th HP in period $t$; and $\Delta \beta^l_{m,3}$ is the remaining deviation between the power load and power supply in period $t$.

3) WHEN $|\Delta L^t| \leq \varepsilon$, THE POWER SUPPLY AND THE POWER LOAD ARE BALANCED

In this case, the power generation plan of all HPs does not need to change.

F. THE OVERALL SOLUTION FRAMEWORK

The detailed solution framework is shown in Figure 8.

IV. CASE STUDIES

A. ENGINEERING BACKGROUND

The hydropower system in Yunnan Province is mainly composed of Basin-1, Basin-2, Basin-3 and Basin-4. Figure 9 shows the geographic distribution of these basins. Basin-1 and Basin-2 are the main basins with the largest number of HPs and highest installed capacity. The total installed capacity accounts for approximately 84% of that of the hydropower system in Yunnan Province. The cascaded HPs in the two basins are abundant, have diverse regulation standards and have complex hydraulic connections. Basin-3 and Basin-4 are two small basins characterized by a large number of HPs, poor regulation performance, uncertain local inflows and many spillage issues. These basins have distinct characteristics and require strong complementary scheduling. Therefore, the model proposed in this paper was investigated using 23 HPs located in Basins 1 to 4. To focus on the core theoretical method, other power sources (such as thermal power, wind power, solar power and other HPs) are assumed to operate according to the actual values when the power load demand is balanced. Table 1 shows the basic parameters of the 23 HPs.

The proposed algorithm is implemented by adopting the Java language in the Java 2 platform Enterprise Edition (J2EE). This program has been integrated into the UST power generation dispatching and auxiliary decision-making system of the Yunnan power grid, and the waiting interval for rolling calculations is 1 hour. The time horizon of each calculation is a variable from $t_{now}$ to $T$. In this paper, to accelerate the testing process, the waiting interval for rolling calculations is changed to 30 seconds. All tests were performed on a workstation containing a 3.70-GHz Intel Core i7-8700K CUP with 32 GB of RAM. Each calculation takes 10-15 seconds. In a real scenario, this time is negligible compared to the 1-hour waiting interval.

Moreover, to test the validity of the proposed UST model, two different typical daily series from the flood season and dry season were selected. Each typical series consists of four days. In the dry season, the start and end times of simulated scheduling are 8:00 on March 10 and 13, 2018, respectively. In the flood season, the start and end times were 8:00 on August 10 and 13, 2018, respectively. Thus, there were four forecasted water levels for each HP. The total number of rolling calculations for each case was 72.

B. ANALYSIS OF THE RESULTS OF LOCAL INFLOW FORECASTING

Table 2 shows the maximum error of local inflow forecasting $Q^\text{max}_{m,\text{local}}$ and the average error of local inflow forecasting $Q^\text{ave}_{m,\text{local}}$ for 72 rolling calculations by using the method in Section III.A. The two errors can be expressed as follows:

$$
\begin{align*}
\Delta Q^\text{max}_{m,\text{local}} &= \max_{1 \leq \text{times} \leq 72, t_{\text{now}} \leq t \leq T} \left| Q^\text{times},t_{m,\text{local}} - Q^\text{real},t_{m,\text{local}} \right| \\
\Delta Q^\text{ave}_{m,\text{local}} &= \frac{1}{72} \sum_{\text{times}=1}^{72} \left[ \frac{1}{T - t_{\text{now}}} \sum_{t=t_{\text{now}}}^{T} \left| Q^\text{times},t_{m,\text{local}} - Q^\text{real},t_{m,\text{local}} \right| \right]
\end{align*}
$$

where $Q^\text{times},t_{m,\text{local}}$ is the local inflow forecasting value of the $m$th reservoir for a given rolling calculation (based on times) in period $t$ and $Q^\text{real},t_{m,\text{local}}$ is the actual local inflow of the $m$th reservoir in period $t$. The table shows the following results.

