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Decarbonizing Energy Systems: Smart Grid and Renewable Technologies
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Modelling and operation of electrical grids considering techno-economic multi-objective functions

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Abstract. Analysing the functionality of electrical systems allows for an evaluation of the characteristics of different power sources over varying periods and enables the coordination of multiple units. This is crucial for assessing the effects of uncertainty on the system considering load and energy generation for the effectiveness of power system monitoring and smart scheduling and cost-effectiveness of electrical grid operation. This research introduces an approach for simulating the operation of an electrical grid considering different time scales based on economic and technical indices. First, a series of standard source load scenarios is established. Subsequently, multiple scenarios are produced to show the stochastic nature of renewable energy and demand and utilise the probability features of uncertain data. The system described in this paper shifts the power balance issue from a yearly scale to weekly and daily electricity balances based on different time scales. The performance of the stochastic simulation solution is significantly enhanced by effectively coordinating in different time periods. The total coal consumption, economic index, abandoned renewable energy, and the rate of abandoned renewable energy are all closely monitored to maintain a high level of accuracy in reflecting the system's performance.

Keywords: Electrical systems, Uncertainty, Smart scheduling, Different time scales, Power balance.

1 Introduction

1.1 Background and aims

The low dual-carbon strategy involving carbon neutrality and carbon peak is modelled for the expanding modern power system centered on renewable energy sources [1, 2]. This strategy involves extensive clean energy production in the grids, as well as the growing acceptance of new energy consumers such as electric vehicles. Consequently, this alteration has caused a significant increase in the unpredictability and variability of the power grid's supply and demand dynamics [2, 3]. The power grid has experienced a significant transformation, leading to a wider variety and more intricate operational modes. The power system's functioning showcases complex coupling characteristics, which

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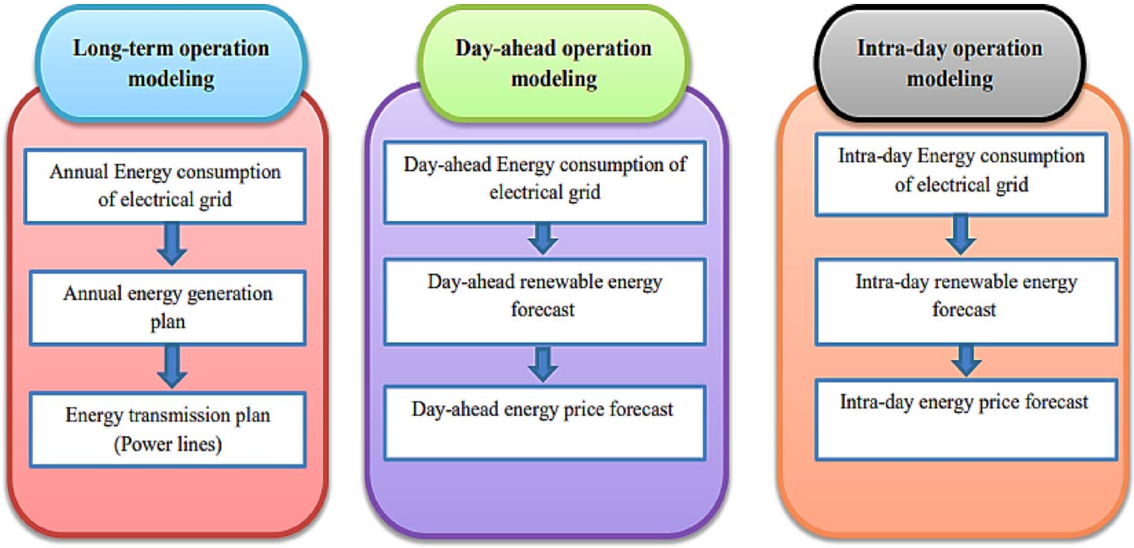

Fig. 1. Operation of electrical grid in different time scales.

