Hybrid Time-Scale Optimal Scheduling Considering Multi-Energy Complementary Characteristic

SONGKAI WANG1,3, RONG JIA2,3, (Member, IEEE), XIAOYU SHI2,3, YUAN AN2,3, QIANG HUANG1,4, PENGCHENG GUO1, AND CHANG LUO5

1 School of Water Resources and Hydropower, Xi’an University of Technology, Xi’an 710048, China
2 School of Electrical Engineering, Xi’an University of Technology, Xi’an 710048, China
3 Key Laboratory of Smart Energy in Xi’an, Xi’an University of Technology, Xi’an 710048, China
4 State Key Laboratory of Eco-Hydraulics in Northwest Arid Region, Xi’an University of Technology, Xi’an 710048, China
5 Hanjiang-To-Weihe River Valley Water Diversion Project Construction Company Ltd., Xi’an 710048, China

Corresponding author: Xiaoyu Shi (sxy_xaut@126.com)

This work was supported in part by the National Natural Science Foundation of China under Grant 51779206, in part by the Key Projects of Science and Technology Department of Shaanxi Province under Grant 2018ZDXM-GY-169, and in part by the Key Industry Innovation Chain Project of Science and Technology Department of Shaanxi Province under Grant 2019ZDLGY18-03.

ABSTRACT
Evaluating the potential utilization of hybrid energy systems and determining the multi-scale optimal operation strategy is critical to power system planning in the context of energy structure adjustment, especially for large-scale hybrid energy systems. Considering the long-term and short-term complementary characteristics, this paper puts forward a coordinated optimization framework for the integrated energy system in the world’s largest multi-energy complementary base on Yellow River’s upper reaches. The main procedures are as follows: 1) cross-correlation method is introduced for individually analyzing the long- and short-term complementary characteristics of wind power, photovoltaic, and hydropower in this multi-energy complementary base; 2) a double-layer model combining the long-term optimal operation model and short-term optimal operation model for determining the proportion of multiple energy and optimizing the maximum peak-shaving ability; 3) Large-Scale System Decomposition-Coordination Method is applied for solving the proposed double-layer operation model. The results show that wind power 23%, photovoltaic 35%, hydropower 42% can keep the most stable generation in the long-term complementary operation. This proportion results can improve the system peak regulation capacity with 50.8% (sunny day’s morning peak) and 24.2% (rainy day’s morning peak) in the optimal short-term operation.

INDEX TERMS
Hybrid time-scale, large-scale energy, multi-energy complementary characteristics, optimal operation strategy.

I. INTRODUCTION
It is recently urgent to replace traditional energy sources with renewable energy sources to mitigate the large consumption of non-renewable resources such as coal, oil, and natural gas. According to statistics, the annual solar energy received by the earth is equivalent to about 2000 times the power generated by the solid, liquid, and gas fossil fuels burned every year. The total storage of solar energy resources is equivalent to more than 10,000 times the energy currently used by humans [1]. The global wind energy potential is about five times the current global electricity consumption [2]. However, for the intermittence and volatility of renewable energy sources, large-capacity wind power and photovoltaic access to the power system will seriously affect the power quality and the stable operation of the primary power grid. It will also easily lead to curtailed wind energy, photovoltaic, and even off-grid problems [3], [4].

Under this circumstance, complementarily operating photovoltaic and wind power with other renewable energy sources (e.g., hydropower or energy storage) offers a promising option to accommodate more PV power without
compromising the security and reliability of the power system. The definition of energy complementarity means that when a specific type of energy function is damaged or even missing in the energy system, the partial or total compensation can be obtained by adjusting the output of other energy sources [5]. In the United States, Brazil, Italy, UK, China, and other countries, the cumulative installed capacity of energy complementarity has increased every year [6]–[10]. Due to natural resources limitation, the development of energy complementarity in other countries mostly focuses on small-scale distributed systems and on-site electricity consumption [11].

China’s photovoltaic and wind power are mainly distributed in the northwest and southwest regions because of its geographical and climatic characteristics. China’s hydropower is also primarily concentrated in those regions, especially in the Yellow River’s upper reaches [12]. This area has the world’s largest multi-energy complementary base, including the world’s largest Longyangxia hydro-photovoltaic complementary power station [13]. How to ensure the stability and economy of complementary operation of large-scale photovoltaic, wind power, and hydropower has become the focus of current research.

Due to the geographical location, weather conditions, installed capacity, and other factors, it is not easy to integrate large-scale photovoltaic, hydropower, and wind energy into a traditional power system [14]. The power generation capacity, utilization time, etc., may all vary significantly on a monthly, daily, or even hourly basis, which means the system operators need to select the appropriate time scale to control multi-energy complementary operations according to their own or power-grid needs. The general time scale can be divided into annual scale, quarterly scale, monthly scale, daily scale, hour scale, and minute scale.

Countries worldwide have launched some research on multi-energy complementary operations in different time scales. Reference [15] analyzed the complementarity of Portuguese wind, photovoltaic, and hydropower and proposed a novel multi-objective method to optimize the renewable system mix, maximizing its contribution to the daily peak load. Reference [16] investigated the complementary potential of small hydropower stations, wind power stations, and photovoltaics power stations in Rio de Janeiro, Brazil, to obtain the optimized mix generation through a year. Reference [17] analyzed the output characteristics of wind-solar complementary systems in Hong Kong from an hour-by-hour simulation to provide a reliable and environmentally friendly power supply. Reference [18] analyzed Italy’s small hydropower stations and photovoltaic power generation’s complementarity across different temporal scales (hourly, daily, and monthly) to obtain the theoretical storage required for balancing generation and load. Reference [19] considered the uncertainty of operation cost of a power system and natural gas system, proposed a full-day ahead scheduling model for the integrated energy system’s optimal coordinated operation. Reference [20] used reanalysis data to study the daily variation of wind and solar radiation in the UK and its impact on the balance of renewable energy supply. Reference [21] calculated the correlation and cross-correlation between wind speed and solar radiation time in northeastern Brazil and confirmed the feasibility of long-term complementary operation of wind power and photovoltaic. Reference [22] presented a hybrid-scenario and Monte Carlo approach to gauge the uncertainty involved in Islanded microgrids’ multi-energy demands, i.e., electrical, heating, and cooling loads, together with correlation among wind and solar generations. Reference [23] proposed the robust optimization approach (ROA) to cope with the uncertainties associated with the PV production and electric and heat load demands.

