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Two-layer Optimal Scheduling of Integrated Electric-hydrogen Energy System with Seasonal Energy Storage

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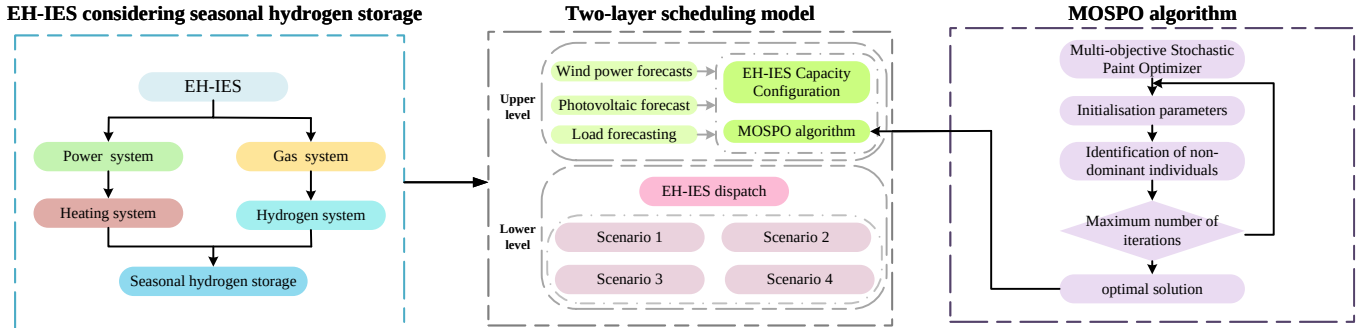
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Abstract

Hydrogen is characterized by zero carbon emissions and high energy density, which can effectively support the consumption of a high proportion of intermittent new energy. Considering the seasonal nature of renewable energy sources, a seasonal hydrogen storage model is incorporated in an electric-hydrogen integrated energy system (EH-IES). In this paper, a two-layer optimization method is proposed for EH-IES with seasonal hydrogen storage. The problem of co-optimizing the equipment capacity and configuration in the proposed system is coordinated by establishing a two-layer optimization framework. Specifically, the system is optimized to minimize cost and carbon emissions at the upper layer using the multi-objective stochastic paint optimizer (MOSPO) algorithm, with the capacity configuration results being transmitted to the lower layer. The lower layer, aiming to reduce the total system cost, utilizes a commercial solver to obtain the optimal economic scheduling results for a typical day. The final analysis of the four scenarios shows that the increase in renewable energy reduces the purchasing cost of electricity by 1.89%, while in contrast, the total cost increases by 4.4% in the system with a lower proportion of renewable energy. In the case of higher heating and cooling loads, the increase in renewables reduces the purchase cost of natural gas by 9.10%. The results demonstrate that the proposed method can leverage the seasonal complementary benefits to drive new energy consumption, enhance system operation efficiency, and effectively reduce EH-IES's total operation cost and carbon emission.



Index Terms

Electric hydrogen-integrated energy system, Seasonal hydrogen storage, Two-layer optimization model

NOMENCLATURE

V_{gas}	Natural gas consumed by gas turbines, m ³	η_{AC}	Electric cooler efficiency
β_1	Gas turbine power generation efficiency	η_{AR}	Absorption refrigerator efficiency
δ	Minimum combustion calorific value of natural gas	σ_{HS}	Self discharge efficiency of heat storage tank
ε	Gas turbine waste heat loss coefficient	η_{HS}^{cha}	Charging efficiency of thermal storage tank
C_{el}	thermal capacity of electrolytic cell	η_{HS}^{dis}	Discharge efficiency of thermal storage tank
R_{el}	thermal resistance of electrolytic cell	η_{SHS}^{cha}	Charging efficiency of hydrogen storage tank
η_{WH}	Heating efficiency of waste heat boiler	η_{SHS}^{dis}	Discharge efficiency of hydrogen storage tank
η_{MR}	Gas production efficiency of the methane reactor	$c_{e/gbuy}$	Price of electricity/gas per unit of time
		ε_{HS}^{cha}	Charging state of thermal storage tanks

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ε_{HS}^{dis}	Discharge state of thermal storage tanks	$Q_{AR}^{in}(t)$	Heat absorbed by absorption refrigerator, kW
$\varepsilon_{s,t}^{SHS+}$	Charging state of the hydrogen storage tank,	$Q_{WH}(t)$	Heat generated by waste heat boiler, kW
$\varepsilon_{s,t}^{SHS-}$	Discharging state of the hydrogen storage tank,	$Q_{HS,t}^{cha}$	Heat charging in the heat storage tank, kW
μ_{s-1}	Probability of the scenario,	$Q_{HS,t}^{dis}$	Heat release in the heat storage tank, kW
P	Outer perimeter of the hydrogen storage tank	$Q_{AC}(t)$	Cold power of electric cooler, kW
X	Location of the hydrogen	$Q_{AR}(t)$	Cold power of absorption refrigerator, kW
H	Height of the tank	$H_{WH}(t)$	Total waste heat absorbed by waste heat boiler, kW
r	Radius of the tank	$P_{MR}^g(t)$	Natural gas produced by the methane reactor, kW
T^{amb}	Outdoor temperature	$P_{MR}^h(t)$	Hydrogen power consumed by the methane reactor, kW
T^{min}	Minimum temperatures allowed for the equipment	$S_{HST}(t)$	Capacity of the intraday hydrogen storage, kWh
T^{max}	Maximum temperatures allowed for the equipment	$S_{s,0}^{SHS}(t)$	Initial hydrogen storage capacity, kWh
F_1	Operating cost of the equipment	$S_{s,t}^{SHS}(t)$	Hydrogen storage capacity, kWh
F_2	Carbon dioxide emissions	$S_{NS,24}^{SHS}(t)$	Final hydrogen storage capacity, kWh
F_u	Cost of purchasing electricity and gas	$P_{s,t}^{SHScha}(t)$	Hydrogen charging power, kW
F_{con}	Maintenance cost of the equipment	$P_{s,t}^{SHSdis}(t)$	Hydrogen release power, kW
F_c	Investment construction costs for equipment	S_{HST}	Capacity of the intraday hydrogen storage, kWh
f	Capital recovery coefficient	$P_{e/g, buy}^t$	Purchased electric/gas power, kW
Cu_i^t	Unit investment cost of the equipment	τ_1	Converter conversion efficiency
$CE_{co2}^{1/2/3}$	Carbon emission factor	τ_2	Electrolysis of electrolytic devices
$P_{GT}(t)$	Power generation of gas turbines, kW	τ_3	Efficiency of hydrogen fuel cells
$P_{st}^{el/in}(t)$	Hydrogen production in electrolysis tanks, kW	γ_{loss}^{SHS}	Hydrogen storage tank self discharge
$P_{st}^{out/in}(t)$	Electricity consumed in electrolysis tanks, kW	τ_{SHS}	Power capacity ratio of hydrogen storage tank
$Q_{GT}(t)$	Waste heat from gas turbines, kW	α_{HS}^{lo}	Minimum capacity state coefficient of heat storage tank, MJ/m ³
$Q_{st}^{el}(t)$	Electrolytic cell heating, kW	α_{HS}^{up}	Maximum capacity state coefficient of heat storage tank, MJ/m ³
$Q_{st}^{loss}(t)$	Heat dissipated by electrolytic cells, kW		
$Q_{WH}^{in}(t)$	Heat absorbed by waste heat boiler, kW		

I. INTRODUCTION

To achieve the carbon peaking and carbon neutrality goals, integrated energy systems (IES), which are characterized by the interconversion and efficient utilization of various energy sources such as cold, heat, and electricity, have received wide attention and become a meaningful way to consume renewable energy on a large scale [1–3]. The connection of renewable energy to the grid is essential for deep decarbonization. However, its intermittent output characteristics challenge the safe and economic operation of IES. As the integration of renewable energies into the IES expands, energy wastage attributed to the inherent intermittency of renewables also increases [4–6]. Utilizing complementary multiple energy sources in the IES is of great significance for the efficient operation of IES.

