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A Multi-Timescale Low Carbon Scheduling Optimization Method for Integrated Energy System Considering Source-load

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Abstract: In order to reduce the instability of integrated energy system caused by wind power, load prediction error, and low-carbon and low-cost operation, a multi-time scale low-carbon scheduling optimization method for integrated energy system is proposed. The fuzzy variables and fitting loads under different time scales are obtained by analyzing the change of prediction error of wind energy, load and user response law under the time-sharing price. To achieve deviation control at different time scales, minimize the cost of daily power purchases, gas purchases, wind discards and carbon emissions. To satisfy load balance, active backup, power purchase constraint and energy storage capacity constraint to construct an optimized scheduling model for integrated energy system. Implementation of low carbon optimization scheduling requirements for integrated energy systems. The experimental results show that this method can realize the optimal dispatch of electric, gas and heat load of integrated energy system. The higher the accuracy of wind power and load prediction, the lower the optimal dispatch cost of integrated energy system.

1. Introduction

Integrated Energy System (IES) is a multi-energy complex with distributed energy, cold, hot, and gas supply. Energy efficiency objectives are achieved within the system through collaborative and complementary operation of multiple sources of energy. [1] In integrated energy system optimization scheduling, Taking practical measures to achieve low-carbon operation of the system is a great initiative which can let the later generations enjoy a happy life.

Guo Zun et al. plan wind power output and load prediction scenarios, because the method is only optimized for the same time scale control, resulting in the algorithm wind power, load prediction error is still large [2];He Ching et al. put forward synergistic control method of energy optimization of integrated energy system. The system fluctuation problem caused by source-load uncertainty is reduced by scene analysis method. Optimized scheduling of real-time 5min intervals with minimum adjustment of unit power. The method effectively reduces the disturbance caused by source load prediction error. However, the user response behavior under the timeshare tariff was not adequately measured. [3]Therefore, the optimization method of multi-time scale low-carbon scheduling for integrated energy system is proposed.

2. Optimization of Multi-time Scale Low Carbon Scheduling for Integrated Energy Systems

2.1 Analysis of Source Load Uncertainty

With the change of running time, the prediction deviation of wind energy and load shows a decreasing trend. This paper analyzes the uncertainty problem caused by the prediction deviation of wind energy and load by triangular fuzzy number.

$$\tilde{P}_{WDA,t} = \left(\delta_{1DA} P_{WDA,t}, P_{WDA,t}, \delta_{3DA} P_{WDA,t}\right) \tag{1}$$

$$\tilde{P}_{LDA0,t} = \left(q_{1DA} P_{LDA0,t}, P_{LDA0,t}, q_{3DA} P_{LDA0,t}\right) \tag{2}$$

Therein: For wind energy prediction, its fuzzy variable is expressed as $\tilde{P}_{WDA,t}$, for daily load prediction,its fuzzy variable is expressed as $\tilde{P}_{LDA0,t}$;At the previous point t in time, the wind energy forecast is expressed as $P_{WDA,t}$,ignoring the impact of the tariff response on the load, the forecast is expressed as $P_{LDA0,t}$,

When forecasting wind energy, the upper and lower boundary coefficients of the error interval are expressed as δ_{3DA}, δ_{1DA},The upper and lower boundary coefficients of the error interval are expressed as follows: q_{3DA}, q_{1DA}.The same method is used to determine the fuzzy variables of wind energy and load day prediction,and they are separately expressed as $\tilde{P}_{WID,t}$, $\tilde{P}_{LID0,t}$;Real-time stage wind power, load fuzzy variable is expressed as $\tilde{P}_{WRT,t}$, $\tilde{P}_{LRT0,t}$.