In China, [24] presented a stochastic scheduling model to find a base-case solution with relatively stable operation cost in the presence of uncertain renewable generation by studying the multi-source power system’s day-ahead coordination. Reference [25] studied hydro-solar complementary coordination operation and capacity allocation to indicate that hydropower installed capacity and annual solar curtailment rate play crucial roles in optimizing a photovoltaic plant. Reference [26] proposed the combined generation monitoring system’s critical technologies, including day-ahead optimal scheduling, active coordination control, and reactive voltage control. Reference [27] used the Progress Optimality Algorithm (POA) for the optimal short-term operation of Wind-PV-Hydro combinations in the Yalong River multi-energy complementary clean energy base. Ref. discussed the co-operation of integrated electricity-heat system, and showed that the co-operation could provide a more economical and reliable solution than the decoupled operation of the heat network and electricity network. Reference [28] proposed an optimal combination of the short-term operation scheme of pumped storage hydropower and hybrid photovoltaic complementary power generation. The automatic scheduling of pumped storage hydropower can effectively restrain or compensate for wind and solar power generation’s output deviation. Reference [29] proposed a model that can predict hydropower station’s compensation for photovoltaic power fluctuation and consider the influence of power quality’s short-term complementary regulation. Reference [30] used the long-term stochastic optimization method to calculate the uncertainty of both flow and photovoltaic power output and establish the optimization model of maximizing the total capacity and guarantee rate. Reference [31] modeled the probability of renewable power uncertainty according to output probabilities obtained over a long-term planning horizon based on available historical data using a hybrid probability uncertainty set constructed using 1-norm and infinity-norm metrics. Reference [32] proposed an interval method-based planning model for microgrids to describe uncertainties of renewable energy and demand uncertainties as intervals. Based on the interval linear programming theory, the corresponding uncertain constraints could be converted to deterministic ones. Reference [33] discussed the cooperation of integrated electricity-heat systems, proposed a distributed algorithm based on the alternating direction method of
The previous research has some common insufficiency on the optimal scheduling of multiple energy sources: 1) As we all know, it mainly focuses on small-scale distributed systems and isolated islands. Based on this, the long-term complementary operation and short-term complementary operation are not considered for determining the installed capacity. 2) In addition, the existing approaches for assessing complementarity are essentially unidimensional, which means they cannot evaluate the overall complementary characteristics for more than two kinds of renewable energy.

Therefore, as an extension of the previous studies, this paper puts forward a coordinated optimization framework for the integrated energy system by considering the long- and short-term complementary characteristics. The main procedures are as follows: 1) cross-correlation method is introduced for individually analyzing the long- and short-term complementary characteristics of wind power, photovoltaic, and hydropower in this multi-energy complementary base; 2) a double-layer model combining the long-term optimal operation model and short-term optimal operation model for determining the proportion of multiple energy and optimizing the maximum peak-shaving ability; 3) Large-Scale System Decomposition-Coordination Method is applied for solving the proposed double-layer operation model. The proposed framework is verified by the world’s largest multi-energy complementary base on Yellow River’s upper reaches in Qinghai Province, China.

The rest of the paper’s structure is as follows: Section 2 provides a detailed description of the complementarity study, the long-term and the short-term optimal scheduling by different time scales. Section 3 presents and discusses a case study and Section 4 discusses its results. Finally, the conclusions are presented in Section 5.

II. METHODS

Through the combination on the complementary characteristics of renewable energy, this paper divides the optimal scheduling model of wind-photovoltaic-hydropower multi-energy complementary system coordinated operation into the multi-energy complementary capacity optimization configuration based on long-term complementary characteristics (the annual complementary characteristics) and the peak-shaving ability based on short-term complementary characteristics (the daily complementary characteristics). The research structure is shown in Fig.1.

A. COMPLEMENTARITY STUDY

In the study of the complementarity of renewable energy, the correlation coefficients such as the Pearson correlation coefficients, the Spearman correlation coefficients, the Kendall correlation coefficients, etc., are usually used to embody the complementarity of different kinds of energy. The values of these correlation coefficients are generally in the interval $[-1, 1]$. A correlation coefficient value close to 0 indicates almost no correlation between the two groups of variables. A positive correlation coefficient value means that as one group of variables increases or decreases, the other variables also increase or decrease. A negative correlation coefficient indicates that when one set of variables increases, the other set of variables decreases; when one group of variables decreases, the other set of variables increases, which corresponds to the complementarity of different energy sources: in a multi-energy complementary system, when one energy output decreases, the additional energy output increases; when one energy output increases, the other energy output decreases. This mode of complementary energy operation will reduce output fluctuations and maintain the power generation system’s stability. According to Canales et al. [35], a possible interpretation of the energy complementarity system’s correlation coefficient values is presented in Table.1. This paper will study the standard centralized correlation coefficients individually and choose the correlation coefficient which is most appropriate for this study.

The Pearson correlation coefficient is only valid for the data conforming or close to the normal distribution. The wind
power, photovoltaic, and hydropower output do not obey the normal distribution, so the Pearson correlation coefficient cannot reflect the complementary characteristics between different energy sources. The Spearman correlation coefficient is a non-parametric statistical method that uses the rank-size data for linear correlation analysis. The correlation coefficient’s size depends only on the order of the data and cannot describe the correlation coefficient according to the time-series. This paper selects the Kendall correlation coefficient to analyze the output’s complementarity of various energy sources in a time-series manner.

The Kendall correlation coefficient is a kind of dependent measure based on the rank of random variables, reflecting the monotonic dependence between variables and the consistency of changing trends.

Suppose \( [(x_1, y_1), (x_2, y_2), \ldots, (x_N, y_N)] \) is a sample space composed of \( N \) sets of observations of a random vector \( (X, Y) \), where \( X \) and \( Y \) are continuous random variables, and \( x_i \) and \( y_i \) are one-to-one correspondence in time. \((x_i, y_i)\) and \((x_j, y_j)\) are any two sets of observations in the sample space, if \( (x_i, y_i)(x_j, y_j) > 0 \), \((x_i, y_i)\) and \((x_j, y_j)\) are consistent; if \( (x_i, y_i)(x_j, y_j) < 0 \), so \((x_i, y_i)\) and \((x_j, y_j)\) are inconsistent. The Kendall correlation coefficient represents the difference between the consistent probability and the varying probability of two sets of randomly selected observations from the sample. It can be calculated as follows

\[
\tau_k = \frac{C - D}{\frac{1}{2}N(N-1)}
\]  

(1)

where \( C \) denotes the logarithm of the coefficient elements in the sample, \( D \) denotes the logarithm of the inconsistent elements in the sample, \( \tau_k \) ranges from \([-1, 1]\).

