Scientific and Social Research, 2024, Volume 6, Issue 7
https://ojs.bbwpublisher.com/index.php/SSR
Online ISSN: 2981-9946
Print ISSN: 2661-4332

Low-Carbon Distributed Optimal Operation of Integrated Energy System Considering Wind and Solar Uncertainty

Feng Ning, Hongshan Lin, Yiming Lei*

Department of Electric Power Engineering, North China Electric Power University, Baoding 071000, Hebei Province, China

***Corresponding author:** Yiming Lei, lei_yiming01@163.com

Abstract: To ensure the supply and demand balance of integrated energy systems (IES) in the electric-carbon market and solve the complicated interest relationship among participants in the system, a distributed optimal scheduling model based on the extended carbon emission flow theory of integrated energy systems was proposed. Firstly, hydrogen energy production and utilization devices are introduced into the energy supply side to establish an expanded carbon emission flow model of the hydrogen-energy coupling integrated energy system based on carbon emission flow theory. Then, the fuzzy membership function is used to characterize the uncertainty of wind and light output. The distributed optimization algorithm based on goal cascade analysis realizes the decoupling of the integrated energy service provider and the user. This achieves the independent solution of the integrated energy service provider. A numerical example is given to verify that the proposed strategy can realize the stable and optimal operation of the integrated energy system in an uncertain environment.

Keywords: Electric carbon coupling; Expand carbon emission flow model; Comprehensive demand response; Uncertain environment; Distributed optimization

Online publication: July 26, 2024

1. Introduction

The integrated energy system (IES) breaks the original "electricity" energy form to meet the supply and demand balance of various energy forms of electricity and gas, so it is believed that IES has great potential in carbon emission reduction [1–2]. With the continuous increase of the usage rate of renewable energy, its output volatility and randomness bring great challenges to the operation of the system. Therefore, how to cope with the stable operation of electric-carbon coupling supply and demand under the uncertain environment of renewable energy output has become a current research hotspot [3–5].

At present, some research results have been obtained in the optimization and market trading of IES. A study considers the collaborative optimal scheduling of the electric heating integrated energy system with electric heating demand response and fully mobilizes the flexible resources on the load side to reduce the economy and carbon emissions of the system operation [6]. Another study establishes the system "carbon emission flow" model, considers the flow of carbon emission flow in energy hub units, combines the power grid and gas network system with the energy hub, and implements demand response through CEF to achieve low-carbon economic operation [7]. Based on the improved consistency algorithm, a study proposes a distributed mechanism of IDR in industrial parks, which can be consistent between the optimal IDR scheme of individual users and the optimal IDR scheme of the whole park under a balanced state [8]. The above research provides a good idea for the research of distributed demand response.

The current research on the impact of uncertainty of new energy output on the operation of the electric power energy system is relatively comprehensive [9–11]. However, the effect of considering the balance of electro carbon coupling system in an uncertain environment is relatively small. To sum up, under the electric-carbon coupling market environment, it is necessary to consider the uncertainty of new energy output to realize the stable operation of system supply and demand.

Given the above problems, this paper takes into account the randomness of wind-wind output and proposes a distributed optimization model of the integrated energy system based on the carbon emission flow theory. Firstly, the internal coupling utilization of hydrogen energy is considered in the IES system, and the carbon emission flow theory is introduced into the hydrogen energy coupled integrated energy system (HIES). Secondly, the wind-wind uncertain output model is established based on the chance fuzzy theory, and the distributed source load coordination optimization scheduling under uncertainty is established according to the above-established source load model. The target cascade analysis method is adopted to solve the distributed solution of the integrated energy production unit to maximize the operating profit.

2. HIES system model and carbon emission flow model

The structural composition of the HIES model of the H-energy coupled integrated energy system considered in this paper is shown in **Figure 1**.