Incentive demand response (DR) strategies also cause errors in user response and prediction. When Integrated Energy Systems Adopt Time sharing Rates (TEC) After the policy, the user generates an incentive response. Therefore, this paper introduces the prediction error in response elasticity to achieve a comprehensive analysis of load side uncertainty. Based on the consumer psychology model, using dead, linear and saturated zones to reflect load transfer at different time points, the error interval of load transfer rate is analyzed thoroughly. Peak valley load transfer rate can be described by:

$$\tilde{\kappa}_{pv} = \begin{cases} 0, \Delta p_{pv} \le \Delta p_{pv0} \\ \alpha_{pv}\Delta p_{pv} - \alpha_{pv}\Delta p_{pv0} \pm \bar{d}_{pv} \\ \Delta p_{pv0} \le \Delta p_{pv} \le \Delta p_{pv,\max} \\ \kappa_{pv,\max}, \Delta p_{pv} \ge \Delta p_{pv,\max} \end{cases} \tag{3}$$

Therein: For peak valley load, the difference in the price of electricity is expressed as Δp_{pv}, $\tilde{\kappa}_{pv}$'s difference between the electricity prices of the dead zone boundary is expressed as Δp_{pv0},The difference in the price of the saturated zone is expressed as $\Delta p_{pv,\max}$, $\tilde{\kappa}_{pv}$'s potential maximum value is expressed as $\kappa_{pv,\max}$, $\tilde{\kappa}_{pv}$ in the Online Zone, the slope in which the change occurred is expressed as α_{pv} ,the error interval is expressed as $\bar{d}_{pv}$ .when Δp_{pv} has changed, $\bar{d}_{pv}$ changed with it, the curve changes after the first ascent, the $\bar{d}_{pv}$ formula can be described as:

$$\bar{d}_{pv} = \begin{cases} \alpha_a \Delta p_{pv} - \alpha_a \Delta p_{pv0}, \Delta p_{pv0} \le \Delta p_{pv} \le \Delta p_{pv}^{IP} \\ d_{pv,\max} + \alpha_b \Delta p_{pv} - \alpha_b \Delta p_{pv}^{IP}, \Delta p_{pv}^{IP} \le \Delta p_{pv} \le \Delta p_{pv,\max} \\ 0, \Delta p_{pv} \le \Delta p_{pv0} \text{或} \Delta p_{pv} \ge \Delta p_{pv,\max} \end{cases} \tag{4}$$

Where: For peak valley load transfer rate, the maximum value of its error is expressed as $\Delta p_{pv,\max}$;the difference in the price of electricity at the turning point of the peak valley is expressed as Δp_{pv}^{IP} ,is a description of the response error mainly determined by the power price factor before and after the boundary spread;The coefficients of the response error interval of the power price as the main determinant of response error are expressed as follows: α_a , α_b .On the basis of a comprehensive analysis of the load prediction deviation and the uncertainty caused by load transfer at each time point of the time-sharing tariff strategy [4], A fitting analysis of each point-in-time load in the pre-day, intra-day, real-time optimization control phase. Where the fitting of the loads at each point in time before the date can be described by:

$$\tilde{P}_{LDA,t} = \begin{cases} \tilde{P}_{LDA0,t} - \left(\tilde{\kappa}_{pf} + \tilde{\kappa}_{pv}\right) P_{LDA,pav}, t \in p \\ \tilde{P}_{LDA0,t} - \left(\tilde{\kappa}_{fv} P_{LDA,fav} - \tilde{\kappa}_{pf} P_{LDA,pav}\right), t \in f \\ \tilde{P}_{LDA0,t} + \tilde{\kappa}_{pv} P_{LDA,pav} + \tilde{\kappa}_{fv} P_{LDA,fav}, t \in v \end{cases} \tag{5}$$

Therein: At the previous point t in time, the load fuzzy variable is expressed as $\tilde{P}_{LDA0,t}$,For crest, flat peak, and trough time points, the load set is expressed as p , f , v ,when response errors are introduced, the load transfer rates are expressed as $\tilde{\kappa}_{pf}$, $\tilde{\kappa}_{pv}$, $\tilde{\kappa}_{fv}$ .The prediction results of the load at the peak and point in the peak can be determined, and the load mean can be determined by operation, which is expressed as $P_{LDA,pav}$, $P_{LDA,fav}$ .The load fitting results for the day optimization phase are expressed as $\tilde{P}_{LRT,t}$.