**B. LONG-TERM OPTIMAL OPERATION**

1) MULTI-ENERGY COMPLEMENTARY CAPACITY OPTIMIZATION CONFIGURATION MODEL

Wind power, photovoltaic, and hydropower are affected by reservoir regulation capacity, inflow runoff, climate change, solar radiation, wind speed, etc., which will produce inevitable fluctuations in the long-term operation complementary system.

Based on the long-term complementary characteristics of wind power, photovoltaic, and hydropower in the whole year, this section establishes the optimal configuration model of wind-photovoltaic-hydropower multi-energy complementary capacity. The model is used to study the feasibility of wind-photovoltaic-hydropower's complementary operation and the collaborative process's stability in a long period and to calculate and analyze the most stable complementary capacity configurations.

Using the year’s energy generation data, this section analyzes the 100% wind-photovoltaic-hydropower complementary output scenario for reducing the dependence on traditional fossil energy and make full use of the abundant wind, solar, and water resources. The model is aimed at the minimum annual output fluctuation of the multi-energy complementary system, which calculates how the power generation changes its average value and obtains various energy capacity configurations under the complementary scheme’s minimum annual output fluctuation. The model will be calculated as follows

\[
\min P_{SD} = \sqrt{\frac{1}{N-1} \sum_{t=1}^{N} P_t - \bar{P}_t^2}
\]

(2)

\[
P_t = \alpha P_h + (1-\alpha)\beta P_p + (1-\alpha)(1-\beta)P_w
\]

(3)

where \( P_{SD} \) is the standard deviation of \( P_t \); \( P_t \) refers to the total combined power of renewable energy, the larger the \( P_{SD} \) value, the greater the total output fluctuation, vice versa; \( P_h, P_w \) and \( P_p \) denotes the hydropower, wind power, and photovoltaic power generation, their calculation formulas will be introduced in Chapter 3; \( \alpha \) and \( \beta \) denote the weight——\( \alpha \) is the ratio of hydropower to total power, \((1-\alpha)(1-\beta)\) is the photovoltaic power proportion. Then, when \( \alpha = 1 \), it is combined into 100% hydropower; when \( \alpha = 0 \) and \( \beta = 1 \), the whole power is composed of photovoltaic; when \( \alpha = 0 \) and \( \beta = 0 \), there is only wind power generation.

2) POWER MODELING

This section only considers multi-energy sources based on photovoltaic, wind and hydropower, and describes the power sources obtained from time series.

**a: WIND POWER MODEL**

The daily wind power generation is calculated according to the various wind turbines’ power generation corresponding to the wind speed conditions. The output power \( P_w \) will be calculated as follows [6]

\[
P_w = \begin{cases} 
0 & v < v_l \\
v - v_l & v_l \leq v < v_r \\
(v_r - v_l)v & v_r \leq v \leq v_o \\
(P_r) & v_o \leq v \leq v_o 
\end{cases}
\]

(4)
where \( P_w \) denotes the wind power’s output power; \( P_r \) denotes the rated wind output power under the standard rated conditions; \( v \) refers to the wind speed at the height of the wind turbine hub; \( v_i \) denotes the cut-in wind speed, which means the minimum wind speed for wind turbine to start generation; \( v_u \) denotes the cut-out wind speed, which means the maximum wind speed of the wind turbine generation. If the wind speed exceeds this, the wind turbine will be shut down; \( v_r \) denotes the rated wind speed.

**b: PHOTOVOLTAIC MODEL**

The output power of the photovoltaic element is approximately linearly related to the solar light intensity. We assume that the photovoltaic element’s output is the maximum power. Then, the output power \( P_p \) is calculated as follows [18]

\[
P_p = P_r \frac{G}{G_r} [1 + \alpha_r (T - T_r)]
\]

where \( P_p \) denotes the output power of the photovoltaic power; \( r \) refers to the standard rated condition; \( P_r \) denotes the rated photovoltaic output power under the standard rated conditions; \( G \) denotes the actual solar irradiance (W/m\(^2\)); \( G_r \) denotes the rated solar irradiance (1000W/m\(^2\)); \( \alpha_r \) denotes the temperature coefficient of power; \( T \) denotes the actual surface temperature of the photovoltaic cells (\(^\circ\)C); \( T_r \) denotes the rated surface temperature of the photovoltaic cells (25\(^\circ\)C).

**c: HYDROPOWER MODEL**

The hydropower is generated by the river flow’s potential energy falling through the turbine by energy conversion. Compared with photovoltaic and wind power, hydropower has the advantages of convenient start-stop and fast regulation. This study only deals with reservoir power plants. Environmental flows (such as snow meltwater, rainwater, evaporable water, etc.) and tributary flows are not considered to simplify the analysis. The output power \( P_h \) will be calculated as follows [25]

\[
P_h = \eta_h g h \rho Q
\]

where \( P_h \) denotes the output power of the hydropower; \( g \) denotes the gravitational acceleration (9.81 m/s\(^2\)); \( \eta_h \) denotes the efficiency of the generator; \( \rho \) denotes the density of the water (1000 kg/m\(^3\)); \( Q \) denotes the water flow (m\(^3\)/s); \( h \) denotes the height of the water drop (m).

The constraints of wind power, photovoltaic, and hydropower are as follows

\[
\begin{align*}
0 & \leq P_w \leq P_{w,\text{max}} \\
0 & \leq P_p \leq P_{p,\text{max}} \\
V_{t+1} & = V_t + (I_t - Q_t) \Delta t \\
V^l_t & \leq V_t \leq V^u_t \\
Q_{t,\text{min}} & \leq Q_t \leq Q_{t,\text{max}} \\
N^l_t & \leq N_t \leq N^u_t \\
N_s & = N_t - N^l_t
\end{align*}
\]

\( P_{w,\text{max}} \) denotes the wind power rated output (MW); \( P_{p,\text{max}} \) denotes the photovoltaic rated output (MW); \( V_{t+1} \) and \( V_t \) denotes the reservoir storage (m\(^3\)) at the end and the beginning of the period \( t \); \( I_t \) denotes the reservoir inflow (m\(^3\)/s); \( V^l_t \) and \( V^u_t \) denote the lower and upper limits for reservoir storage (m\(^3\)); \( Q^l_t \) and \( Q^u_t \) denote the lower and upper limits for river discharge flow (m\(^3\)/s) of the period \( t \); \( N^l_t \) denotes the lower limits for hydropower output (MW) of the period \( t \); \( N_s \) denotes the schedulable output (MW), which refers to the output that the hydropower can operate in combination with photovoltaic and wind power on the premise of satisfying water dispatching.