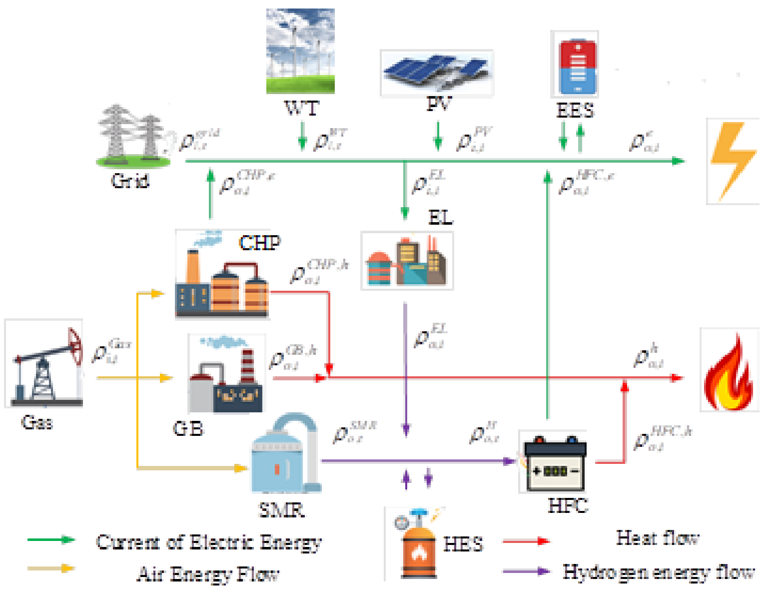


Figure 1. HIES structure

Based on the HIES framework of the hydrogen-energy coupled system in **Figure 1** above, the effective conversion between different energy forms is realized. The CEF theoretical model is introduced to analyze the carbon emissions in the process of energy production and conversion, transfer the responsibility of carbon emissions from the source side to the user side, and realize the interactive carbon emission reduction between supply and demand.

3. Consider an uncertain source-load distribution model

3.1. Objective function

The goal of energy supply for integrated energy service providers is to maximize operating profits, including external energy purchase cost, operation and maintenance cost, wind and light abandonment cost, demand response compensation cost, and income from energy sales.

$$min\, F^{HIES} = \sum_{t=1}^{24} \Delta t(C_t^{sell} - C_t^{buy} - C_t^{om} - C_t^{dis} - C_t^{IDR}) \quad (1)$$

Where F^{HIES} represents the operating profit of comprehensive energy service providers; C_t^{sell} is energy supply revenue for operators to users; C_t^{buy} is external purchasing and selling capacity expenses for service providers; C_t^{om} is the operating cost of the equipment; C_t^{dis} is the cost of abandoning wind and light; C_t^{IDR} is to compensate user demand response costs; $\Delta t = 1$ hour.

$$C_t^{sell} = c_{e,t}^{user} P_{e,t}^{user} + c_{h,t}^{user} P_{h,t}^{user} \quad (2)$$

$$C_t^{buy} = c_{e,t}^{buy} P_{e,t}^{buy} + c_{g,t}^{buy} P_{g,t}^{buy} - c_{e,t}^{grid} P_{e,t}^{grid} \quad (3)$$

$$C_t^{om} = c_k^{om} P_{k,t} \quad (4)$$

$$C_t^{dis} = c^{dis}(P_{e,t}^{wt} - P_{e,t}^{wt,pre}) + c^{dis}(P_{e,t}^{pv} - P_{e,t}^{pv,pre}) \quad (5)$$