pose a new obstacle in power equilibrium over durations [4]. In the long term, a disparity arises between the generation of renewable resources and the need for power, leading to seasonal shortages in power supply during certain periods annually [5]. Hence, it is essential to take into account variations in supply and demand and to conduct extended stochastic operational modelling of local power networks with coordination across multiple time scales. Many approaches aim to provide an accurate depiction of the system's operation and effectively minimise risks associated with power equilibrium [6]. Examining the power equilibrium through thorough and extensive operational simulation can act as a crucial basis for making decisions in power system planning and operational control [6, 7]. When simulating the operation of energy systems with a large amount of renewable energy, it is crucial to consider the unpredictable variations in renewable resources and constraints of conventional units. This is because of the uncertainty and variability of solar and wind resources in the seasonal patterns [6–8]. The operation of power systems based on simulation approaches can be classified into three distinct time scales: medium- to long-term operation simulation, real-time operation simulation, intra-day and day-ahead operation simulations [9]. In Intra-day and day-ahead operation simulations generation resources illustrate stochastic volatility and uncertainty through short-term scenarios [10, 11]. Calculations include power abandonment, system reliability, and cutting costs. Medium and long-term simulations typically span one year, utilizing source load output curves to quantify operating costs, fuel consumption, power generation, unit utilization, transmission channel usage, and renewable energy abandonment rates [12, 13]. The foundation of the operation of the electrical grid in the coordinated operation across multiple time scales, as illustrated in Figure 1. The maintenance approach for the generation units is organized by conducting simulations of long-term operations, ensuring that the water rate is appropriately distributed to the power plants with hydropower units and the ability to make annual and monthly adjustments. Next, a simulation for day-ahead operations is conducted using the maintenance schedule and power distribution plan mentioned earlier. Furthermore, the day-ahead operation simulation results are optimized by incorporating more precise intra-day source load prediction data and fine-tuning them with intra-day simulation to minimize errors by stochastic factors.

The general structure of the electrical grid operation simulation outlined in this paper can be seen in Figure 2.

In this framework, the input data link consists of load forecast information for the power grid system, plans for power flow modelling, energy generation planning, units' parameters, grid information, renewable energy data, and operating data. To fulfil the data requirements for simulating operations at different time scales, it is necessary to modify the input data. The operations simulation link encompasses simulating load and renewable resources, maintenance for long-term and medium scales, and a core module for coordinated simulation across multiple time scales. The simulation module creates different uncertainties to simulate the stochastic operation approach in order to tackle the unpredictable nature of load and renewable resources. The maintenance results are utilized as constraints for the daily simulation approach. Hence, the expanded successful performance results of hydroelectric power act as the boundaries for the daily simulation approach. It also integrates a security assessment of the power system to guarantee the reliability of grids. During the day-ahead period, the output of units and transmission lines plan for the upcoming hours are established using forecasted data on renewable energy and load. This process is continuously updated on a rolling basis. In the intra-day timeframe, the optimization results of the day are further refined using the intra-day data. The production schedule and electricity distribution plan have been modified to reflect a reduced timeframe of approximately 4 h in advance. The operational simulation indicators, including