**C. SHORT-TERM OPTIMAL OPERATION**

1) PEAK-SHAVING ABILITY MODEL

The multi-energy complementary peak-shaving ability research model is used to measure the complementarity of wind power, photovoltaic, and hydropower in a day. Hydropower units have the advantages of rapid start and stop, fast output adjustment speed, etc. They can quickly compensate for wind power and photovoltaic, with strong output fluctuations and instability, as shown in Fig.2. When the reservoir has a relatively large storage capacity, it can generally meet the multi-energy complementary operation’s feasibility and reliability.

![Figure 2. Hydropower compensate for wind power and photovoltaic.](image-url)
is used during the power grid’s peak load periods, it will improve the complementary system’s peak-shaving ability.

This section establishes the short-term scheduling model based on the short-term complementary characteristics of wind power, photovoltaic, and hydropower in the day. Taking the maximum peak-shaving ability as the objective function, the model uses the Large-Scale System Decomposition-Coordination Method (LSSDCM) to solve. The model will be calculated as follows

$$\max P_m = \text{MAX} \{P_{T,i}\}$$  \hspace{1cm} (8)

where $P_m$ denotes the maximum system load assumed by multi-energy complementarity system; $P_{T,i}$ denotes the total complementary output in the $i$ period; $T$ denotes the scheduling period.

Restrictions:

\(\alpha\): POWER CONSTRAINT

The complementary system must meet the power balance conditions during each period of operation. This means the total power generated by wind farms, photovoltaic power stations, and hydropower stations should be the same as the power on the power system’s demand-side in each period.

$$P_{T,i} - P_{L,i} \geq 0$$  \hspace{1cm} (9)

$$P_{T,i} = P_{H,i} + P_{W,i} + P_{P,i}$$  \hspace{1cm} (10)

where $P_{L,i}$ denotes the system load requirements in period $i$; $P_{H,i}, P_{W,i}$ and $P_{P,i}$ denote the output(MW) of hydropower, wind power, and photovoltaic in period $i$ and follow the constraints of Eqs. (7).

\(\beta\): SYSTEM SPINNING RESERVE CONSTRAINT

For maintaining the system’s reliability, a certain amount of spinning reserve must be reserved to meet the power balance of the load and the fluctuation of photovoltaic power plants and wind power plants, in addition to meeting the load’s demand for power supply. Since wind power and photovoltaic output have strong randomness and volatility, it is generally believed that they cannot provide adjustable capacity. Therefore, the spinning reserve is entirely borne by the hydropower unit.

$$P_{H,\text{max}} - P_{H,i} \geq \alpha P_{L,i} + \beta P_{W,i} + \delta P_{P,i}$$  \hspace{1cm} (11)

$P_{H,\text{max}}$ denotes the maximum hydropower output, $\alpha$ denotes the load fluctuation coefficient; $\beta$ denotes the wind power fluctuation coefficient; $\delta$ denotes the photovoltaic fluctuation coefficient.

\(\gamma\): UNIT RAMP RATE CONSTRAINT

$$R_{d,j} \leq P_{j,i} - P_{j,i-1} \leq R_{u,j}$$  \hspace{1cm} (12)

$R_{d,j}$ and $R_{u,j}$ denote the maximum downhill climbing capacity and the maximum climbing capacity of unit $j$.

\(d\): PEAK SHAVING TIME CONSTRAINTS

$$t_i \{P_P\} = t_i \{P_{H,i}\}$$  \hspace{1cm} (13)

$t_i \{P_P\}$ denotes the peak corresponding time of multi-energy complementary; $t_i \{P_{H,i}\}$ denotes the peak corresponding time of hydropower. Since wind power and photovoltaic do not have peak regulation capacity, the peak regulation time of multi-energy complementary systems will correspond to hydropower’s original peak regulation time. And the peak regulation capacity will be improved on it.

2) LARGE-SCALE SYSTEM DECOMPOSITION-COORDINATION METHOD (LSSDCM)

The multi-energy complementary system structure is complex, and there are many differences and nonlinear relations between different wind farms, hydropower plants, and photovoltaic power plants. When the model is solved using conventional algorithms, the calculation amount is large, and the calculation results are relatively inaccurate. In this paper, the Large-Scale System Decomposition-Coordination Method (LSSDCM) is selected to solve the maximum multi-energy complementary peak-shaving ability model.

The LSSDCM decouples the complex system, divides it into a series of subsystems, and then performs independent optimization of each subsystem. Based on the subsystem’s partial optimality, the coordination factor between each subsystem is obtained. A new round of subsystem optimization is carried out until the whole system reaches the optimization.

Wind farms, photovoltaic power plants, and hydropower stations realize multi-energy complementarity through the power balance constraint and spinning reserve constraint. The power balance constraint coordination variable $\lambda$ and the spinning reserve constraint coordination variable $\mu$ are respectively set. According to the principle of the LSSDCM, the Lagrangian system function is constructed by model expression (8), constraint condition Eqs. (9) and Eqs. (11):

$$L = P_{T,i} - \lambda^i (P_{H,i} + P_{W,i} + P_{P,i} - P_{L,i})$$

$$- \mu^i ((P_{H,\text{max}} - P_{H,i}) - \alpha P_{L,i} - \beta P_{W,i} - \delta P_{P,i})$$  \hspace{1cm} (14)

Organize and simplify:

$$L = (1 - \lambda^i) P_{H,i} - \mu^i (P_{H,\text{max}} - P_{H,i}) + (1 - \lambda^i) P_{W,i}$$

$$+ \mu^i \beta P_{W,i} + (1 - \lambda^i) \mu^i P_{P,i} + \mu^i \delta P_{P,i} + \lambda^i P_{L,i}$$

$$+ \mu^i \alpha P_{L,i}$$  \hspace{1cm} (15)

Which is:

$$L_H = (1 - \lambda^i) P_{H,i} - \mu^i (P_{H,\text{max}} - P_{H,i})$$  \hspace{1cm} (16)

$$L_W = (1 - \lambda^i) P_{W,i} + \mu^i \beta P_{W,i}$$  \hspace{1cm} (17)

$$L_P = (1 - \lambda^i) P_{P,i} + \mu^i \delta P_{P,i}$$  \hspace{1cm} (18)

$$L_L = \lambda^i P_{L,i} + \mu^i \alpha P_{L,i}$$  \hspace{1cm} (19)

The objective function is the maximum value of Eqs. (14) under the condition of the coordination variables $\lambda^i$ and $\mu^i$. 