$$C_t^{IDR} = c_e^{cut} P_{e,t}^{cut} + c_h^{cut} P_{h,t}^{cut} \quad (6)$$

Where $C_{e,t}^{user}$, $C_{h,t}^{user}$ is the unit price of electricity and heat sold by service providers to users respectively. $P_{e,t}^{user}$, $P_{h,t}^{user}$ is amount of power supply and heat supply for service providers to users respectively. $C_{e,t}^{buy}$, $C_{e,t}^{grid}$, $C_{g,t}^{buy}$ is the unit price of external purchase, sale of electricity and purchase of gas for service providers respectively $P_{e,t}^{buy}$, $P_{g,t}^{buy}$, $P_{e,t}^{grid}$ refers to the external purchase, sale and purchase of electricity and gas by the service provider; c_k^{om}, $P_{k,t}$ is the operating cost factor of the *k* equipment and the energy consumption/production of the *t* period, respectively. c^{dis} is the cost factor of wind and light abandonment; $P_{e,t}^{wt}$, $P_{e,t}^{wt,pre}$, $P_{e,t}^{pv}$, $P_{e,t}^{pv,pre}$ is the actual consumption and predicted amount of wind power and photovoltaic respectively; C_e^{cut}, C_h^{cut} is the compensation unit price of electricity and heat load reduction respectively; $P_{e,t}^{cut}$, $P_{h,t}^{cut}$ is the reduction of electrical and thermal load respectively.

3.2. Constraint condition

The constraints of the IES scheduling model mainly include wind-power constraint, coupling device constraint, energy balance constraint, energy storage device constraint, and tie-line constraint.

3.2.1. Constraints on wind power and photovoltaic output

The output of new energy is easily affected by natural conditions and other external unknown factors, and there are still errors between the predicted results and the actual power output and load power. It is necessary to introduce fuzzy parameters of wind power and photovoltaic [12].

3.2.2. Operation constraints of coupling equipment

$$0 \le P_{k,t} \le P_k^{max} \tag{7}$$

$$\Delta P_{k,t}^{min} \le P_{k,t+1} - P_{k,t} \le \Delta P_{k,t}^{max} \tag{8}$$

Among them, k = {CHP, GB, EL, SMR, HF}. P_k^{max} is the maximum output power of device k. $\Delta P_{k,t}^{min}$, $\Delta P_{k,t}^{max}$ indicate the maximum downward and upward climbing power of the device.

3.2.3. Energy balance constraint

$$\begin{cases} P_{e,t}^{buy} + P_{e,t}^{dis} + P_{e,t}^{CHP} + \widetilde{P}_{e,t}^{wt} + \widetilde{P}_{e,t}^{pv} + P_{e,t}^{HFC} = P_{e,t}^{user} + P_{e,t}^{cha} + P_{e,t}^{EL} + P_{e,t}^{grid} \\ P_{h,t}^{CHP} + P_{h,t}^{GB} + P_{h,t}^{HFC} = P_{h,t}^{user} \\ P_{g,t}^{buy} = P_{g,t}^{CHP} + P_{g,t}^{GB} + P_{g,t}^{SMR} \\ P_{H,t}^{EL} + P_{H,t}^{dis} + P_{H,t}^{SMR} = P_{H,t}^{HFC} + P_{H,t}^{cha} \end{cases} \tag{9}$$

Where $P_{e,t}^{cha}$, $P_{e,t}^{dis}$, $P_{H,t}^{cha}$, $P_{H,t}^{dis}$ are the charging and discharging power of the storage and hydrogen devices respectively.

3.2.4. Energy constraint of the liaison line

$$\begin{cases} 0 \le P_{e,t}^{buy}, P_{e,t}^{sell} \le P_{e,max}^{sell} \\ 0 \le Q_{g,t}^{buy} \le Q_{g,max}^{buy} \end{cases} \tag{10}$$

Where $P_{e,max}^{sell}$ and $Q_{g,max}^{buy}$ are respectively the upper limits of the contact lines of the electricity and gas networks.

4. Distributed optimization model based on objective cascade analysis

Based on the idea of analytical target cascading (ATC), the decoupling between integrated energy service providers and distributed users is realized [13]. Therefore, the coupling variables between the integrated energy service provider and the user are electric power and thermal power. When the integrated energy service provider is solving its own economic optimization operation, the optimal scheduling results obtained through decision optimization are passed to the lower user body as a decision variable. Here, only comprehensive energy service providers are independently solved.