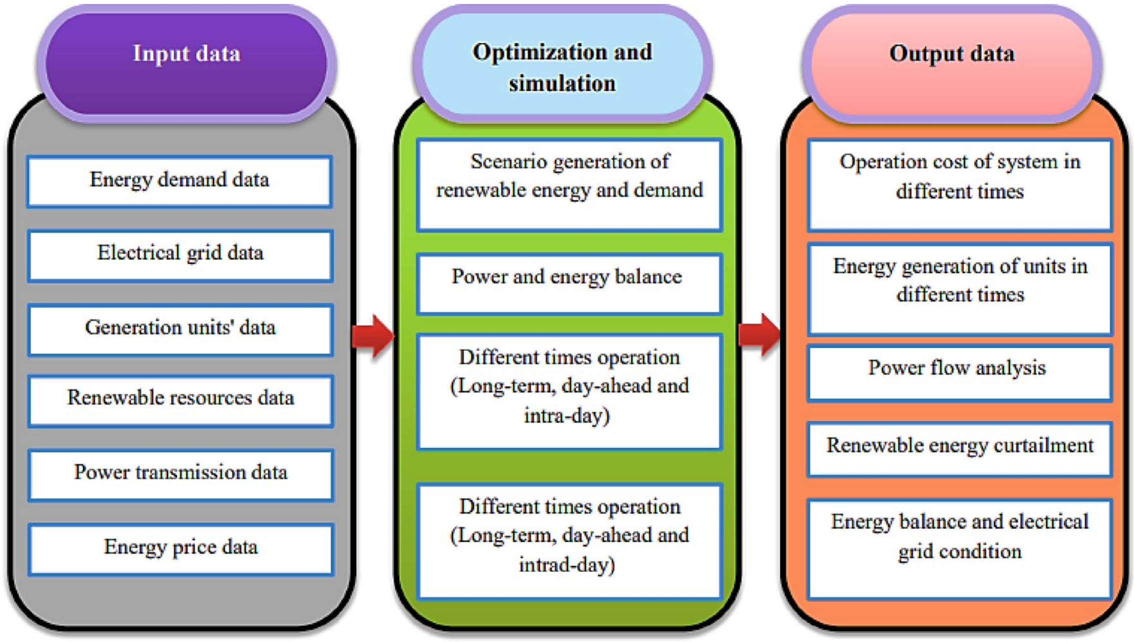

Fig. 2. Framework of our operation of electrical grids in this study.

system operating expenses, unit power generation, power purchase expenses, environmental preservation, and more, are measured through the outcome output connection. The line flow, unit output, and other data collected from coordinated simulations across various time scales are used to derive these indicators.

1.2 Related researches

Several investigations have been carried out on the functioning of electrical and power grids using diverse methodologies. A robust model is developed in [14] to address the uncertainty of consumption and power generation in energy systems. In reference [15], an optimization approach is utilized to predict the variability of wind power, and load demand. This facilitates the achievement of electrical grid management with various goals in consideration. In [16], a novel approach is presented for stochastic Model Predictive Control (MPC). This approach utilizes probability prediction and rolling stochastic optimization techniques. The study focuses on analysing the output of renewable resources at various times. Additionally, a simulation model is developed to address the system balance problem in operation. The authors in [17] explore the increased unpredictability of demand in an energy system by analysing daily situations over a year. The modelling energy system in [18] operates in a stochastic, and diverse manner, posing a challenge in accurately predicting source load uncertainty with only a few standard scenarios. In [19], the conventional approach of simulating time series operations for small-scale power systems has proven to yield optimal solutions in theory. As the power system size increases and the optimization time scale includes various stochastic load and renewable energy scenarios, the model's binary variables grow exponentially. This results in a notable increase in computational complexity and expansion of the optimization space. The computation is confronted with disasters, leading to a decrease in computational efficiency. Consequently, obtaining an optimization scheme within a reasonable timeframe becomes challenging, and large-scale system calculations over a long duration often result in memory overflow [20]. In [21], an evaluation index system and simulation approach for coordinating medium, long- and short-terms of power systems is introduced. In reference [22], the unit and annual energy planning are determined during the long-term phase. The literature [23] presents a power system maintenance schedule model that is capable of simulating weekly scheduling over a year. The maintenance schedule is created every week in [24] whereas the operation model is resolved hourly and week by week.

1.3 Research gaps and contribution

Based on the analysis above, it is evident that current power system simulations are capable of factoring in the substantial influence of uncertainty in a wide range of renewable resources. Verifying the precision of demand uncertainty continues to pose a difficulty. The robust optimization method presents a challenging task, with inaccuracies present in the process of approximating transformations. Solving stochastic programming with complex opportunity constraints often involves transformation, making it hard to ensure solution accuracy. The method for generating scenes evaluates the uncertainty of the power grid by producing various deterministic cases, allowing the scene set to more accurately depict the real stochastic variations in load and renewable energy production. Therefore, delving into and debating the thorough examination of resource endowment features for different energy types over varying time periods by establishing source load scenario collections, along with devising a power system operation simulation technique capable of aligning diverse time scales while upholding power equilibrium, is a crucial matter warranting in-depth scrutiny. According to the latest research findings, the existing methods are unable to successfully conduct a prolonged time simulation of power systems with uncertainty of demand and the intricate coupling features of system modelling. This study presents a simulation technique for power networks that emphasizes scenario and scale synchronization. Hence, our contributions are as follows.