2.2 Low Carbon Optimization Scheduling Model

2.2.1 Optimizing Scheduling Model

One day of optimized control of the integrated energy system, with a scheduling cycle of 24h, in order to obtain a power generation plan for each unit for the next day. A comprehensive analysis of the forecasting error of wind power, load and the uncertainty caused by the time-sharing tariff strategy will be aimed at minimizing the daily operating cost and realizing the optimization of its recent stage. The formula is described as:

$$\min H = H_1 + H_2 + H_3 + H_4 \tag{6}$$

Where: Electricity purchase cost is expressed as H_1, Gas purchase costs are expressed as H_2,The cost of abandonment is expressed as H_3,The cost of carbon emissions is expressed as H_4.

$$\begin{cases} H_1 = \sum_{t=1}^{T} B_e(t) P_{cha}(t) \\ H_2 = \sum_{t=1}^{T} B_g(t) V_{cha}(t) \left(F_{ng}\right)^{-1} \\ H_3 = \sum_{t=1}^{T} \sum_{w=1}^{N_w} \rho_w \left(P_{ycwt} - P_{wt}\right) \\ H_4 = R_e \left[\sum_{t=1}^{T} \left(\sum_{i=1}^{N_i} \mu_i P_{cha}(t) - \sum_{i=1}^{N_i} \vartheta_i P_{cha}(t) \right) \right] \end{cases} \tag{7}$$

Therein: For point-in-time t, the timeshare unit price is expressed as $B_e(t)$,rating is $V_{cha}(t)$; The heat value of natural gas is expressed as F_{ng},the total optimization scheduling time is expressed as T;The number of wind power scenarios is expressed as N_w,the discard cost factor is expressed as ρ_w,the wind power output forecast value is expressed as P_{ycw},The actual output power is expressed as P_{wt};The purchase/sale price per unit of carbon emissions is expressed as R_e,the total number of fossil fuel engines is expressed as N_i,For the i th generator,the size of carbon emissions per unit of power is expressed as μ_i,carbon emissions per unit of active power are expressed as ϑ_i.

The operation of an integrated energy system is subject to the real-time operating conditions of the equipment, the climbing conditions [5-6], and, at the same time, to the load balance limits, the constraint formula is described as:

$$\begin{aligned} &P_{pv}(t) + P_{wt}(t) + P_{mt}(t) + P_{cha}(t) + P_{edis}(t) \\ &-\left[P_{ech}(t) + P_{p2g}(t) + P_{eb}(t) + L_e(t)\right] = 0 \end{aligned} \tag{8}$$

$$\begin{aligned} &V_{cha}(t) + F_{p2g}(t) + P_{gdis}(t) \\ &-\left[P_{gch}(t) + V_{gas}(t) + L_g(t)\right] = 0 \end{aligned} \tag{9}$$

$$Q_{mt}(t) + Q_{eb}(t) + Q_{hdis}(t) - \left[Q_{hch}(t) + L_h(t)\right] = 0 \tag{10}$$

Where: For t time point, the active power of the photovoltaic unit is represented $P_{pv}(t)$, the power of the battery at the time of the power reserve is $P_{ech}(t)$,the output power is $P_{edis}(t)$;The inflatable power of the tank is $P_{gch}(t)$,its deflating power is $P_{gdis}(t)$,the heating power of the heat storage tank is $Q_{hch}(t)$,thermal Output Power is $Q_{hdis}(t)$, For miniature gas turbines, the electrical power output value is $P_{mt}(t)$,active Thermal Power Representation $Q_{mt}(t)$,during natural gas consumption,its power is expressed as $V_{gas}(t)$,P2G device converts electricity to natural gas with an active power output of $F_{p2g}(t)$,the input power is expressed as $P_{p2g}(t)$;For electric boilers, the thermal output power when the heat supply is provided is expressed as $Q_{eb}(t)$,power consumption is expressed as $P_{eb}(t)$,the total amount of load, gas load, and heat load required is expressed as $L_e(t)$, $L_g(t)$, $L_h(t)$.