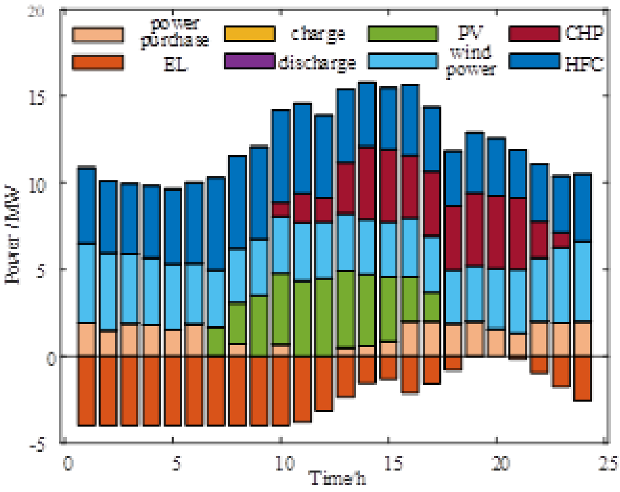
After ATC decoupling is adopted, the objective function model of comprehensive energy service providers is updated as follows.

$$min\, F^{HIES} + \sum_{i=1}^{n} \sum_{t=1}^{24} [\beta_{i,t}(X_{i,t} - \overline{X_{i,t}}) + \alpha_{i,t}(X_{i,t} - \overline{X_{i,t}})^2] \tag{11}$$

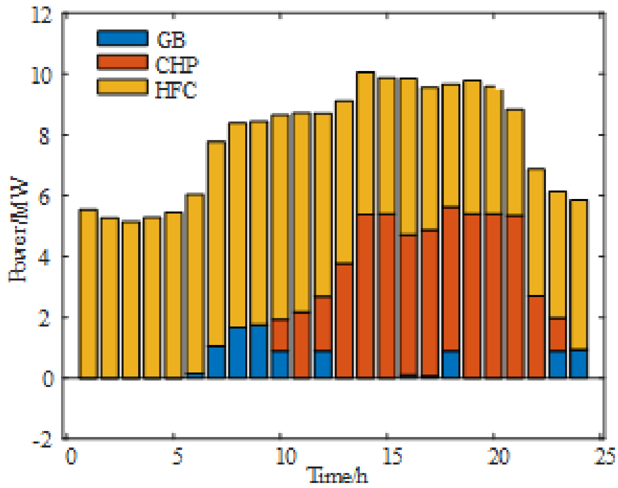
Where $X_{i,t}$ is the interactive power value that user i optimizes and feeds back to the integrated energy service provider; $\bar{X}_{i,t}$ is the coupling variable reference value optimized by the integrated energy service provider and transmitted to user i.

5. Example analysis

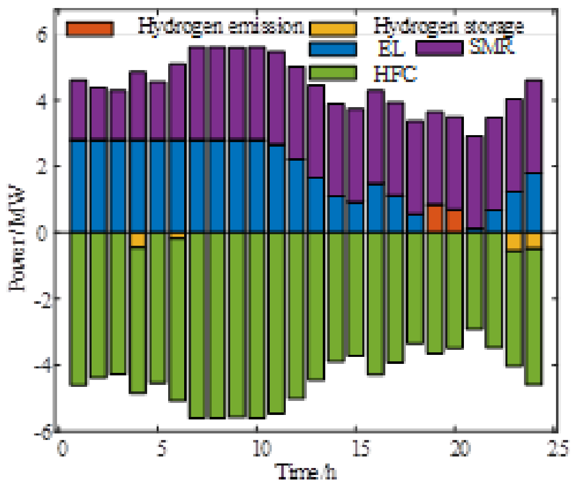
This paper takes an integrated energy system in a northern region as an example, which contains one integrated energy service provider with hydrogen energy coupling and three types of integrated energy users. Equipment operating parameters, wind power, photovoltaic output, and user load data are cited [12]. The price of natural gas is 3 ¥/m^3, and the heating value is 39 MJ/m^3. The upper limit values of transferable load and reducible load in electrical load and heat load are 20% and 10% of the total load respectively. The wind-landscape output confidence level is set to 0.9.