At first, this research creates a set of typical situations for both demand and supply via the Latin backward method and hypercube sampling. Through the creation of different deterministic scenarios, we can accurately illustrate the random fluctuation patterns of demand and renewable energy, ultimately surpassing the limitations of outcome constraints in a single simulation scenario. Additionally, the power balance spanning annually is converted into an electricity balance challenge for weeks and a daily power balancing power for days. This approach enables the coordinated operation across various time scales, significantly cutting down on computational complexity. The enhanced efficiency in model solving allows for time operation simulations of power systems in diverse cases. The method presented in this paper for simulating the long-term operation of the power system accurately reflects the system's actual operation status with high precision. Through in-depth stochastic simulation analysis of power balance processes, it provides a vital groundwork for making decisions in power system operation and control.

2 Modelling scenarios

To fully consider the fluctuations in load demand and renewable energy production, this research first creates the probability distribution of both variables using non-parametric kernel density estimation based on past data. Then, the standard deviation and average of each variable are used to establish the parameters in the time period. The Latin hypercube approach is employed to make different scenarios for renewable resources and load demand. Therefore, a smaller set of representative scenarios is chosen through simultaneous backward reduction, resulting in a few specific probability scenarios that preserve the main characteristics of the original data with minimal computational effort [25, 26].

3 Modelling mathematical

3.1 Modelling objective functions

The first objective function is minimizing costs in operation time, which is modelled as follows:

$$f_1 = \min \sum_{t=1}^{T} \left\{ \sum_{i=1}^{N_g} [c_1(P_{i,t}) + c_2(u_{i,t})] \right\}. \quad (1)$$

Where:

$$c_1(P_{i,t}) = a_i P_{i,t}^2 + b_i P_{i,t} + c_i \quad (2)$$

$$c_2(u_{i,t}) = u_{i,t}(1 - u_{i,t-1}) D_{s,i} + u_{i,t-1}(1 - u_{i,t}) D_{d,i}. \quad (3)$$

Also:
f_1 = Cost in operation time.
$c_1(P_{i,t})$ = Fuel cost of thermal units.
$c_2(u_{i,t})$ = Strat up and cost of thermal units.
t = Planning time.
N_g = Thermal units' number.
$P_{i,t}$ = Power generated by thermal units.
$a_i,\ b_i,\ c_i$ = Fuel factor of thermal units.
$u_{i,t}$ = Binary variable for start-up and down of thermal units.
$D_{s,i}$ and $D_{d,i}$ = Factor of cost for start-up and down of thermal units.

The second objective function is modelling minimizing renewable energy curtailment as follows:

$$f_2 = \min \sum_{t=1}^{T} \left(\sum_{w=1}^{N_{\rm w}} D_{{\rm W}w,t} + \sum_{p=1}^{N_{\rm pv}} D_{{\rm PV}p,t} + \sum_{s=1}^{N_{\rm s}} D_{{\rm S}s,t} \right). \quad (4)$$

Where:
f_2 = Abandoned value.
N_s, N_{pv} and N_w = Number of cascade reservoirs, photovoltaic power plants and wind farms, respectively.
$D_{{\rm S}s,t}, D_{{\rm PV}p,t}, \text{and} D_{{\rm W}w,t}$ = Abandoned value of cascade reservoir, photovoltaic power plants and wind farms, respectively.

3.2 Modelling constraints

The constraints of the system are modelled as follows.

The power generation limit of the thermal power units is modelled as follows:

$$u_{i,t} P_{i,\min} \le P_{i,t} \le P_{i,\max} u_{i,t}. \quad (5)$$

Where:
$P_{i,\min}$ = Minimum power of thermal unit.
$P_{i,\max}$ = Maximum power of thermal unit.