The introduction of energy storage technology will address the problem of stability and reliability of the power supply of an IES containing a high proportion of intermittent renewable energy sources. Hydrogen energy has received great attention in recent years. With the development of water electrolysis technology, power generation from renewable energy can be stored in the form of hydrogen by electrolyzing water. When power supply is insufficient, hydrogen can be used to produce electricity via hydrogen fuel cells or hydrogen gas turbines [7–10]. In addition, hydrogen energy shows significant superior benefits in large-scale, long-term energy storage compared to alternatives like compressed air energy storage [11–17].

Generally, energy storage systems like batteries are employed to deal with short-term imbalance caused by intermittent power sources such as wind and solar energy in an IES [18]. However, beyond short-term fluctuations, renewable energy output and load show significant seasonal imbalance characteristics. Meanwhile, hydrogen can be stored on a year-round timescale, so it can be utilized to compensate for both short-term and long-term imbalances [19, 20]. The medium- and long-term optimal operation of integrated energy systems in hydrogen-containing areas is the critical basis for hydrogen energy system planning, technical and economic benefits assessment, and improving the efficiency of integrated energy systems [21–25]. Literature [26] addresses the problem of significant differences in user loads and renewable energy sources between seasons and establishes an integrated district energy system, including a seasonal thermal energy storage system. Literature [27] proposes a new optimization selection framework for hybrid hydrogen battery energy storage systems considering a year-round period but does not consider the effect of different seasonal characteristics on hydrogen storage. Literature [28] proposes an energy storage capacity planning method that takes into account multi-timescale uncertainties by considering the impact of source-load bilateral long-term delays on the robustness of the planning results of integrated electric-hydrogen energy storage stations. Literature [29] proposes an integrated energy microgrid optimal scheduling model considering multi-timescale energy storage, which can stabilize the seasonal imbalance of source and load and achieve seasonal energy storage. Literature [30] proposes optimal system configuration strategies for integrated regional energy systems quantified by multi-energy complementarities, considering the quantitative relationship between complementarities and economics at early investment and long-term scales.

TABLE I: Summary of the literature.

Eq.	Energy consumption			Hydrogen storage		Two-layer modelling	Solution method
	Electricity	cold	heat	seasonal hydrogen storage	hydrogen storage		
18	✓	×	✓	×	×	×	Gurobi
19	✓	×	✓	×	✓	✓	KKT
20	✓	×	×	×	✓	×	IPOPT
21	✓	×	✓	×	×	×	ALO
25	✓	✓	✓	×	✓	×	BPSOSA
26	✓	✓	✓	✓	✓	×	GAN
27	✓	×	×	×	✓	×	CPLEX
29	✓	✓	✓	✓	✓	×	CPLEX
Our paper	✓	✓	✓	✓	✓	✓	MOSPO+CPLEX

The above studies on integrated energy systems predominantly focus on configuration considerations over extended time scales. However, they tend to overlook the constraints and correlations between system equipment capacity and operational concerns.

To effectively realize the EH-IES low-carbon economic dispatch, seasonal energy storage, renewable energy output uncertainty, and seasonal operating characteristics are taken into account, and a seasonal hydrogen storage model is included in the EH-IES. In contrast, a two-layer EH-IES low-carbon economic model is proposed. The model carefully considers the coupling between equipment output and load characteristics on seasonal and intraday time scales to determine the optimal capacity allocation of the system using the MOSPO algorithm to minimize the total investment cost, operating cost, and carbon emission cost in the upper layer. The optimal scheduling of the system using the MOSPO algorithm minimizes the system's operating cost and the cost of purchased energy in the lower layer while adhering to the operational and scheduling constraints. In addition, constraints are placed on the system's ramping and peaking capabilities to meet system requirements. The main contributions of this paper are as follows:

- 1) The imbalance between renewable energy output and load demand at long time scales is considered, and seasonal hydrogen storage is introduced into the electric-hydrogen integrated energy system model.
- 2) A two-layer optimization model is developed for the collaborative optimization of equipment capacity and daily schedules in EH-IES. The capacity configuration of the system in terms of years is determined in the upper layer, and then the system scheduling results for a typical day in terms of days are obtained in the lower layer.
- 3) A Multi-objective Stochastic Paint Optimizer (MOSPO) method is employed to solve the EH-IES planning problem on long time scales, which performs well in speed and accuracy.

The rest of this paper is organized as follows. Section II introduces the EH-IES model with seasonal hydrogen storage. Section III establishes the two-layer scheduling model. Section IV presents the simulation results and discussion.

II. INTEGRATED ELECTRIC-HYDROGEN ENERGY SYSTEM WITH SEASONAL ENERGY STORAGE

Figure 1 is a block diagram of an integrated electric-hydrogen energy system with seasonal energy storage. The system consists of five main components: an electric power system, a hydrogen storage system, a cooling system, a heating system, and a natural gas system. The load side includes the electric power load, the cooling load, and the heating load. In the figure, the green color indicates power flow, the red color indicates heat flow, the blue color indicates cooling flow, and the orange color indicates natural gas flow. The purple color indicates hydrogen flow. Renewable energy sources, hydrogen fuel cells, gas turbines, and the grid supply electricity to users. Renewable energy sources generate surplus electricity, which is converted to hydrogen through electrolyzers, compressed and stored in hydrogen storage tanks, or supplied to power-to-gas (P2G) equipment to create natural gas. Electric refrigeration equipment converts electrical energy into cooling energy for users. The thermal energy is mainly provided by the heat generated by the electrolyzer and the waste heat boiler, and the excess heat is stored in thermal storage tanks. Absorption chillers convert heat energy into cooling energy for supply to users.

A. Modeling of EH-IES

The power system mainly consists of power producing and consuming devices which are mathematically modeled as shown below:

$$\begin{cases} V_{gas}(t) = \frac{P_{GT}(t)T(t)}{\beta_1 \delta} \\ Q_{GT}(t) = P_{GT}(t) \frac{1-\beta_1-\varepsilon}{\beta_1} \end{cases} \quad (1)$$

$$\begin{cases} P_{st}^{el,out}(t) = a_1 P_{st}^{el,in}(t) + b_1 T_{st}^{el}(t) \\ Q_{st}^{el}(t) = a_2 P_{st}^{el,in}(t) + b_2 T_{st}^{el}(t)^{el} \\ T_{st}^{el}(t+1) = T_{st}^{el}(t) + \frac{\Delta t}{C^{el}} (Q_{st}^{el}(t) - Q_{st}^{loss}(t)) \\ Q_{st}^{loss}(t) = \frac{1}{R^{el}} (T_{st}^{el}(t) - T_{st}^{out}(t)) \end{cases} \quad (2)$$