VOLUME 9, 2021
\[
L = \max H(\lambda^t, \mu^t) \tag{20}
\]
\[
H = \max_{\lambda^t, \mu^t} (L_H + L_W + L_P + L_L) \tag{21}
\]
Eqs. (16)(17)(18) correspond to the hydropower station sub-problem, wind farm sub-problem, and photovoltaic power plant sub-problem. Given the power balance constraint coordination variable \(\lambda^t\) and the spinning reserve constraint coordination variable \(\mu^t\), for each group of coordinated variables \(\lambda^t\) and \(\mu^t\), a specific \(H\) value corresponding to it can always be obtained by solving the sub-problems of each power station. Changing the coordination variables \(\lambda^t\) and \(\mu^t\) through some methods to maximize the \(H\) value, the \(L_H\), \(L_W\), and \(L_P\) values calculated by the coordination variables which maximize the \(H\) value are the optimal solutions to the original problem. Eqs. (19) is a fixed value when the coordination variables \(\lambda^t\) and \(\mu^t\) are known.

Find the partial derivative of \(\lambda^t\) and \(\mu^t\) for \(H(\lambda^t, \mu^t)\) as follows
\[
\frac{\delta H(\lambda^t, \mu^t)}{\delta \lambda^t} = -(P_{H,i} + P_{W,i} + P_{P,i} - P_{L,i}) \tag{22}
\]
\[
\frac{\delta H(\lambda^t, \mu^t)}{\delta \mu^t} = -(P_{H,max} - P_{H,i} - \alpha P_{L,i} - \beta P_{W,i} - \delta P_{P,i}) \tag{23}
\]
For each given \(\lambda^t\) and \(\mu^t\), the corresponding gradient value can be calculated, so the gradient method can be used to update the values of \(\lambda^t\) and \(\mu^t\).

A two-layer solution algorithm structure and the flowchart can be obtained by summarizing the above description shown in Fig.3 and Fig.4.

III. CASE STUDY
The upper reaches of the Yellow River are located between 95° and 111.10° east longitude and 32.5° and 41.80° north latitude in the southeast of Qinghai Province, China, with a total land area of 434,000 km². The region is rich in water resources and has exploitable hydropower installed capacity of about 10,000 MW, making hydropower resources one of the energy advantages. Meanwhile, the annual average solar radiation of this region is 6381 MJ/m², the annual average sunshine hours are over 2719 hours, and the annual average sunshine percentage is between 55% and 80%, which makes the region has rich solar energy resources [25]. The study area is located at an altitude of 3,000 meters. It has many new regions for renewable energy sources such as wind power, solar thermal power, etc. The topographic map of the study area is illustrated in Fig.5.
IV. RESULTS AND DISCUSSION

A. CAPACITY OPTIMIZATION CONFIGURATION MODEL

The monthly average output of wind power, photovoltaic, and hydropower in the Yellow River’s upper reaches and the Qinghai’s annual load curve [30] is shown in Fig.7. The load fluctuations little within a year, while the wind power, photovoltaic, hydropower output have intense volatility by influencing seasons, climate, rainfall, etc., throughout the year. By using renewable energy in a complementary manner, an output curve with less volatility and closer to the load characteristics can be obtained. According to the complementary characteristics research in Chapter 2, this section first calculates the Kendall correlation coefficient for the annual output data of wind power, photovoltaic, and hydropower and then study the long-term complementarity of the multi-energy. The results are shown in Table.2:

The annual correlation coefficient of wind power and photovoltaic is $-0.046$, which proves that the two energy sources have weak complementarity on the long-term scale. The annual correlation coefficient of wind power and hydropower is $-0.626$, demonstrating that the two energy sources have moderate complementarity on the long-term scale. The annual correlation coefficient of photovoltaic and hydropower is 0.424, proving a reasonable similarity between the two energy sources on the long-term time scale. The average similarity between photovoltaic and hydropower shows that the two energy sources have the same change trend in a particular year because the impacts of climate, rainfall, etc., on PV and hydropower are similar. For example, in April, the photovoltaic output will increase as the sunshine duration increases, and hydropower output will also increase as it enters the flood season. Taken together, wind power, photovoltaic, and hydropower are complementary in the long-term time scale, which can be further analyzed and studied.

Using MATLAB to simulate the standard deviation of multi-energy complementary output, the multi-energy complementary total installed capacity is selected as 1000MW. To accurately reflect various energy combinations, it is assumed that each energy generation has the same capacity and the same contribution to the combined system. The value range of weight $\alpha$ and $\beta$ from Eqs. (3) is $[0,1]$, and the change step is 0.01. The calculation results are shown in Fig.8. It can be found through the figure that when $\alpha = 0.42$ and $\beta = 0.61$, the smallest $P_{SD}$ is 2.685. This means when wind power accounts for 23%, photovoltaic accounts for 35%,
FIGURE 9. The hourly output and daily load curve.

and hydropower accounts for 42%, the multi-energy complementary system has the lowest output standard deviation, the highest total output stability, and the smallest volatility.

The maximum standard deviation is 9.264, which appears at the pure wind power generation scenario ($\alpha = 0$ and $\beta = 0$). Simultaneously, the system output fluctuation is the largest and consistent with the fluctuation of the annual output curve shown in Figure 6. When there is only one energy source to be used to generate ($\alpha = 0$ and $\beta = 0$—pure wind power; $\alpha = 0$ and $\beta = 1$—pure photovoltaic; $\alpha = 1$—pure hydropower), the standard deviation is greater than the energy mix, which has a reduction of 71.1% from the maximum to the minimum case. The result proves that the complementary mode can obtain more stable and reliable power output in this study area than the single energy mode.

B. PEAK-SHAVING ABILITY MODEL

The output of wind power, photovoltaic power, and hydropower in an hour and the daily load curve in the study area are shown in Fig.9. Photovoltaic is most affected by weather and is divided into sunny and rainy days, which has different impacts on peak-shaving ability. To avoid the impact of uncertainty on the system, this paper selects the different weather typical daily renewable energy output and load data as the model’s input data.