The ramp-up and ramp-down of units are modelled as follows:

$$-P_{i,\rm down} \le P_{i,t} - P_{i,t-1} \le P_{i,\rm up} \quad (6)$$

$P_{i,\rm down}$ = Ramp down of thermal unit.
$P_{i,\rm up}$ = Ramp up of thermal unit.

The minimum and maximum up and down times of units are modelled as follows:

$$(u_{i,t-1} - u_{i,t})\left(T_{i,t-1}^{on} - T_{min,i}^{on}\right) \ge 0 \quad (7)$$

$$(u_{i,t} - u_{i,t-1})\left(T_{i,t-1}^{\rm off} - T_{{\rm min},i}^{\rm off}\right) \ge 0. \quad (8)$$

Where:
$T_{i,t-1}^{\rm on}$ = Minimum up time.
$T_{i,t-1}^{\rm off}$ = Minimum down time.
The constraints of the hydropower units are as follows:

$$P_{h,t} = f(q_{h,t}, V_{s,t}) \tag{9}$$

$$P_{h,\min} \le P_{h,t} \le P_{h,\max} \tag{10}$$

$$u_{h,t} Q_{h,\min} \le q_{h,t} \le u_{h,t} Q_{h,\max} \tag{11}$$

$$P_{h,t} = f(q_{h,t}, V_{s,t}). \tag{12}$$

Where:
h = Number of hydropower units.
$u_{h,t}$ = Binary variable.
$P_{h,t}$ = Power generation of hydropower unit.
$q_{h,t}$ = Power flow of hydropower unit.
$V_{h,t}$ = Storage capacity.
The constraints of the reservoir discharge are as follows:

$$Q^s_{h,\min} \le \sum_{h\in s} q_{h,t} + D_{S_{s,t}} \le Q^s_{h,\max} \tag{13}$$

$$D_{S_{s,t}} \ge 0 \tag{14}$$

$$V_{s,0} = V^0_s \tag{15}$$

$$V_{s,T} \ge V^T_s \tag{16}$$

$$V_{s,\min} \le V_{s,t} \le V_{s,\max}. \tag{17}$$

Where:
$Q^s_{h,\max}$ and $Q^s_{h,\min}$ = Maximum and minimum rates of the discharge of reservoir.
$V_{s,0}$ = Initial storage capacity of reservoir.
V^0_s = Final storage capacity of reservoir.
The water balance formula for the main reservoir is stated as:

$$V_{s,t} = V_{s,t-1} + \left[I_{s,t} - \left(\sum_{h\in s} q_{h,t} + D_{Ss,t}\right)\right] = 1. \tag{18}$$

The downstream reservoir's water balance expression is stated below:

$$V_{s,t} = V_{s,t-1} + \left[I_{s,t} + \left(\sum_{h\in us} q_{h,t} + D_{S_{us,t}}\right) - \left(\sum_{h\in s} q_{h,t} + D_{Ss,t}\right)\right],\ s \ge 2. \tag{19}$$

Where:
$I_{s,t}$ = Interval inflow of reservoir.
The calculation for the reserve of thermal power plants is as follows:

$$R^{\text{up}}_{i,t} \le B_{i,t} \min\{P_{i,\max} - P_{i,t}, P_{i,\text{up}}\} \tag{20}$$

$$R^{\text{down}}_{i,t} \le B_{i,t} \min\{P_{i,t} - P_{i,\min}, P_{i,\text{down}}\}. \tag{21}$$

Where:
$R^{\text{up}}_{i,t}$ = Positive rotating reserve capacity.
$R^{\text{down}}_{i,t}$ = Negative rotating reserve capacity.