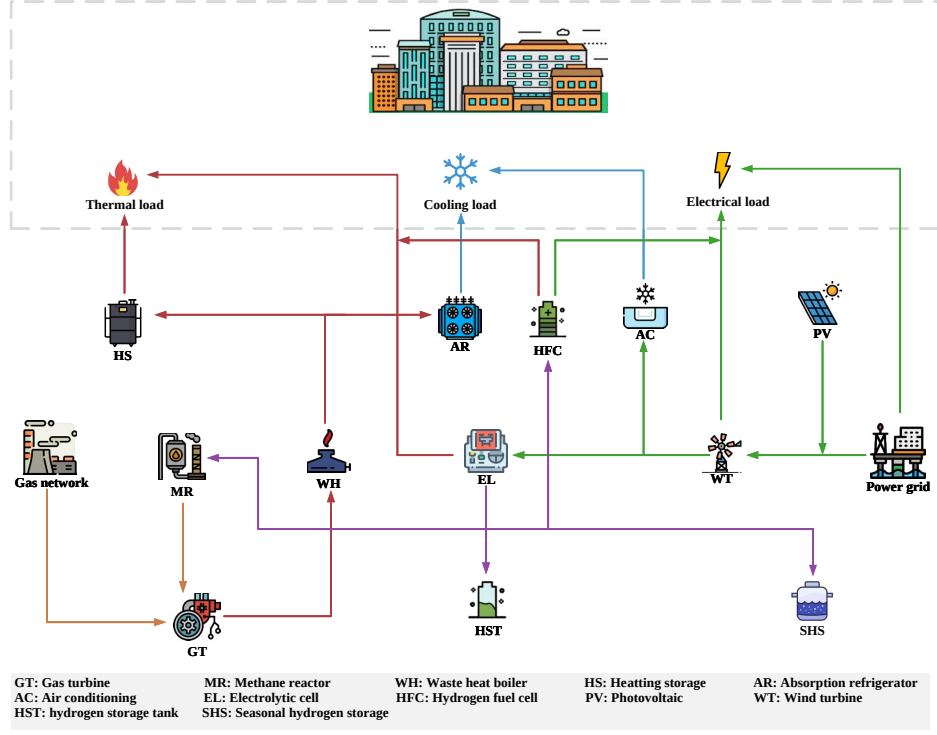


Fig. 1: System framework.

Equation (1) is the mathematical model of a gas turbine, where a_1, b_1, a_2, b_2 are the linearization approximation parameters, V_{gas} indicated natural gas consumed by gas turbines, P_{GT} indicated power generation of gas turbines, T indicated time, P_{GT} indicated waste heat from gas turbines, β_1 indicated gas turbine power generation efficiency, δ indicated minimum combustion calorific value of natural gas, ε indicated gas turbine waste heat loss coefficient [31]. Equation (2) is a mathematical model of an alkaline electrolyser, where $P_{st}^{el/in}$ indicated hydrogen production in electrolysis tanks, $P_{st}^{out/in}$ indicated electricity consumed in electrolysis tanks, T_{st}^{el} indicated operating temperature of the electrolytic bath, Q_{st}^{el} indicated electrolytic cell heating, Q_{st}^{loss} indicated heat dissipated by electrolytic cells, R_{el} and C_{el} indicated thermal resistance/capacity of electrolytic cell, T_{st}^{out} indicated outdoor temperature. Alkaline electrolyzers can be used in conjunction with renewable energy sources to generate hydrogen for energy storage by electrolysis with alkaline electrolyte. However, temperature affects the conductivity and reaction rate of the electrolyte. Within a specific range, increasing the temperature can improve the electrolysis efficiency, but too high a temperature may lead to energy loss and corrosion. Therefore, considering the electrolysis efficiency of the electrolyzer, the mathematical expression of temperature and its heat production is added to the mathematical model of the electrolyzer.

The heating system consists of heat production and consumption units, which are mathematically modeled as shown below:

$$\begin{cases} H_{WH}(t) = Q_{WH}^{in}(t) + Q_{AR}^{in}(t) \\ Q_{WH}^{in}(t) = Q_{GT}(t) \\ Q_{WH}(t) = \eta_{WH} H_{WH}(t) \end{cases} \quad (3)$$

$$\begin{cases} S_{HS}^t = S_{HS}^{t-1} (1 - \sigma_{HS}) + \left(Q_{HS,t}^{cha} \eta_{HS}^{cha} - \frac{Q_{HS,t}^{dis}}{\eta_{HS}^{dis}} \right) \Delta t \\ S_{HS}^T = S_{HS}^0 \\ 0 \leq Q_{HS,t}^{cha/dis} \leq \lambda_{HS}^{cha/dis} S_{HS}^{max} \\ \varepsilon_{HS}^{cha} + \varepsilon_{HS}^{dis} \leq 1 \\ \alpha_{HS}^{lo} S_{HS}^{max} \leq S_{HS}^t \leq \alpha_{HS}^{up} S_{HS}^{max} \end{cases} \quad (4)$$

Equation (3) is the mathematical model of the waste heat boiler, where H_{WH} indicated total waste heat absorbed by waste heat boiler, Q_{WH}^{in} indicated heat absorbed by waste heat boiler, Q_{AR}^{in} indicated heat absorbed by Absorption refrigerator, Q_{WH} indicated heat generated by waste heat boiler, η_{WH} indicated heating efficiency of waste heat boiler. The waste heat boiler absorbs the waste heat generated by the gas boiler to generate heat to supply the user. Equation (4) is the mathematical model of the heat storage tank, mainly used to store the excess heat generated by the system, where S_{HS} indicated heat storage tank capacity, $Q_{HS,t}^{cha}$ indicated heat charging in the heat storage tank, $Q_{HS,t}^{dis}$ indicated heat release in the heat storage tank, ε_{HS}^{cha}

indicated charging state of thermal storage tanks, ε_{HS}^{dis} indicated discharge state of thermal storage tanks, σ_{HS} indicated self discharge efficiency of heat storage tank, η_{HS}^{cha} indicated charging efficiency of thermal storage tank, η_{HS}^{dis} indicated discharge efficiency of thermal storage tank, α_{HS}^{lo} indicated minimum capacity state coefficient of heat storage tank, α_{HS}^{up} indicated maximum capacity state coefficient of heat storage tank, $\lambda_{HS}^{cha/dis}$ indicated maximum heat storage tank charge/discharge efficiency, S_{HS}^{max} indicated rated heat storage capacity of heat storage tank [32–34].

The cooling system consists of refrigeration equipment and the mathematical model is shown below:

$$Q_{AC}(t) = \eta_{AC} P_{AC}(t) \quad (5)$$

$$Q_{AR}(t) = \eta_{AR} Q_{AR}^{in}(t) \quad (6)$$

Equation (5) is the mathematical model of an electric cooler, where Q_{AC} indicated cold power of electric cooler, η_{AC} indicated electric cooler efficiency, P_{AC} indicated electricity consumed for electric cooler. Electric cooler mainly use electricity to supply cold for the user. Equation (6) represents the mathematical model of an absorption refrigerator, where Q_{AR} indicated cold power of absorption refrigerator, η_{AR} indicated absorption refrigerator efficiency. Absorption refrigerator primarily absorb the heat generated by the waste heat boiler to supply cold for the user.

The natural gas system is a methane reactor that absorbs hydrogen and carbon dioxide from the electrolyzer to natural gas for use in the system, and its mathematical model is shown below:

$$P_{MR}^g(t) = \eta_{MR} P_{MR}^h(t) \quad (7)$$

Equation (7) is a mathematical model of a methane reactor, where η_{MR} indicated gas production efficiency of the methane reactor, P_{MR}^h indicated hydrogen power consumed by the methane reactor, P_{MR}^g indicated natural gas produced by the methane reactor.