Due to their characteristics, wind power and photovoltaics do not have peak-shaving capabilities. Therefore, in multi-energy complementary systems, hydropower is responsible for peak-shaving, and the peak value of hydropower output corresponds to the system’s peak load. This section firstly calculates the Kendall correlation coefficient for the output data of wind power, photovoltaic, and hydropower in an hour, then study the short-term complementarity of the multi-energy complementation. The results are shown in Table.3:

|                | Photovoltaic (sunny) | Photovoltaic (rainy) | Wind Power | Hydropower |
|----------------|----------------------|----------------------|------------|------------|
| Photovoltaic   | 1.000                | 0.883                | -0.125     | -0.467     |
| Photovoltaic   | 0.883                | 1.000                | -0.038     | -0.171     |
| Wind Power     | -0.125               | -0.038               | 1.000      | -0.391     |
| Hydropower     | -0.467               | -0.171               | -0.391     | 1.000      |

The daily correlation coefficient of photovoltaic and hydropower is −0.391, which proves that the two energy sources have moderate complementarity on the short-term scale. On sunny days: the daily correlation coefficient of wind power and photovoltaic is −0.125, which is weakly complementary, and the daily correlation coefficient of photovoltaic and hydropower is −0.467, which is moderately complementary. On rainy days: the daily correlation coefficient of wind power and photovoltaic is −0.038, which is weak complementary, and the daily correlation coefficient of photovoltaic and hydropower is −0.171, which is weakly complementary. The correlation coefficient between photovoltaic for sunny days and rainy days is 0.883. This is because although the photovoltaic output is smaller and the volatility is stronger on rainy days, the changing trend is still roughly the same as that on sunny days. Hence, the two have a strong correlation. Taken together, wind power, photovoltaic, and hydropower are complementary in the short-term time scale.

According to the calculation results of the capacity configuration in Section 4.1, the multi-energy complementary system, which has a total installed capacity of 1000MW, is selected for daily peak regulation research, including 230MW wind power, 350MW photovoltaic, and 420MW hydropower. This section considers the constraints described above based on the hourly output curve, then simulates the model with the maximum peak-shaving ability by the LSSDCM and the ADMM described in [33]. Algorithm comparison results are shown in Fig.10:

The LSSDCM finds the optimal solution in the 19th iteration, while the ADMM finds the optimal solution in the 24th iteration. The convergence rate of the LSSDCM is 20.83% faster than the ADMM to obtain the system output.
In addition, from the smoothness of the objective function curve, it can be seen that the optimization effect of LSSDCM is better than that of ADMM. Fig.11 is the complementary output curve of sunny days, and Fig.12 is the complementary output curve of rainy days.

The photovoltaic output looks like a sine half-wave on sunny days. The output is most evident between 8:00 and 19:00, and the output reaches its peak from 12:00 and 15:00. Wind power output is higher between 6:00 and 10:00 and reaches its highest level at 10:00. Hydropower is responsible for peak-shaving. The peak-shaving periods are 9:00 and 12:00 in the morning and 18:00 and 21:00 in the evening.

When the wind power and photovoltaic generation gradually increase in the morning peak period, they can participate in peak-shaving together with hydropower. When the peak-shaving ends at 12:00, the hydropower output is reduced, the photovoltaic and wind power are mainly responsible for providing load. During this period, hydropower’s reduced output is equivalent to converting wind power and photovoltaic power generation into water power to be stored in the reservoir.

In the evening peak period, photovoltaic has no power at this time, wind power and hydropower jointly participate in peak-shaving. Hydropower needs to reserve a part for adjusting the possible volatility of wind power, so the peak-shaving effect of the evening peak is slightly worse than that of the morning peak.

On rainy days, the light intensity is unstable, the fluctuation is more substantial, so the photovoltaic output is lower than on sunny days, and the output is more evident between 10:00 and 13:00. Wind power output is higher between 2:00 and 5:00. The peak-shaving time of hydropower is the same as a sunny day.

When the wind power and photovoltaic generation gradually increase in the morning peak period, they can participate in peak-shaving together with hydropower, yet the peak-shaving output is lower than on sunny days. When peak-shaving ends at 12:00, because of the large fluctuations of wind power and photovoltaic power output on rainy days, it is necessary to reduce hydropower output to compensate, adjust wind power and photovoltaic power, and maintain the stability of complementary system output.

In the evening peak period, photovoltaic has no power at this time, wind power and hydropower jointly participate in peak-shaving. Due to the large fluctuations of wind power and flood prevention, and water storage on rainy days, the peak-shaving output is less improved.

The peak-shaving capabilities before and after complementation are shown in Fig.13. After the complementary operation, the peak-shaving capacity of the system has been increased. Compared with separate peak shaving of hydropower, the sunny day’s morning peak output increased by 50.8%, the evening peak output increased by 14.9%, and the daily peak-shaving average production increased by 32.9%. While the morning peak output of the rainy day increased by 24.2%, the evening peak output increased by 2.7%, and the daily peak-shaving average production increased by 13.5%. The results show that especially in sunny days, the comprehensive utilization of wind power,
photovoltaic power, and hydropower in a complementary manner can effectively improve the peak-shaving capacity of the system, which had improved the present situation that photovoltaic and wind power do not have peak-shaving capabilities due to their output characteristics.

V. CONCLUSION

This paper’s research shows that using the complementary characteristics of wind power, photovoltaic power, and hydropower to use various types of energy resources jointly can effectively increase the utilization rate of energy resources. Compared with a single energy, the complementary operation mode can obtain more stable power (the standard deviation of the output value has been reduced by 71.1%). Wind power 23%, photovoltaic 35%, hydropower 42% can keep the most stable generation in the long-term complementary operation. The multi-energy complementary system can improve the peak-shaving capacity by 32.9% (sunny days) and 13.5% (rainy days) in the short-term optimal operation. This operation mode connects renewable energy to the grid more efficiently, weakens the dependence on non-renewable energy, and provides greater peak-shaving capacity.

In practical projects, the steady renewable energy combination is highly dependent on hydropower generation, because the intermittence and volatility of the photovoltaic and wind power will still have adverse effects during the process of complementary operation. Therefore, other energy sources, such as battery storage, air energy storage, biomass energy, etc., should be appropriately added to the existing energy combination to reduce the intermittence and volatility of photovoltaics and wind power and help the energy combination to obtain more stable power. Future work in this area will further assess the complementarity of wind power, photovoltaic power, and hydropower among different weathers and different regions to achieve more efficient use of energy.

ACKNOWLEDGMENT

The data was obtained from Construction of the China Integrated Meteorological Information Sharing System (CIMISS). Computer codes used in this article based on the MATLAB and PYTHON Software. The authors declare that they have no financial and personal relationships with other people or organizations that can inappropriately influence their work, there is no professional or other personal interest of any nature or kind in any product, service and/or company.