(1) $\Delta Q^\text{max}_{m,\text{local}}$ and $\Delta Q^\text{ave}_{m,\text{local}}$ for the first-stage cascaded HPs (such as Plant-1, Plant-7, Plant-14 and Plant-20) are very
small. Thus, the method in Section III.A(1) is suitable for local inflow forecasting for these cascaded HPs. Additionally, we note that $\Delta Q_{m, local}^{max}$ and $\Delta Q_{m, local}^{ave}$ for Plant-13, which is a nonfirst-stage cascaded HP, are also relatively small. The main reason for this result is that Plant-13 is far from upstream Plant-12 (see Fig. 9). The inflow of Plant-13 is minimally

FIGURE 8. The overall solution framework.
TABLE 1. The basic parameters of 23 HPs.

| Basin | Plant | Installed capacity (MW) | Regulation performance | Normal water level (m) | Dead water level (m) | Mean annual runoff |
|-------|-------|-------------------------|------------------------|-----------------------|---------------------|------------------|
| 1     | 1     | 900                     | Day                    | 1307                  | 1303                | 666              |
| 2     | 4200  | Multiyear               |                        | 1240                  | 1166                | 1225             |
| 3     | 1670  | Season                  | 994                    | 982                   | 1242               |
| 4     | 1350  | Year                    | 899                    | 882                   | 1271               |
| 5     | 5850  | Multiyear               | 812                    | 765                   | 1727               |
| 6     | 1750  | Season                  | 602                    | 591                   | 1862               |
| 7     | 2400  | Week                    | 1618                   | 1608                  | 1410               |
| 8     | 2000  | Week                    | 1504                   | 1492                  | 1384               |
| 9     | 2400  | Week                    | 1418                   | 1398                  | 1629               |
| 10    | 1800  | Week                    | 1298                   | 1289                  | 1679               |
| 11    | 2160  | Week                    | 1223                   | 1216                  | 1746               |
| 12    | 3000  | Week                    | 1134                   | 1122                  | 1841               |
| 13    | 6300  | Year                    | 600                    | 540                   | 4554               |
| 3     | 120   | Season                  | 835                    | 818                   | 122                |
| 15    | 130   | Week                    | 756                    | 740                   | 130                |
| 16    | 285   | Season                  | 639                    | 605                   | 190                |
| 17    | 285   | Week                    | 522                    | 514                   | 371                |
| 18    | 450   | Year                    | 456                    | 446                   | 407                |
| 19    | 165   | Day                     | 368                    | 365                   | 421                |
| 4     | 108   | Runoff                  | 788                    | 781                   | 208                |
| 21    | 70    | Runoff                  | 725                    | 732                   | 217                |
| 22    | 200   | Runoff                  | 592                    | 580                   | 349                |
| 23    | 875   | Runoff                  | 585                    | 580                   | 364                |

TABLE 2. Local inflow forecasting error of 72 rolling calculations.

| Basin | Plant | Flood season | Dry season |
|-------|-------|--------------|------------|
|       |       | ΔQ_{m,local}^{max} (%) | ΔQ_{m,local}^{ave} (%) | ΔQ_{m,local}^{max} (%) | ΔQ_{m,local}^{ave} (%) |
| 1     | 1     | 2.76         | 1.73       | 0.81        |
| 2     | 12    | 10.39        | 9.27       | 6.99        |
| 3     | 15    | 13.24        | 13.94      | 9.02        |
| 4     | 18    | 13.20        | 11.73      | 10.70       |
| 5     | 19    | 12.25        | 16.31      | 9.10        |
| 6     | 20    | 14.57        | 16.32      | 8.45        |
| Avg.  |       | 11.07        | 14.59      | 7.63        |

FIGURE 9. The geographic distribution of 23 HPs in Yunnan, China.

affected by the release of the upstream Plant-12, and the natural flow process is dominant.

(2) ΔQ^{max}_{m,local} in the flood season is similar to that in the dry season, but ΔQ_{m,local}^{ave} in the flood season is larger than that in the dry season. The main reason for this result is that the local inflow in the flood season is larger and more heterogeneous than that in the dry season, which is generally smaller and more stable.