The mathematical models of photovoltaic and wind power generation are shown in eq. (8) and eq. (9):

$$\begin{cases} P_{PV}(t) = N_{PV} P_{rPV} f_{PV} \left(\frac{R_a(t)}{R_s} \right) [1 + k(T_a(t) - T_{sout})] \\ T_a(t) = T_{out}(t) + 0.0256 R_a(t) (c_1 - 1) \end{cases} \quad (8)$$

$$P_{WT} = \begin{cases} 0 & v_t \leq v_{in}, v_t \geq v_{out} \\ P_{rWT} \frac{v_t - v_{in}}{v_r - v_{in}} & v_{in} \leq v_t \leq v_r \\ P_{rWT} v_r & v_r \leq v_t \leq v_{out} \end{cases} \quad (9)$$

where, P_{PV} indicated photovoltaic power generation, N_{PV} indicated number of photovoltaic panels, P_{rPV} indicated PV panel power rating, f_{PV} indicated attenuation factor, R_a actual light intensity, R_s light intensity in a standard light environment, k indicated power temperature coefficient, T_a indicated actual temperature of the PV panel, T_{sout} indicated standard ambient temperature, c_1 indicated correlation coefficient is a constant value, T_{out} indicated actual ambient temperature, P_{WT} indicated wind power, P_{rWT} indicated WT rated power, v_t indicated actual wind speed, v_{in} indicated cut-in wind speed, v_{out} indicated cut out wind speed, v_r indicated rated wind speed.

B. Hydrogen Storage Systems

Two high-pressure hydrogen gas storage units store hydrogen at different pressures. The HS operates to provide the charging and releasing of hydrogen during the daytime, while the SHS operates during the daytime to realize the charging and releasing of hydrogen between different typical days. Here, we assume that the SHS has only one charging and releasing state within each typical day, which is determined by the overall supply and demand of hydrogen within a typical day. Intraday hydrogen storage is modeled in two cases, excluding the power consumption of the electrolyzer. If the system generates more power than it uses:

$$\begin{cases} P_{sum}(t) \geq \frac{P_{TE}(t)}{\tau_1} \\ S_{HST}(t-1) = S_{HST}(t) + \left(P_{sum}(t) - \frac{P_{TE}(t)}{\tau_1} \right) \tau_2 \end{cases} \quad (10)$$

$$\begin{cases} P_{sum}(t) = P_{GT}(t) + P_{PV}(t) + P_{WT}(t) \\ P_{TE}(t) = P_{load}(t) + P_{AC}(t) \end{cases} \quad (11)$$

Excluding the power consumption of the electrolyzer, if the power generation of the system is less than the power consumption:

$$\begin{cases} P_{sum}(t) \leq \frac{P_{TE}(t)}{\tau_1} \\ S_{HST}(t-1) = S_{HST}(t) - \left(\frac{P_{TE}(t)}{\tau_1} - P_{sum}(t) \right) \tau_3 \end{cases} \quad (12)$$

Equations (10) and (11) is a mathematical model of the hydrogen storage unit during the day when the system produces electricity surplus to the user, Equation (12) is the power generation of the system is less than the power consumption, where P_{sum} indicated electricity generated by the system, P_{TE} indicated electricity consumed on the consumer side and

by electricity-using equipment, S_{HST} indicated capacity of the intraday hydrogen storage, τ_1 indicated converter conversion efficiency.

Seasonal hydrogen storage devices aim to enable energy transfer on long-time scales and is planned on a seasonal basis. In contrast, whereas other devices are scheduled directly intraday, seasonal energy storage comprises a single charging or discharging activity within a day. Here are two seasonal hydrogen storage models: a model for when energy is plentiful and a model for when energy is scarce. The plentiful energy hydrogen storage model is as follows:

$$S_{1,0}^{SHS} = 0.5W^{SHS} \quad (13)$$

$$S_{1,t}^{SHS} = (1 - \gamma_{loss}^{SHS}) S_{1,t-1}^{SHS} + (P_{1,t}^{SHScha} / \eta^{SHScha} - P_{1,t}^{SHSdis} / \eta^{SHSdis}) \Delta t \quad (14)$$

$$S_{s,0}^{SHS} = (1 - \gamma_{loss}^{SHS} \mu_{s-1} \Delta t) \cdot (S_{s-1,24}^{SHS} + \mu_{s-1} (S_{s-1,24}^{SHS} - S_{s-1,0}^{SHS})) \quad (15)$$

Other seasonal hydrogen storage models:

$$S_{s,t}^{SHS} = (1 - \gamma_{loss}^{SHS}) S_{s,t-1}^{SHS} + (P_{s,t}^{SHScha} / \eta^{SHScha} - P_{s,t}^{SHSdis} / \eta^{SHSdis}) \Delta t \quad (16)$$

The constraints of the seasonal hydrogen storage model are as follows:

$$\begin{cases} S_{1,0}^{SHS} = S_{NS,24}^{SHS} \\ 0 \leq S_{s,t}^{SHS} \leq W^{SHS} \\ 0 \leq P_{s,t}^{SHS+/-} \leq \varepsilon_{s,t}^{SHS+/-} \tau^{SHS} W^{SHS} \\ \varepsilon_{s,t}^{SHS+} + \varepsilon_{s,t}^{SHS-} \leq 1 \end{cases} \quad (17)$$

Equations (13) and (15) represent the initial capacity of the seasonal hydrogen storage device, and Equation (14) and (16) represent the charging/discharging of the seasonal hydrogen storage device, where, $S_{s,0}^{SHS}$ indicated initial hydrogen storage capacity, $S_{s,t}^{SHS}$ indicated hydrogen storage capacity, $\varepsilon_{s,t}^{SHS+}$ indicated charging state of the hydrogen storage tank, $\varepsilon_{s,t}^{SHS-}$ indicated discharging state of the hydrogen storage tank, γ_{loss}^{SHS} indicated hydrogen storage tank self discharge, τ^{SHS} indicated power capacity ratio of hydrogen storage tank, $S_{NS,24}^{SHS}$ indicated final hydrogen storage capacity, $P_{s,t}^{SHScha}$ indicated hydrogen charging power, $P_{s,t}^{SHSdis}$ indicated hydrogen release power, μ_{s-1} indicated probability of the scenario, W^{SHS} indicated installed capacity of hydrogen storage tank.

Considering that the energy storage device is subject to environmental influences leading to energy losses, we include the energy loss in the hydrogen storage model:

$$Loss = (T^{\min} - T^{amb}) (PX + r^2\pi) U + (T^{\max} - T^{amb}) (P(H - X) + r^2\pi) U \quad (18)$$

Equation (18) is the mathematical formulation of the energy loss of the energy storage device considering the environmental impacts, where $T^{\min}$ indicated minimum temperatures allowed for the equipment, T^{amb} indicated outdoor temperature, U indicated capacity per square metre of equipment, X indicated location of the hydrogen, r indicated radius of the tank, H indicated height of the tank, P indicated outer perimeter of the hydrogen storage tank.

C. Time series modeling of simulation runs and selection of typical days

To obtain the required typical daily data, it is first necessary to get the annual time series of the target scenario. Historical data on annual load and wind power output are utilized to forecast the load and wind power output. After obtaining the annual time load and wind power forecast curves, the typical day data are obtained by clustering the annual data using the K-mean clustering method with day as the basic clustering unit.