REFERENCES

[1] I. Stevović, D. Mirjanić, and S. Stevović, “Possibilities for wider investment in solar energy implementation,” Energy, vol. 180, pp. 495–510, Aug. 2019, doi: 10.1016/j.energy.2019.04.194.

[2] Q. Tian, G. Huang, K. Hu, and D. Niyogi, “Observed and global climate model based changes in wind power potential over the northern hemisphere during 1979–2016,” Energy, vol. 167, pp. 1224–1235, Jan. 2019, doi: 10.1016/j.energy.2018.11.027.

[3] J. C. Lomas, E. Muñoz-Cerón, G. Nofuentes, and J. de la Casa, “Sale of profitable but unaffordable PV plants in Spain: Analysis of a real case,” Energy Policy, vol. 117, pp. 279–294, Jun. 2018, doi: 10.1016/j.enpol.2018.03.014.

[4] N. Sezer, Y. Biço, and M. Koç, “Design and analysis of an integrated concentrated solar and wind energy system with storage,” Int. J. Energy Res., vol. 43, no. 8, pp. 3263–3283, Jun. 2019, doi: 10.1002/er.4456.

[5] L. Xu, Z. Wang, and Y. Liu, “The spatial and temporal variation features of wind-sun complementarity in China,” Energy Convers. Manage., vol. 154, pp. 138–148, Dec. 2017, doi: 10.1016/j.enconman.2017.10.031.

[6] D. Heide, L. von Bremen, M. Greiner, C. Hoffmann, M. Speczmann, and S. Boﬁnger, “Seasonal optimal mix of wind and solar power in a future, highly renewable Europe,” Renew. Energy, vol. 35, no. 11, pp. 2483–2489, Nov. 2010, doi: 10.1016/j.renene.2010.03.012.

[7] Y. Zhu, Q. Tong, X. Yan, Y. Liu, J. Zhang, Y. Li, and G. Huang, “Optimal design of multi-energy complementary power generation system considering fossil energy scarcity coefﬁcient under uncertainty,” J. Cleaner Prod., vol. 227, Nov. 2020, Art. no. 112732, doi: 10.1016/j.jclepro.2020.112732.

[8] P. E. Bett and H. E. Thornton, “The climatological relationships between wind and solar energy supply in Britain,” Renew. Energy, vol. 87, pp. 96–110, Apr. 2016, doi: 10.1016/j.renene.2015.10.006.

[9] R. Antunes Campos, L. Rafael do Nascimento, and R. Räther, “The complementary nature between wind and photovoltaic generation in Brazil and the role of energy storage in utility-scale hybrid power plants,” Energy Convers. Manage., vol. 221, Oct. 2020, Art. no. 113160, doi: 10.1016/j.enconman.2020.113160.

[10] M. P. Cantão, M. R. Bessa, R. Bettgea, D. H. M. Dzelt, and J. M. Lima, “Evaluation of hydro-wind complementarity in the Brazilian territory by means of correlation maps,” Renew. Energy, vol. 101, pp. 1215–1225, Feb. 2017, doi: 10.1016/j.renene.2016.10.012.

[11] Hothica, C. E. and I. H. Rowlands, “Solar and wind resource complementarity: Advancing options for renewable electricity integration in Ontario, Canada,” Renew. Energy, vol. 36, no. 1, pp. 97–107, 2011, doi: 10.1016/j.renene.2010.06.004.

[12] Y. Zhang, J. Lian, C. Ma, Y. Yang, X. Pang, and L. Wang, “Optimal sizing of the grid-connected hybrid system integrating hydropower, photovoltaic, and wind considering cascade reservoir connection and photovoltaic-wind complementarity,” J. Cleaner Prod., vol. 274, Nov. 2020, Art. no. 123510, doi: 10.1016/j.jclepro.2020.123510.

[13] F. Zhu, P.-A. Zhong, Y. Sun, B. Xu, Y. Ma, W. Liu, D. Zhang, and J. Dawa, “A coordinated optimization framework for long-term complementary operation of a large-scale hydro-photovoltaic hybrid system: Nonlinear modeling, multi-objective optimization and robust decision-making,” Energy Convers. Manage., vol. 226, Dec. 2020, Art. no. 113543, doi: 10.1016/j.enconman.2020.113543.

[14] M. Zhai, G. Huang, L. Liu, and X. Zhang, “Ecological network analysis of an energy metabolism system based on input-output tables: Model development and case study for Guangdong,” J. Cleaner Prod., vol. 227, pp. 434–446, Aug. 2019, doi: 10.1016/j.jclepro.2019.04.039.

[15] P. S. Moura and A. T. de Almeida, “Multi-objective optimization of a mixed renewable system with demand-side management,” Renew. Sustain. Energy Rev., vol. 14, no. 5, pp. 1461–1468, 2010, doi: 10.1016/j.rser.2010.01.004.

[16] F. de Oliveira Costa Souza Rosa, K. Costa, E. da Silva Christo, and P. B. Bertahone, “Complementarity of hydro, photovoltaic, and wind power in Rio de Janeiro State,” Sustainability, vol. 9, no. 7, p. 1130, Jun. 2017, doi: 10.3390/su9071130.

[17] T. Ma, H. Yang, L. Lu, and J. Peng, “Technical feasibility study on a standalone hybrid solar-wind system with pumped hydro storage for a remote island in Hong Kong,” Renew. Energy, vol. 69, pp. 7–15, Sep. 2014, doi: 10.1016/j.renene.2014.12.005.

[18] B. François, M. Bornot, I. D. Creutin, B. Hingray, D. Raynaud, and J. F. Sauterleute, “Complementarity between solar and hydro power: Sensitivity study to climate characteristics in northern-italy,” Renew. Energy, vol. 86, pp. 543–553, Feb. 2016, doi: 10.1016/j.renene.2015.08.044.

[19] C. He, T. Liu, L. Wu, and M. Shahidehpour, “Robust coordination of interdependent electricity and natural gas systems in day-ahead scheduling for facilitating volatile renewable generations Via power-to-gas technology,” J. Mod. Power Syst. Clean Energy, vol. 5, no. 3, pp. 375–388, May 2017, doi: 10.1007/s40565-017-0278-z.

[20] H. Zhang, Z. Lu, W. Hu, Y. Wang, L. Dong, and J. Zhang, “Coordinated optimal operation of hydro–wind–solar integrated systems,” Appl. Energy, vol. 242, pp. 883–896, May 2019, doi: 10.1016/j.apenergy.2019.03.064.