The calculation for the reserve rate of hydropower system is:

$$R^{\text{up}}_{h,t} \le B_{h,t} \min\{P_{h,\max} - P_{h,t}, P_{h,\text{up}}\} \tag{22}$$

$$R^{\text{down}}_{h,t} \le B_{h,t} \min\{P_{h,t} - P_{h,\min}, P_{h,\text{down}}\}. \tag{23}$$

Where:
$R^{\text{up}}_{h,t}$ = Upper reserve capacity.
$R^{\text{down}}_{h,t}$ = Lower reserve capacity.
$P_{h,\text{down}}$ = Rate of down-climbing.
$P_{h,\text{up}}$ = Rate of up-climbing rate.
The power balance constraint is modelled as follows:

$$\sum_{i=1}^{N_g} P_{i,t} + \sum_{h=1}^{N_h} P_{h,t} + \sum_{w=1}^{N_w} (P_{w,t} - D_{W_{w,t}}) + \sum_{p=1}^{N_{pv}} (P_{p,t} - D_{PV_{p,t}}) = P_{L,t}. \tag{24}$$

Where:
$P_{L,t}$ = Load demand at time t.
The thermal units' power tracking is modelled as follows:

$$E^{\text{week}}_i (1 - \alpha_{2,i}) \le \sum_{t=1}^{T} P_{i,t} \Delta T \le E^{\text{week}}_i (1 + \alpha_{1,i}) \tag{25}$$

$$\alpha_{1,i}, \alpha_{2,i} \ge 0. \tag{26}$$

The hydropower units' tracking is modelled as follows:

$$E^{\text{week}}_h (1 - \alpha_{2,h}) \le \sum_{t=1}^{T} \sum_{h=1}^{N_h} P_{h,t} \Delta T \le E^{\text{week}}_h (1 + \alpha_{1,h}) \tag{27}$$

$$\alpha_{1,h}, \alpha_{2,h} \ge 0. \tag{28}$$

Where:
E^{week}_i = Contracted electricity quantity in week.
E^{week}_h = Contracted for whole cascade in week.
$\alpha_{1,i}$ and $\alpha_{2,i}$ = Power deviation for thermal unit.
$\alpha_{1,h}$ and $\alpha_{2,h}$ = Percentage deviation for hydropower.
The line power constraints are modelled as follows:

$$-P_{l,\max} \le P_{l,t} \le P_{l,\max} \tag{29}$$

$$P_{l,t} = \sum_{n=1}^{N} G_{l,n} (P_{n,t} - P_{L,n,t}). \tag{30}$$

Where:
$P_{l,t}$ = Limit power of transmission line.
N = Number of buses.
$G_{l,n}$ = Network transfer factor.
$P_{n,t}$ = Power supply of bus.
The DC tie line power constraint is as follows:

$$P_{DC,t} \le P_{DC,\max}. \tag{31}$$

Where:
$P_{DC,t}$ = transmission power of DC tie line.

4 Results analysis

The operational data for a proposed electrical grid is sourced from references [27–31] to illustrate the validity of the theory presented in this paper. The study period covers 8760 h, equivalent to one year, with a maximum system load of approximately 53 GW. The power system capacity is around 100 GW. The capacities include hydropower accounting for 75.561 GW, thermal power at 15.108 GW, wind and photovoltaic powers at 8.806 GW and 3.926 GW. Renewable energy sources, including photovoltaic, hydropower, and wind power are equal to 85.4% of the installed capacity. Hence, the results are analysed as follows.

4.1 Operation of system considering stochastic scenarios and actual model

The use of Latin hypercube sampling allows for the generation of multiple scenarios for renewable energy output and load demand, drawing from historical operational data. The simultaneous backward reduction method is utilized to select typical scenarios. Figure 3 illustrates the obtained scenarios for load, wind power, and photovoltaic.

The stochastic operation scenario generation results depicted in Figure 3 reveal that the curves of renewable energy and demand are characterized by uncertain, stochastic and fluctuating patterns in the short-term. Nevertheless, they exhibit distinct regular seasonal features in the long term. The generated scenarios accurately reflect the real operational conditions of the system and offer scenario assistance for an extended stochastic approach. Table 1 illustrates the contrast in algorithm precision and solution velocity for the one-year power system simulation based on the method outlined in this study under a specific scenario. From the data in Table 1, it is evident that the proposed method has a lower total power generation cost, with a relative reduction of 88 billion \$. The decrease brings it nearer to the real operational scenario, showing that the suggested approach provides improved cost-effectiveness and a reduced margin of error in calculations. The method's efficiency is significantly improved by 73.54%, allowing for faster operation simulation calculations. This is due to the limitations of single-thread computing when simulating the power grid for a year, which hinders the full potential of processors. The large model scale during operation simulation can lead to memory overflow and prolonged problem-solving times.