The Long Short Term Memory (LSTM) Network model assembles extended short memory modules into a recurrent neural network that uses a gate structure to filter and restrict information, enabling the network to remember long-term details and solve the vanishing gradient problem [35]. The prediction process mainly includes the forgetting, selective memory, and output stages. The forgetting step especially involves selectively removing the information transmitted from the previous node. By reading the output status of the last node and the output status of the current node, the activation function determines the proportion of cell state information forgotten at the last time. The selective memory stage is the selective screening of input information, selecting important information to input into the current cell. The selection of the memory stage mainly includes two steps: the first step is to determine which data needs to be updated by the activation function of the input layer, the tanh layer generates an alternative update content, and then the cell state is updated. The current cell state is obtained from the output state of the forgetting phase and the alternative updated cell state. The output stage will use the activation function to determine the proportion of output cell states and then multiply the cells processed by the tanh layer with the output cell states to obtain the final output result. Considering the time series characteristics of wind and solar output and cooling and thermal load data, a recurrent neural network model with a "memory" function is most suitable as a prediction model for wind and solar production and cooling and thermal load.

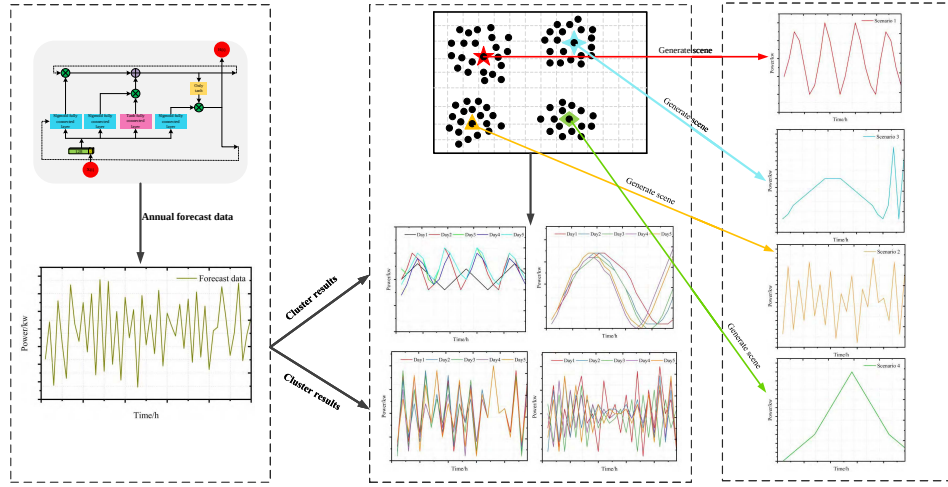


Fig. 2: Typical day scenario generation.

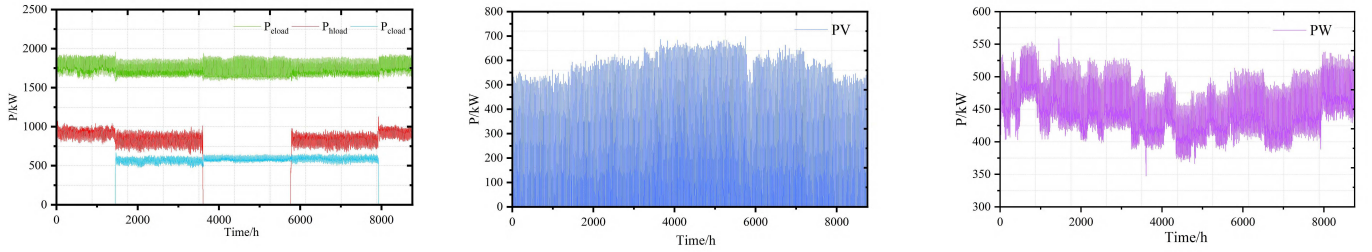


Fig. 3: Annual load forecast data.

The LSTM model assembles the long and short-term memory modules into the recurrent neural network, using the gate structure to filter and limit the information so that the network can remember the long-term knowledge, thus solving the problem of gradient disappearance. Considering that the data of wind power and cooling and heating load are time series, the recurrent neural network model with the "memory" function is the most suitable for the forecasting model of wind power and cooling and heating load [36]. The annual wind power output and cooling and heating electric load data obtained from historical data are shown in Fig. 3.

To obtain the required typical day data, it is first necessary to get the annual time series for the target scenario. The yearly load series and annual wind power generation forecasts are obtained through the LSTM forecasting model. After receiving the annual time series curves, the yearly time series data are clustered using the K-means clustering method with day as the basic clustering unit to get the typical day series [37]. The obtained typical day scenario is shown in Fig. 4, Fig. 5, Fig. 6 and Fig. 7.

Scenario 1: Simulation of scenarios with high wind power.

Scenario 2: Simulation of scenarios where wind power is higher than PV.

Scenario 3: Simulation of summer i.e. no heat load scenario.

Scenario 4: Simulation of winter i.e. no cold load scenario.

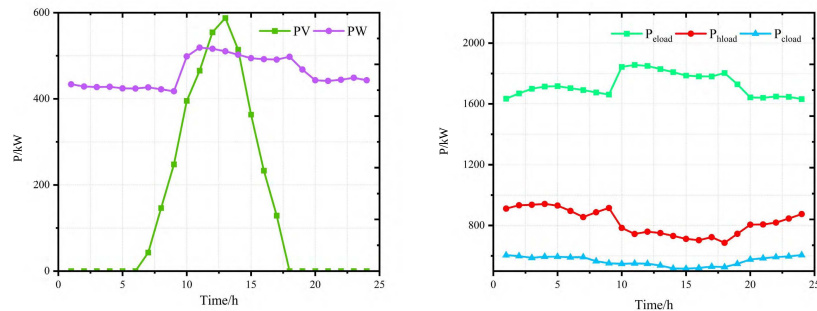


Fig. 4: Typical daily wind and PV output and load profiles for Scenario 1.

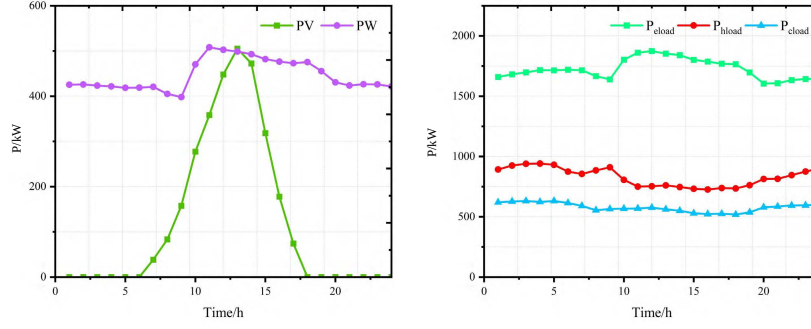


Fig. 5: Typical daily wind and PV output and load profiles for Scenario 2.

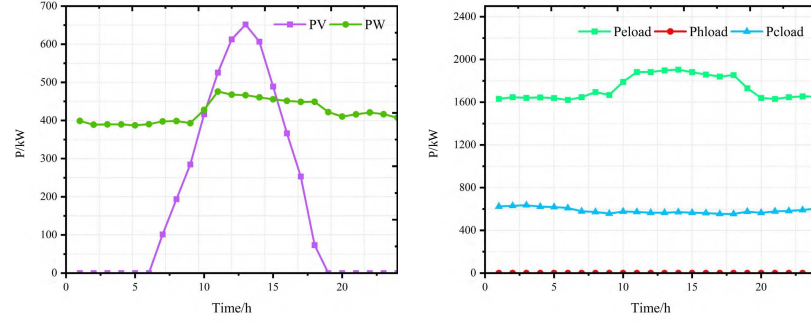


Fig. 6: Typical daily wind and PV output and load profiles for Scenario 3.