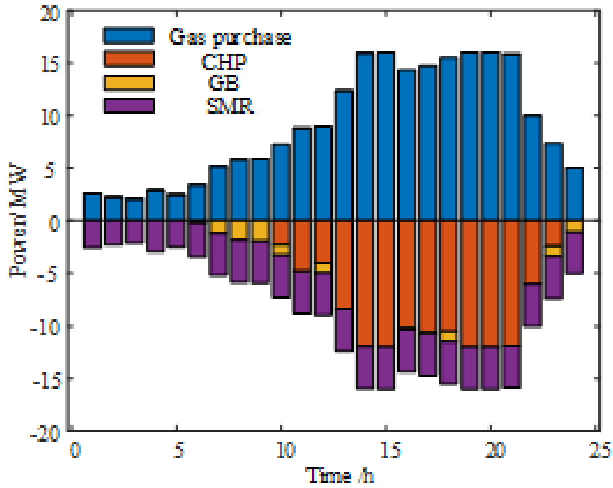
(a) Electric power optimal scheduling results



(b) Thermal power optimization scheduling results



(c) Hydrogen power optimal scheduling results



(d) Gas power optimal scheduling results

Figure 2. Power scheduling results of electricity, heat, hydrogen, and gas

Distributed optimization model considering carbon emission theory and uncertainty of wind power and photovoltaic of the integrated energy service provider unit output and the energy required by each user is shown in **Figure 2**. The carbon emission factors of electricity, heat, and hydrogen energy flow in the system are shown in **Figure 3**.

Figure 3 shows the size of the carbon potential of each energy flow in the system. It can be seen that the carbon emission factors and trends of electricity, heat, and hydrogen energy flows are basically the same. From 9:00 to 21:00, the carbon emission factor suddenly increases, which is because the demand for electricity and heat load increases during this period, and they are in the peak period of energy consumption as shown in **Figure 2(a)** and **Figure 2(b)**. As shown in **Figure 2(c)**, the optimal scheduling results of hydrogen power in this period are mainly SMR. Therefore, the carbon potential of hydrogen energy rises. In this period, GB and CHP mainly consume natural gas for energy supply (**Figure 2(d)**), which also leads to the increase of carbon emission factors in this period. Therefore, the carbon emission flow model considering hydrogen energy expansion in this paper can more accurately reflect the carbon emission of the system and track the carbon footprint of the system.

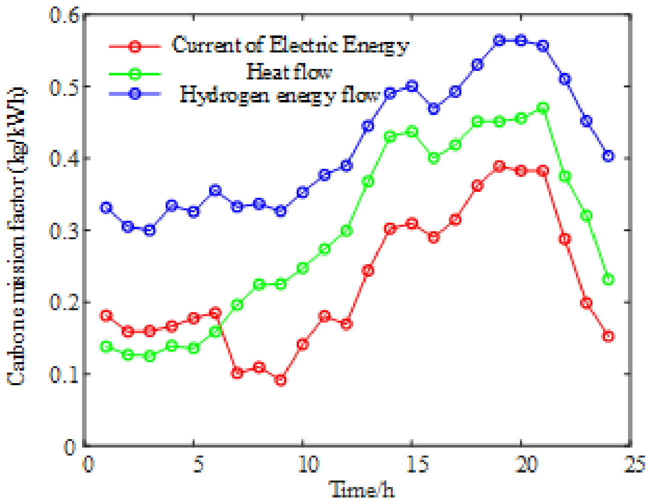


Figure 3. Carbon emission factors of each energy flow

6. Conclusion

Based on the carbon emission flow theory, this paper established a distributed and coordinated optimization scheduling model of the supply and demand of the integrated energy system containing hydrogen energy coupling under the uncertain wind-wind output environment. The following conclusions can be obtained through the calculation example verification.

The uncertainty of the output is described based on fuzzy chance constraints, and the distributed optimal scheduling strategy is adopted to realize the stable operation of the system.

The extended carbon emission flow theoretical model considering the coupling of hydrogen and energy ascribes the responsibility of system carbon emission to the energy consumption side, which can reflect the dynamic changes of system carbon emission factors more completely and more accurately.

Disclosure statement

The authors declare no conflict of interest.

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