(3) ΔQ^{max}_{m,local} and ΔQ_{m,local}^{ave} for the nonfirst-stage cascaded HPs are larger than the values for the first-stage cascaded HPs. This finding indicates that when the hourly local inflow varies considerably (see Fig. 6(a)), the prediction accuracy of the method introduced in Section III.A(2) for the nonfirst-stage cascaded HPs must be improved. Moreover, the average values of the four basins are less than 20%. In the flood season, the ΔQ^{max}_{m,local} values of Basins 1-4 are 16.41%, 14.39%, 19.07% and 15.9%, respectively, and the ΔQ_{m,local}^{ave} values are 11.07%, 10.98%, 14.64% and 10.71%, respectively. In the dry season, the ΔQ^{max}_{m,local} values of the four basins are 14.59%, 9.58%, 16.36% and 8.46%, respectively, and the ΔQ_{m,local}^{ave} values are 7.63%, 4.89%, 12.77% and 4.51%, respectively. Compared with the results of other hydrological models (such as distributed hydrological models), the results in this paper seem to be worse. However, the local inflow forecasting method in this paper is only based on historical runoff trends without any data inputs from rainfall forecasts. Therefore, ΔQ^{max}_{m,local} and ΔQ_{m,local}^{ave} are considered acceptable within 20%.

C. ANALYSIS OF THE RESULTS OF UPSTREAM RESERVOIR RELEASE FORECASTING

In general, it is difficult to directly assess the accuracy of upstream reservoir release predictions with actual data because the upstream reservoir releases in simulated scheduling are very different from the actual upstream reservoir releases. Therefore, we can only verify the rationality of the method given in Section III.B using a large amount of sample data.

There are five years (2014-2019a) of historical runoff data, including upstream reservoir water release and downstream...
FIGURE 10. The results of forecasting the UST upstream reservoir release.
FIGURE 10. (Continued.) The results of forecasting the UST upstream reservoir release.
FIGURE 11. The water level and day-ahead forecasted value of each HP at 24 hours.

Note: The abscissa is the number of calculations, not the number of hours of the day.
FIGURE 11. (Continued.) The water level and day-ahead forecasted value of each HP at 24 hours.

Note: The abscissa is the number of calculations, not the number of hours of the day.
The total number of sample points is $5 \times 365 \times 24 = 43800$. Fig. 10(a) displays the relation between $Q_{m-1,\text{release}}$ and $R_{m-1,m}^{t}$ by using the method in Section III.B(1). Fig. 10(b) presents the relation between $Q_{m-1,\text{release}}$ and $\tau_{m-1}^{n}$ for the same sample point. The results show the following trends.

(1) Our research results have high credibility. In general, the two data series are highly similar when the correlation between the two data series is greater than 0.75. Therefore, we selected only qualified sample points with $r_{m-1,m}^{t} > 0.75$ from the 43800 samples, as shown in Fig. 10(a) and (b). In Fig. 10(a), the qualification rate (%) is equal to the number of qualified sample points divided by the total number of sample points. Some HPs have high qualification rates, such as Plant-1 (90%), Plant-2 (98%), and Plant-5 (96%). This finding indicates that the method in Section III.B(1) is highly applicable for these HPs. In contrast, other HPs have low qualification rates, such as Plant-3 (42%), Plant-10 (49%), and Plant-12 (6%). This result suggests that the method in Section III.B(1) is not applicable to these HPs.

(2) $\tau_{m-1}^{n}$ is not a constant or a piecewise linear function related to the water release of upstream reservoirs, as shown in Fig. 10(b). In other words, there is no fixed or unambiguous relationship between $\tau_{m-1}^{n}$ and $Q_{m-1,\text{release}}^{n}$. This is an innovative conclusion related to our understanding of the real water delay time problem.

(3) It is very difficult to use historical runoff data to synthesize a fixed linear relationship between the water delay time and upstream releases. Our research shows that there is no fixed linear relationship between these factors.

(4) Determining the water delay time of a river basin is a complex hydraulic problem. Hydraulic scholars [19], [20] have shown that the water delay time is closely related to the water depth in rivers, slope and roughness and is not closely related to the water release of upstream reservoirs. The method in Section III.B(1) can effectively avoid solving complex hydraulic formulas and is applicable in the field of hydrology if the correlation between two data series is greater than 0.75.