4.2 Operation of system considering long-term stochastic scenarios

Throughout the year, the operation results for units and the outgoing energy of tie lines in the power system are illustrated in Figure 4 for 8760 h. The figure highlights the significant role of hydropower resources in the power supply, with wind and photovoltaic power generation making up a smaller percentage. The renewable energy supply in this region varies significantly over the course of the year, with hydropower production peaking during the flood

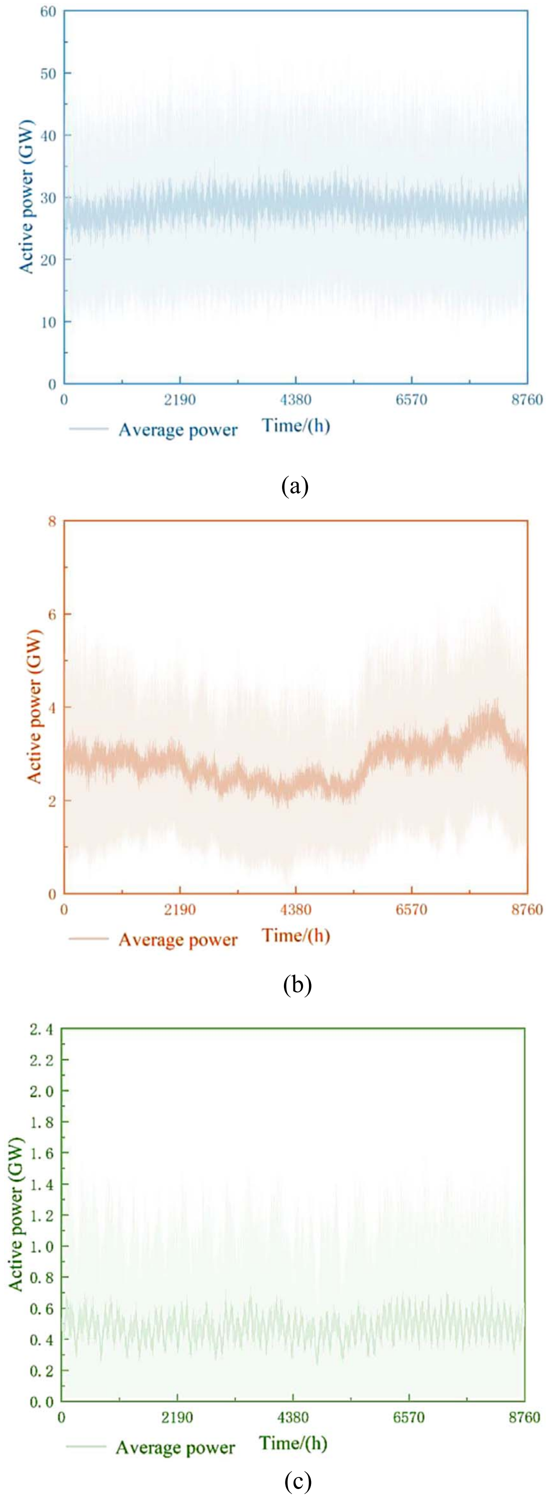

Fig. 3. Generated Scenarios of system. a) Load, b) Wind energy, c) Photovoltaic energy.

season when water flow is concentrated. This aligns closely with the power consumption pattern which rises in the summer months in the local power system.

The power grid has a set outgoing power limit of 40 GW. The tie line's maximum power capacity remains

Table 1. Comparison between the approaches' accuracy in one year.