Due to deviations in wind energy output and load prediction, It has some effect on the stable operation of the integrated energy system, In this paper, the planned power of wind energy and the fitting load of different time points are described by fuzzy variables. Therefore, the comprehensive energy system needs to meet the working and spare constraints, the formula is described as:

$$
\begin{aligned}
& Cr\Big\{(1+\gamma_{DA})\tilde{P}_{LDA,t} \leq \\
& \sum_{i=1}^{N_{RG}} u_{RGi,t} \min\left(P_{RGi,\max}, P_{RGi,t} + 60R_{RGi}^{up}\right) + \\
& \sum_{i=1}^{N_{FG}} u_{FGi,t} \min\left(P_{FGi,\max}, P_{FGi,t} + 60R_{FGi}^{up}\right) \\
& + \tilde{P}_{WDA,t} - \left(P_{WCur,t} - P_{ILj,t}\right)\Big\} \geq \pi_{DA}
\end{aligned}
\tag{11}
$$

$$
\begin{aligned}
& Cr\Big\{\tilde{P}_{LDA,t} + P_{WCur,t} = \\
& \sum_{i=1}^{N_{RG}} P_{RGi,t} + \sum_{i=1}^{N_{FG}} P_{FGi,t} + \tilde{P}_{WDA,t} + P_{ILj,t}\Big\} \geq \theta_{DA}
\end{aligned}
\tag{12}
$$

where: The confidence function,expressed as $Cr\{\cdot\}$,is used to describe the equation or inequality, the set-up condition [7], the confidence condition to be met before the power and spare limit is expressed as θ_{DA}, π_{DA};Rotating the alternate factor before the day is expressed as γ_{DA},fast,slow machine i 1 minute apart climb speed maximum value of R_{FGi}^{up}, R_{RGi}^{up} .At t point in time, $P_{WCur,t}$ is wind abandoning capacity,the output power of the slow machine i is expressed as $P_{RGi,t}$,its scheduling status is $u_{RGi,t}$,the output power of the fast machine i is $P_{FGi,t}$,its scheduling status is $u_{FGi,t}$;The participating capacity of interrupt load j is $P_{ILj,t}$.

The power limitation of an integrated energy system when purchasing electricity and gas is described below:

$$0 \le P_{cha}(t) \le P_{cha}^{\max} \tag{13}$$

$$0 \le V_{cha}(t) \le V_{cha}^{\max} \tag{14}$$

Where: The maximum value of the power purchased is expressed as $P_{cha}^{\max}$,the maximum value of gas power is expressed as $V_{cha}^{\max}$. According to the optimization scheduling scheme, the capacity of each energy storage device within 24h is set without change, and its formula is described as:

$$\begin{cases} S_{oc}(24) = S_{ocf} \\ V_{oc}(24) = V_{ocf} \\ Q_H(24) = Q_{Hf} \end{cases} \tag{15}$$

Where: At 24 o 'clock, the capacity of different energy storage devices is expressed as $S_{oc}(24)$, $V_{oc}(24)$, $Q_H(24)$, the initial value of the corresponding capacity is S_{ocf}, V_{ocf}, Q_{Hf} .

2.2.2 Day Optimization Scheduling Model

The integrated energy system is optimized in one day by 15min apart, and optimized in-day scheduling control is realized through cyclic operation. In-day optimization of each stage objective function is described by:

$$\min \begin{cases} H_1' = \sum\limits_{t=t_0}^{t_0+d\Delta t} B_e(t) P_{cha}(t) \Delta t \\ H_2' = \sum\limits_{t=t_0}^{t_0+d\Delta t} B_g(t) V_{cha}(t) \left(F_{ng}\right)^{-1} \Delta t \\ H_3' = \sum\limits_{t=t_0}^{t_0+d\Delta t} \sum\limits_{w=1}^{N_w} \rho_w \left(P_{ycwt}' - P_{wt}'\right) \Delta t \\ H_4' = R_e \left[\sum\limits_{t=t_0}^{t_0+d\Delta t} \left(\sum\limits_{i=1}^{N_i} \mu_i P_{cha}(t) - \sum\limits_{i=1}^{N_i} \vartheta_i P_{cha}(t) \right) \right] \Delta t \\ H_5 = \sum\limits_{t=t_0}^{t_0+d\Delta t} \sum\limits_{i=1}^{N} I_i(t) \left[p_i(t) - I_i(t-1) p_i(t) \right] \end{cases} \tag{16}$$

Therein: The start time of the day scheduling control is t_0 ,the execution cycle is represented by Δt ,the total number of cycles executed is expressed as d , H_5 is penalty costs arising from the change in the start-stop status of the unit,at t point in time, the start-stop state of unit i is expressed as $I_i(t)$,its value is (0.1).The cost of punishment in this state is $p_i(t)$ .The forecast value for wind power during the day optimization scheduling phase is P_{ycwt}' ,The actual scheduling value is P_{wt}' .