D. ROLLING TRACKING PROCESS OF THE WATER LEVEL AT THE END OF 24 HOURS

After 72 rolling calculations, the actual water level and day-ahead forecasted of each HP at 24 hours are shown in Figure 11. The start and end times of simulated scheduling are 8:00 on March/August 10, 2018, and 8:00 on March/August 13, 2018, respectively. Therefore, there are four different target water levels for four days in each case. The results show the following trends.

(1) In each rolling calculation, the water level of most reservoirs at 24 hours is near the forecasted value and does not considerably deviate from the forecasted value, as observed for Plants 1-20. This result suggests that the method proposed in Section III.E can effectively control the water level at the end of 24 hours based on the forecasted value under hydraulic and electrical constraints. Thus, the objective of the algorithm is achieved.

(2) A small number of reservoirs remain far from the forecasted water level at 24 hours, such as those for Plants 21-23. In this paper, the forecasted water level is based on a short-term scheme. In actual scheduling, “unreasonable” water spilling can occur when the water level of the reservoir and power generation level of the HP are not maximized. The main reason for this phenomenon is that the power supply of the Yunnan power grid exceeds the power demand, and the HPs with poor regulation capacity are generally limited to generating electricity, so the dispatchers of these HPs do not pay attention to the water level of the reservoir. However, in this paper, the operations are still conducted according to the scientific principle that the water level of the reservoir and power generation level are not maximized and that no water spillage occurs when the model is optimized. Therefore, the water level of the reservoir at 24 hours in the rolling calculation is far from the forecasted value.

E. ANALYSIS OF THE RESULTS OF LOAD BALANCING

Figure 12 shows the load balancing results for the first round of calculations in the flood season case and dry season case. In this article, the power supply sources involved in load...
balancing are hydropower plants, thermal plants, wind plants and solar plants. Except for the 23 HPs (Optimized HPs) in figure 9 and table 1, all other power stations (nonoptimized plants) are not participate in optimization calculation and they reference actual power generation in load balancing. In addition, the data before 8 hours is the actual value, and the data between 8 hours and 24 hours is the simulated value. As shown in the figure, although there is a large difference in the load demand between the flood season and dry season, our algorithm achieves a load balance without load deviation. It is further shown that the proposed UST model can achieve the seamless coupling between short-term and real-time scheduling and can quickly meet the actual scheduling needs.

**V. CONCLUSION**

With the unceasing expansion of the hydropower scale in a single provincial power grid in China, the problem of large-scale HP scheduling has become increasingly complicated. More attention needs to be paid to solving practical engineering problems. This paper proposes a UST scheduling model and solution method to solve the actual problem that the short-term scheduling scheme is difficult to apply in real-time scheduling. The developed method is applied to interbasin cascaded HPs located in Yunnan Province, China. The major conclusions obtained from the results are as follows.

(1) The innovation of this model is the use of recent local inflow and power load information to dynamically update the short-term scheduling scheme and effectively overcome the drawbacks of short-term scheduling being difficult to implement in real-time scheduling and real-time scheduling lacking the appropriate planning. The proposed method can achieve seamless coupling between short-term and real-time scheduling.

(2) An innovative conclusion in terms of hyrology is that the water delay time is neither a constant nor a piecewise linear function related to the water release of upstream reservoirs. Instead, the delay time is a complex variable that can be accurately estimated based on the correlation coefficient between real-time upstream reservoir releases and downstream reservoir inflows.

(3) The proposed power generation plan adjustment method is characterized by clear principles, simple methods and good practical effects. This approach can effectively control the water level at the end of 24 hours to the forecasted value under hydraulic and electrical constraints.

The future research directions in this field can be explored from the following perspectives: by considering the effect of intermittent fluctuations in wind and solar power on UST load forecasting, by considering the quantity and price of the transaction contracts in UST scheduling, and by developing a coordinated optimal scheduling model for UST scheduling that includes hydropower, wind power, photovoltaic power and thermal power. In the future, we will perform research on these actual factors and the associated requirements.

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X. Cheng et al.: UST Scheduling of Interbasin Cascaded HPs to Rapidly Balance the Load Demand

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