Solving model	One year operational simulation	Stochastic operations simulation	Actual operation
Operation cost/billion $	287.2	286.35	285.88
Solution time/s	2543	673	–

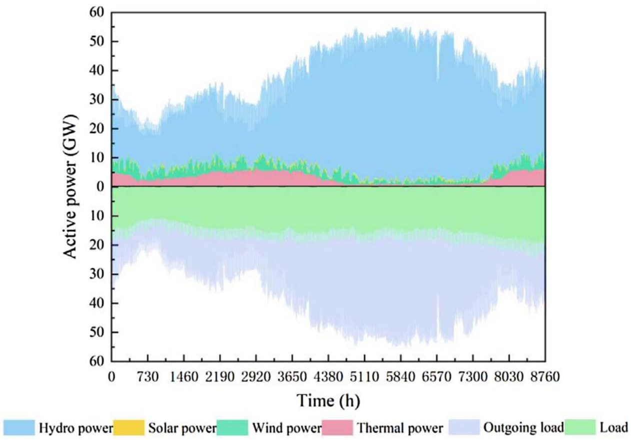

Fig. 4. Operation of system based on long-term stochastic model.

steady at around 35 GW per year. This demonstrates that the proposed approach is capable of efficiently accommodating a significant surplus of power generated by hydropower output during the flood seasons.

4.3 Operation of system with different methods

To emphasize the superiority and effectiveness of the approach, this paper compares the long-term simulation for the power system with the MPC strategy, stochastic method, and robust method, as illustrated in Table 2.

Table 2 illustrates long-term operation simulation results to be the most accurate when compared to actual operation. The long-term simulation yielded a total cost of $28.592 billion. The robust and stochastic methods have errors in their approximate transformation process. Additionally, the model MPC necessitates a high level of accuracy in modelling, making it challenging to guarantee the solution accuracy of these methods. The suggested approach conducts a detailed and extended stochastic simulation of renewable energy and load. This method accurately portrays the system's operational status with precision. Besides the overall power generation cost and coal consumption, the curtailment rate of renewable energy by stochastic is almost the same as the actual system operation. The findings indicate that the method proposed in this paper for simulating long-term operations is capable of effectively managing the distribution patterns of renewable resources and demand. To enhance the consumption rate of renewable energy in the region, one can explore the potential of optimizing energy storage allocation and expanding energy delivery networks in the future.

5 Conclusion

This study presented an approach to simulate the functioning of electrical grids by considering different time scales and utilizing economic and technical indicators. By aligning with different time scales, the system's operation is transformed from a power balance problem for an entire year to an electricity balance for different weeks and days throughout the year. The stochastic simulation's efficiency is greatly improved by effectively coordinating system operation throughout diverse times. The calculated operation index of the system closely corresponds to the actual operation. The numerical simulation shows that renewable resources and demand demonstrate unpredictable and fluctuating behaviour in the short-term but maintain consistent seasonal patterns over extended periods. Latin hypercube sampling and simultaneous backward reduction were utilized to create the source-load scenario in this research. Incorporating a long-term optimization model and stochastic scenarios into the power grid greatly increases the computational complexity of the model, resulting in a significant expansion of the optimization space. This study

Table 2. Operation of system under different methods.

System operating indicators	Robust model	Stochastic model	MPC	Actual model
Total coal consumption/ten thousand tons	1082.53	1012.53	1125.35	952.93
Total power generation cost/billion $	324.73	303.76	337.61	285.88
Abandoned wind power/(GW·h)	279.42	242.34	331.36	158.75
Abandoned photoelectric power/(GW·h)	40.79	35.89	48.77	24.56
Abandoned hydropower/(GW·h)	4072.89	3598.65	4602.93	2483.29
Wind abandonment rate/%	1.13%	0.98%	1.34%	0.64%
Light abandonment rate/%	1.33%	1.17%	1.59%	0.80%
Water abandonment rate/%	1.46%	1.29%	1.65%	0.89%

converts the power balance issue for one year into the electricity balance modelling for weeks and days. By achieving time scale operation, the computational complexity is effectively minimized and simulation of long-term operations of the power grid is done. The proposed method for simulating the power system by long-term modelling considers the impact of various renewable energy generation characteristics and energy dispatch at different time scales. This method serves as a crucial decision-making tool for scheduling and operation of power grids

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