[21] P. S. dos Anjos, A. S. A. da Silva, B. Stošić, and T. Stošić, “Long-term correlations and cross-correlations in wind speed and solar radiation temporal series from Fernando de Noronha Island, Brazil,” Phys. A, Stat. Mech. Appl., vol. 424, pp. 90–96, Apr. 2015, doi: 10.1016/j.physa.2015.01.003.
[22] J. Fithendranath and D. Das, “Stochastic planning of islanded microgrids with uncertain multi-energy demands and renewable generations,” IET Renew. Power Gener., vol. 14, no. 19, pp. 4179–4192, 2020, doi: 10.1049/iet-rpg.2020.0889.

[23] S. Nojavan, A. Akbari-Dibav, A. Farahmand-Zahed, and K. Zare, “Risk-constrained scheduling of a CHP-based microgrid including hydrogen energy storage using robust optimization approach,” Int. J. Hydrogen Energy, vol. 45, no. 56, pp. 32269–32284, 2020, doi: 10.1016/j.ijhydene.2020.08.22.

[24] Y. Yin, T. Liu, and C. He, “Day-ahead stochastic coordinated scheduling for thermal-hydro-wind-photovoltaic systems,” Energy, vol. 187, Nov. 2019, Art. no. 115944.

[25] B. Ming, P. Liu, S. Guo, X. Zhang, M. Feng, and X. Wang, “Optimizing utility-scale photovoltaic power generation for integration into a hydropower reservoir by incorporating long- and short-term operational decisions,” Appl. Energy, vol. 204, pp. 432–445, Oct. 2017, doi: 10.1016/j.apenergy.2017.07.046.

[26] X. Teng, Z. Gao, Y. Zhang, H. Huang, L. Li, and T. Liang, “Key technologies and the implementation of wind, PV and storage co-generation monitoring system,” J. Mod. Power Syst. Clean Energy, vol. 2, no. 2, pp. 104–113, Jun. 2014, doi: 10.1007/s40565-014-0055-1.

[27] X. Zhang, G. Ma, W. Huang, S. Chen, and S. Zhang, “Short-term optimal operation of a wind-PV-hydro complementary installation: Yalong River, Sichuan Province, China,” Energies, vol. 11, no. 4, p. 868, Apr. 2018, doi: 10.3390/en11040868.

[28] K. Sun, K.-J. Li, J. Pan, Y. Liu, and Y. Liu, “An optimal combined operation scheme for pumped storage and hybrid wind-photovoltaic complementary power generation system,” Appl. Energy, vol. 242, pp. 1155–1163, May 2019, doi: 10.1016/j.apenergy.2019.03.171.

[29] M. Zhang, T. Xie, C. Zhang, D. Chen, C. Mao, and C. Shen, “Dynamic model and impact on power quality of large hydro-photovoltaic power complementary plant,” Int. J. Energy Res., vol. 43, no. 9, pp. 4436–4448, Jul. 2019, doi: 10.1002/er.5459.

[30] H. Li, P. Liu, S. Guo, B. Ming, L. Cheng, and Z. Yang, “Long-term complementary operation of a large-scale hydro-photovoltaic hybrid power plant using explicit stochastic optimization,” Appl. Energy, vol. 238, pp. 863–875, Mar. 2019, doi: 10.1016/j.apenergy.2019.01.111.

[31] Z. Liang, H. Chen, S. Chen, Z. Lin, and C. Kang, “Probability-driven transmission expansion planning with high-penetration renewable power generation: A case study in northwestern China,” Appl. Energy, vol. 255, Dec. 2019, Art. no. 113610, doi: 10.1016/j.apenergy.2019.113610.

[32] D. Yang and C. Jiang, “Interval method based optimal planning of multi-energy microgrid with uncertain renewable generation and demand,” Applied Energy, vol. 277, Apr. 2020, Art. no. 115491, doi: 10.1016/j.apenergy.2020.115491.

[33] Y. Chen and Y. Zhang, “Optimal operation for integrated electricity-heat system with improved heat pump and storage model to enhance local energy utilization,” Energies, vol. 13, no. 24, p. 6729, 2020, doi: 10.3390/en13246729.

[34] Z. Liang and H. Chen, “A risk-based uncertainty set optimization method for the energy management of hybrid AC/DC microgrids with uncertain renewable generation,” IEEE Trans. Smart Grid, vol. 11, no. 2, pp. 1526–1542, Mar. 2019, doi: 10.1109/tsg.2019.2939817.

[35] F. A. Canales, J. Jurasz, A. Beluco, and A. Kies, “Assessing temporal complementarity between three variable energy sources through correlation and compromise programming,” Energy, vol. 192, Feb. 2020, Art. no. 116637, doi: 10.1016/j.energy.2019.116637.

SONGKAI WANG received the M.E. degree from the Xi’an University of Technology, Xi’an, China, in 2017, where he is currently pursuing the Ph.D. degree. His research interests include renewable energy generation and integration, and power system dispatch and control.

RONG JIA (Member, IEEE) received the Ph.D. degree from the Xi’an University of Technology, Xi’an, China, in 1999. He is currently a Professor with the School of Electrical Engineering, Xi’an University of Technology. His research interests include power system dispatch and control, condition monitoring and diagnosis of power equipment, and renewable energy generation.

XIAOYU SHI received the Ph.D. degree from the Xi’an University of Technology, Xi’an, China, in 2020. She holds a postdoctoral position with the School of Electrical Engineering, Xi’an University of Technology. Her research interests include the study on long-term operation of cascade reservoirs and short-term predictions about photovoltaic output power.

YUAN AN received the Ph.D. degree from the Xi’an University of Technology, Xi’an, China, in 2016. He is currently an Associate Professor with the School of Electrical Engineering, Xi’an University of Technology. His research interests include power system protection and control, and renewable energy generation and integration.

QIANG HUANG received the Ph.D. degree from the Xi’an University of Technology, Xi’an, China, in 1995. He is currently a Professor with the School of Water Resources and Hydropower, Xi’an University of Technology. His research interests include hydrology and renewable energy operation.

PENGCHENG GUO received the Ph.D. degree from the Xi’an University of Technology, Xi’an, China, in 2006. He is currently a Professor with the School of Water Resources and Hydropower, Xi’an University of Technology. His research interests include vibration and stability control of hydraulic unit, and renewable energy operation.

CHANG LUO received the M.E. degree from Northwestern Polytechnical University, Xi’an, China, in 2016. She is currently working with Hanjiang-To-Weihe River Valley Water Diversification Project Construction Company Ltd., China. Her research interests include hydropower station dispatch and control, and renewable energy informationization.

***