III. SOLUTION APPROACH

A. Two-layer optimisation model

The upper layer planning model has a period of 1 year, and the lower layer operation model has a period of 1 day and a time granularity of 1 hour. The upper layer planning model takes the annual discounted economic cost, carbon emission, and autonomy as the objective function, obtains the multi-objective solution set through the MOSOP algorithm, and applies the upper layer capacity optimization results to the objective function and constraints of the lower layer. The lower layer monthly typical day operation results are multiplied by the corresponding number of days in each month, and then feeds back the whole year's results to the upper layer, and ultimately seeks for the globally optimal solution through the optimization iteration of the upper and lower layers. The two-layer planning framework of the system is shown in Fig. 8.

1) *Upper Level Objective Function:* The upper level planning model is a multi-objective planning whose objective functions are the economic cost of IES, and the carbon emission, mathematical modelling as in eq. (19)-(23) .

$$\begin{aligned} & \min (F_1, F_2) \\ & \begin{cases} F_1 = F_u + F_{con} + F_c \\ F_2 = F_{loss} \end{cases} \end{aligned} \quad (19)$$

$$F_u = \sum_{t=1}^{8760} (c_{ebuy} P_{ebuy}^t + c_{gbuy} P_{gbuy}^t) \quad (20)$$

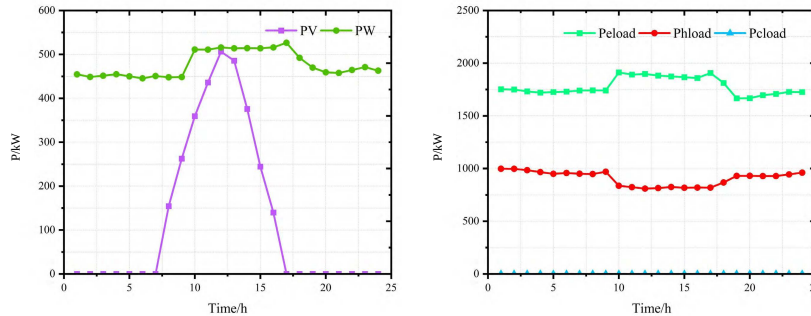


Fig. 7: Typical daily wind and PV output and load profiles for Scenario 4.

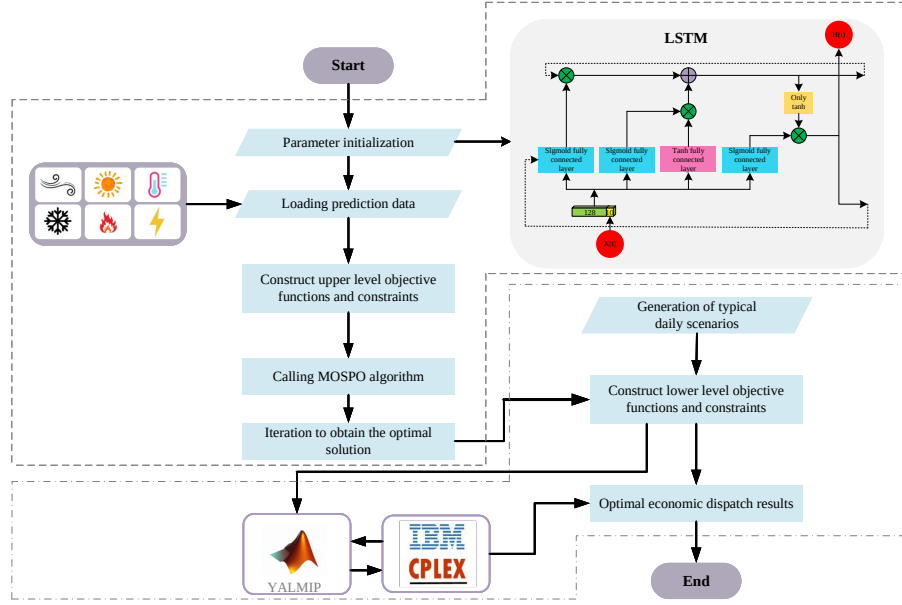


Fig. 8: Double-layer framework.

$$F_{con} = \sum_{t=1}^{8760} (c_i P_{ebuy}^{i,t}) \quad (21)$$

$$F_c = f U_i C u_i \quad (22)$$

$$i \in (PV, WT, GT, WH, HS, SHS, SHST, AC, AR)$$

$$F_{loss} = \sum_{t=1}^{8760} (CE_{co_2}^1 P_j^t + CE_{co_2}^2 P_{ebuy}^t + CE_{co_2}^3 P_{gbuy}^t) \quad (23)$$

Where F_1 indicated operating cost of the equipment, F_2 indicated carbon dioxide emissions, F_u indicated cost of purchasing electricity and gas, F_{con} indicated maintenance cost of the equipment, F_c indicated investment construction costs for equipment, $c_{e/gbuy}$ price of electricity/gas per unit of time, c_i indicated price of maintenance and operation of the equipment per unit of time, f indicated capital recovery coefficient, $C u_i^t$ indicated unit investment cost of the equipment, $CE_{co_2}^{1/2/3}$ indicated carbon emission factor.

There is an upper limit to the installed capacity of the device due to the limitation of the size of the actual installation site [38]. It can be expressed according to equations eq. (1)-(16):

$$P_j^{\min} \leq P_j^t \leq U_j \quad (24)$$

$$j \in (GT, EL, MR, HFC)$$

$$Q_k^{\min} \leq Q_k^t \leq U_k \quad (25)$$

$$k \in (WH, AR, AC)$$

$$S_{HS/HS}^{\min} \leq S_{HS/HS} \leq S_{HS/HS}^{\max} \quad (26)$$

$$Q_{HS-cha/dis}^{\min} \leq Q_{HS-cha/dis}^t \leq Q_{HS-cha/dis}^{\max} \quad (27)$$

2) *MOSPO*: Multi-objective Stochastic Paint Optimizer (MOSPO). A single-objective version of the stochastic paint optimizer (SPO) has been suitably changed to solve the multi-objective optimization problem and described as MOSPO [39]. Color theory, color wheels, and color combination methods are the main concepts of SPO. Thanks to four simple color combination rules without internal parameters, SPO will allow excellent exploration and development. Principles such as using fixed-size external archives make the recommended technique different from the original single-objective SPO. In addition, a leader selection mechanism has been added to SPO to perform multi-objective optimization. The pseudo-code of the MOSPO algorithm is shown below:

Algorithm 1 MOSPO optimization

Input: the *MaxIt*, *Archivesize*, *ColorsNumber*, *nVar* initialization parameters; *WT*, *PV*, *P_{eload}*, *P_{hload}*, *P_{cloud}* predicted data

Output: Objective function *F*;