2.2.3 Real-Time Optimization Scheduling Model

The real-time optimization phase of an integrated energy system is a correction of the output power dispatched within the days of each unit at a point in time after the realization of the t-point of time. The objective function formula of the real-time optimization phase is described as:

$$\min H'' = \sum_{t=1}^{t+1} B_e(t+1) P_{cha}(t+1)\Delta t + \sum_{t=1}^{t+1} B_g(t+1) V_{cha}(t+1)(F_{ng})^{-1}\Delta t + \sum_{t=1}^{t+1}\sum_{w=1}^{N_w} \rho_w \left(P'''_{ycwt} - P'''_{wt}\right)\Delta t \tag{17}$$

Where: the real-time power prediction value of the wind turbine set is P'''_{ycwt} ,The real-time scheduling value is P'''_{wt} .

In-day, real-time optimization scheduling constraints are the same as prior optimization scheduling, only the execution cycle and scheduling interval can be adjusted.

3. Experimental Analysis

Based on an integrated energy system, the system adopts a time-sharing tariff strategy. The price of electricity purchase in different segments is shown in Table 1. Natural gas purchase unit price is 3.22 yuan/m3, from the previous, in-day, real-time three time scale optimized scheduling of the integrated energy system, each optimization stage wind power forecast value is (-25%,25%),(-12%,12%) (-4%, 4%), load at each optimization stage of the forecast error value is (5%, 5%), (3%, 3%) (1%, 1%) This paper analyzes the scheduling performance of this method by multi-time scale low-carbon optimization scheduling of the integrated energy system in this region.

Table 1: Electricity purchase price in different segments

type	Time frame	electrovalence(yuan/kwh)
valley	21:00-4:00	0.38
flat	05:00-6:00,9:00-11:00,13:00-17:00,19:00-21:00	0.75
peak	06:00-8:00,11:00-13:00,17:00-19:00	1.30

Table 2: Comparative analysis of operating scheduling costs of integrated energy systems in different modes

	pattern1	pattern2	pattern3
	25%/12%/4%	15%/8%/4%	5%/4%/4%
Total Scheduling Costs	2588079	2561847	2549741
Operating costs	2233659	2215188	2199651
Start and Stop Costs	112041	112414	136022
Costs of wind abandonment	233725	225733	215613
Costs of carbon emissions	8654	8512	8455

Under the condition of considering time-sharing tariff strategy and prediction error control, the effect of wind power prediction accuracy on low carbon optimization scheduling of integrated energy system is analyzed by calculating the cost of comprehensive energy system under different prediction accuracy modes. The experimental results are shown in Table 2.

As it can be seen from Table 2, the uncertainty of wind power prediction has a direct effect on the optimal scheduling of the integrated energy system. By improving the prediction accuracy, the optimal cost target can be achieved, but after the prediction condition of Mode 3 is reached, the optimization effect is no longer obvious.

The conditions for setting Table 2 Mode 1 are to optimize the wind power prediction deviation at each stage, and different load prediction error conditions are set at each stage of optimization scheduling.

Table 3: Comparative analysis of cost of optimal dispatch of integrated energy system under different modes

	Condition 1	Condition 2	Condition 3
	5%/3%/1%	4%/2%/1%	2%/1%/1%
Total Scheduling Costs	2592303	2584442	2570246
Operating costs	2250430	2240331	2215471
Start and Stop Costs	105041	104500	109566
Costs of wind abandonment	227470	230400	236204
Costs of carbon emissions	9362	9211	9005

Table 3 shows that when the error between user response and load prediction is positive, the wind power utilization rate can be effectively improved, and the marginal cost of peak time unit output can be effectively reduced, to achieve the goal of reducing the operating cost of integrated energy system. When the error is negative, it has the opposite optimization effect.

4. Conclusion

(1)Accurate forecasting of wind power and load reduces optimal scheduling costs for integrated energy systems and reduces carbon emissions.

(2)In this paper, the optimal scheduling of electrical, gas and thermal loads is realized by reducing the influence of source load uncertainty on the system instability through the deviation control mechanism. The prediction results are not very different from the actual scheduling results.

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