- 1: **Initialize** *MOSPO* parameters :*alpha*, *nGrid*, *beta*, *gamma*
- 2: **Load problem instance**
- 3: **for** *i* = 1 to *ColorsNumber* **do**
- 4: **Initialize** *SPO*(*i*) with random position within bounds
- 5: **Calculate** *SPO*(*i*)'s cost $\rightarrow$ objective function
- 6: **Set** *SPO*(*i*)'s best position $\rightarrow$ current position
- 7: **Set** *SPO*(*i*)'s best cost $\rightarrow$ current cost
- 8: **end for**
- 9: **Calculate dominance relationships among SPO particles**
- 10: **Initialize** *Archive* as the non-dominated particles in *SPO*
- 11: **Initialize** *G* (hypercube grid) based on *Archive* – costs
- 12: Split *Colors* into three groups (*Group1st*, *Group2nd*, *Group3rd*) based on *ColorsNumber*
- 13: **for** *Iter* = 1 to *MaxIt* **do**
- 14: **for** *ind* = 0 to *Colors* – *Number* **do**
- 15: Select a *Leader* from *Archive* based on *beta*
- 16: **end for**
- 17: **end for**
- 18: **if** *ind* $\leq$ *N1stColors* **then**
- 19: Combine colors from *Group1st* and *Leader* using analog combination
- 20: **else if** *ind* $\leq$ *N1stColors* + *N2ndColors* **then**
- 21: Combine colors from *Group2nd* and *Leader* using analog combination
- 22: **else**
- 23: Combine colors from *Group3rd* and *Leader* using analog combination
- 24: **end if**
- 25: Combine colors from all groups and *Leader* using triangle combination
- 26: Combine colors from all groups using triangle combination
- 27: Combine colors from all groups using rectangle combination
- 28: Apply boundary constraints to the new particles
- 29: Calculate dominance relationships among new particles
- 30: Merge non-dominated new particles with *Archive*
- 31: Update *Archive*
- 32: Calculate *Archive* – costs and update *G*
- 33: Output the current *iteration* and *Archive* – size
- 34: **return** *Archive* – costs

B. Typical Day Economic Optimization Scheduling

Lower-level scheduling is to schedule individual devices for a day at the lowest economic cost [40, 41]. The mathematical model is shown in eqs. (26)-(27), where the parameters are the same as in eqs. (26)-(27).

$$\min F_u + F_{con} \quad (28)$$

$$\begin{cases} F_u = \sum_{t=1}^{24} (c_{ebuy} P_{ebuy}^{d,t} + c_{gbuy} P_{gbuy}^{d,t}) \\ F_{con} = \sum_{t=1}^{24} (c_i P_{con}^{i,d,t}) \end{cases} \quad (29)$$

$$i \in (PV, WT, GT, WH, HS, SHS, SHST, AC, AR)$$

The lower constraints mainly include the power balance constraints, the upper and lower limits of the equipment output constraints, and the ramping constraints of the equipment.

$$P_{ebuy}^{d,t} + P_{GT}^{d,t} + P_{PV}^{d,t} + P_{WT}^{d,t} + P_{HFC}^{d,t} = P_{eload}^{d,t} + P_{ELe}^{d,t} + P_{AC}^{d,t} \quad (30)$$

$$Q_{HS-dis}^{d,t} + Q_{WH}^{d,t} + Q_{HFC}^{d,t} + Q_{GT}^{d,t} + Q_{EL}^{d,t} = P_{hload}^{d,t} + Q_{HS-cha}^{d,t} + Q_{ARin}^{d,t} \quad (31)$$

$$Q_{AC}^{d,t} + Q_{AR}^{d,t} = P_{cloud}^{d,t} \quad (32)$$

$$P_{MRg}^{d,t} + P_{gbuy}^{d,t} = P_{GTg}^{d,t} \quad (33)$$

$$\Delta P_n^{\min} \leq P_n^{t+1} - P_n^t \leq \Delta P_n^{\max} \quad (34)$$

$$n \in (GT, EL, MR, HFC)$$

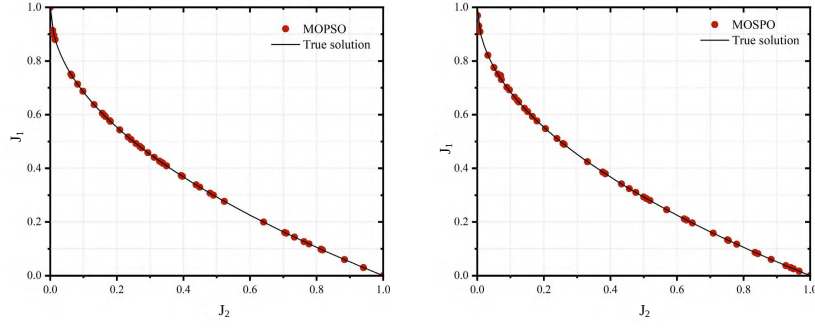


Fig. 9: MOSPO and MOPSO Algorithm comparison.

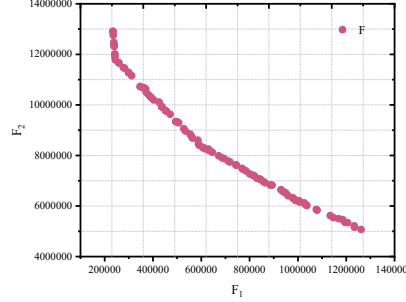


Fig. 10: MOSPO Capacity Configuration Results.

Equation (30)-(33) are equationally constrained models and Eq. (32) is an inequationally constrained model.

Remark: This paper does not consider the case where the system equipment fails for some reason. In this paper, we consider the economic operating conditions of the system during normal operation of the equipment and do not consider the operation of the system during equipment failure.

IV. CASE STUDY

The EH-IES shown in Fig. 1 is used to verify the correctness of the model proposed in the paper. The model is constructed based on the MATLAB simulation platform, and one year's data is used in the upper model for capacity calculation. At the same time, four typical days are clustered to obtain four usual days for comparative analysis in the lower model, which is a 0-1 mixed-integer linear programming model and is solved using CPLEX and YALMIP.

Case 1: EH-IES without hydrogen storage.

Case 2: EH-IES with intraday hydrogen storage.

Case 3: EH-IES with seasonal hydrogen storage.

A. Upper level planning model analysis

The population was set to $npop = 100$, the maximum number of iterations. The capacity of each device is optimally configured between $[1, 1000]$, the power of each energy storage device is optimally configured between $[0, 200]$, and the number of iteration convergence is around 100 generations. The optimization results are shown in Fig. 10 and Table 1. The distance between the true pareto and the obtained pareto frontier is evaluated using the generational distance. The expression is expressed as follows:

$$GD = \sqrt{\frac{\sum_{i=1}^n Dis^2}{n}} \quad (35)$$

Where n is the number of nondominated solutions, and Dis is the euclidean distance between solution i in obtained pareto and its closest solution in true pareto. Notably, a lower value of GD indicates a better convergence of the algorithm.

Figure 9 shows the comparison results of MOSPO algorithm and MOPSO algorithm under the same standard test function; in terms of solution speed, MOSPO is faster than MOPSO by 20 seconds, and in terms of solution results, MOSPO has a GD of 0.027 and MOPSO has a GD of 0.12, the MOSPO algorithm is better able to ensure the global nature of the solution and prevents the local optimal solution. Therefore, the comparison shows that the MOSPO algorithm can improve the speed and accuracy of the solution.

TABLE II: Capacity configuration.

Equipment	GT	WH	AR	AC	EL	MR	HFC	HS
Capacity/kW	1000	400	350	587	500	250	200	100

TABLE III: Cost of each case.

Case	Scenario	Electricity purchasing cost	Gas purchase cost	Equipment maintenance and operation costs	Total cost
Case1	Scenario1	26582.49	31679.18	21580.31	79841.99
	Scenario2	27107.67	34708.40	21621.53	83437.60
	Scenario3	24020.52	0	1002.52	25023.05
	Scenario4	15347.02	50209.62	15347.02	86889.70
Case2	Scenario1	26704.87	31344.58	21557.42	79606.87
	Scenario2	27228.62	34378.07	21598.82	83205.51
	Scenario3	23986.73	0	1007.80	24994.52
	Scenario4	15489.81	49815.79	21309.16	86614.77
Case3	Scenario1	26745.33	30910.12	21552.34	79225.59
	Scenario2	27264.12	34002.22	21594.55	82860.89
	Scenario3	23950.77	0	1005.95	24956.72
	Scenario4	15539.70	49358.00	21303.55	86201.34

B. Lower level planning model analysis

By comparing the various costs between Case 3 and Case 1 and between Case 3 and Case 2 and combining the data for all scenarios, changes can be observed regarding increased electricity purchase costs, decreased natural gas purchase costs, and decreased equipment maintenance and operating costs. Specifically, compared to Case 1, Case 3 had an average increase in electricity purchase costs of 0.58%, an average decrease in natural gas purchase costs of 2.15%, and an average reduction in equipment maintenance and operating costs of 0.08%. Compared to Case 2, Case 3 had an average increase in electricity purchase costs of 0.13%, an average decrease in natural gas purchase costs of 1.69%, and an average reduction in equipment maintenance and operating costs of 0.05%. The total cost of Case 3 decreased by an average of approximately 0.68% compared to Case 1 and roughly 0.42% compared to Case 2.

Based on the four scenarios, the cost results of each case are optimized and obtained. As seen in Table 2, there is a significant difference in the cost of the system under different scenarios. In Scenario 1, due to the higher power of wind and solar, the power purchase cost of the system is reduced by 1.89% compared to Scenario 2. Although the influence of heating and cooling loads is higher in Scenario 1, the purchased cost of gas in Scenario 1 is 9.10% lower than in Scenario 2 due to higher wind power in Scenario 1. The total system cost is 4.40% higher in Scenario 1 than in Scenario 2, despite the lower cooling and heating power in Scenario 2 due to the higher renewable energy share in Scenario 1. Scenario 3 simulates a scenario with no heat load; hence, the purchased gas cost in Scenario 3 is 0. Scenario 4 affects the system with no cooling load, reducing the coupling between hot and cold energy sources; hence, this scenario has the highest purchased gas cost and total cost.

Compared to Case 1, Case 3's purchased cost of electricity increased by an average of 0.58%, purchased cost of natural gas decreased by an average of 2.15%, and equipment maintenance and operating costs decreased by an average of 0.08%. Compared to Case 2, Case 3's purchased cost of electricity increased by an average of 0.13%, purchased cost of natural gas decreased by an average of 1.69%, and equipment maintenance and operating costs decreased by an average of 0.05%. Overall, the total costs for Case 3 decreased by about 0.68% compared to Case 1 and by an average of about 0.42% compared to Case 2. As can be seen from the power distribution graph, Scenario 3 has zero natural gas purchase cost due to no heat load, resulting in the lowest total cost. In contrast, Scenario 4 has the highest natural gas purchase cost due to no cooling load, resulting in the highest total cost. These results indicate that by reducing the dependence on natural gas and increasing the utilization of renewable energy sources, the overall economics of Case 3 are significantly improved.

Table IV shows the cost of energy (COE) for three cases under four scenarios. COE is defined as the average cost per kWh of useful electrical energy generated by the system. The formula for calculating COE is as follows [42]:

$$COE = F/P_E \quad (36)$$

where F denotes the total cost and P_E denotes the useful electrical energy production. As can be seen from the tabular data, there are significant differences in COE across cases and scenarios. Scenario 3 shows the lowest cost of energy in all cases, suggesting it is the most cost-effective option. Scenario 2 shows the highest cost of energy in all cases, suggesting that it is the least cost-effective option. The COEs of Case1 and Case2 are very similar in most scenarios, suggesting that the cost of energy structure is more similar in these two cases.

1) *Power supply system availability*: Figure 11 shows the electrical power output in Scenario 3. In EH-IES, HFCs and GT provide a stable electric power supply to the system; in Scenario 1 and Scenario 2, the power consumption of air conditioners is 1.37% higher than that of Scenario 2 due to the high demand for heat loads. In contrast, Scenario 4 simulates a situation

TABLE IV: Cost of energy.

Case	Scenario	COE
Case1	Scenario1	0.33
	Scenario2	0.31
	Scenario3	0.73
	Scenario4	0.33
Case2	Scenario1	0.32
	Scenario2	0.31
	Scenario3	0.73
	Scenario4	0.33
Case3	Scenario1	0.32
	Scenario2	0.30
	Scenario3	0.72
	Scenario4	0.33

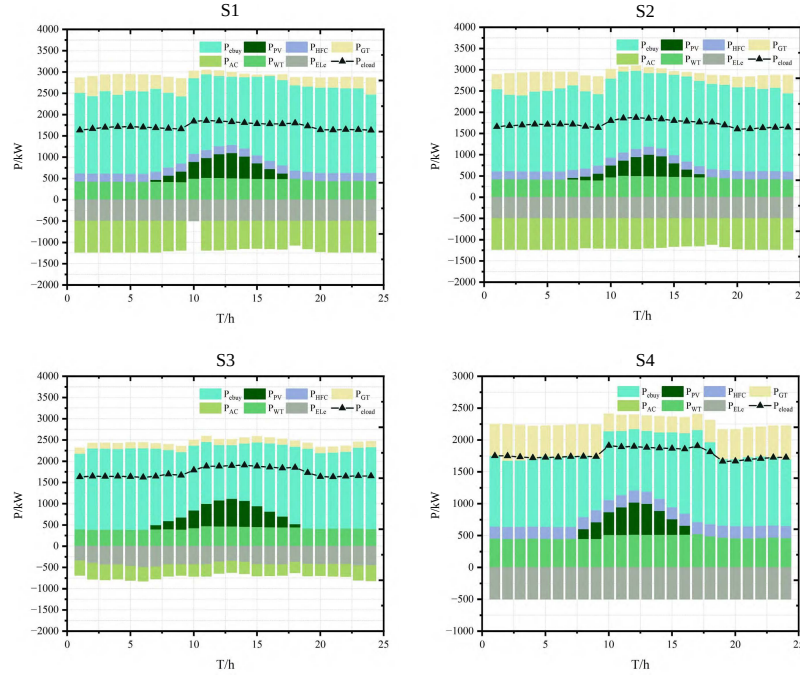


Fig. 11: Electrical load output in each case.

with no cooling loads. Therefore, the air conditioners in Scenario 4 do not participate in the energy scheduling, with 0 power consumption by air conditioners and the highest share of power generation of 18% by GTs. There is a heat load in Scenario 1, Scenario 2, and Scenario 4, so EL consumes electricity from renewable energy sources to generate hydrogen to supply HFCs. In contrast, in Scenario 3, there is no heat load, so the hydrogen generated by EL is only supplied to MR for use. Excess hydrogen generated by EL is stored in a hydrogen storage tank.

2) *Output of heating system:* Figure 12 shows the thermal power output in each case. In EH-IES, thermal power generated by HFC and EL in the presence of thermal load provides thermal power to the users; in the absence of thermal load, steady thermal power is provided to the users by EL, and HS is used to store the excess thermal energy and release it when there is a shortage of thermal energy. In Case 1 and Case 2 at 1:00-5:00 and 23:00-24:00, the thermal load demand of the system is high, the thermal power output from HFC, EL, and WH is high, and the HS releases the thermal energy to be used to solve the thermal load supply-demand shortage. At 17:00-20:00, the thermal load demand of the system is low, so WH produces a low thermal power of 15% of the total thermal energy output, and HS stores the excess heat produced by the system. In Case 3, since the system has no heat load demand, the heat power generated by the system EL and WH is mainly absorbed by AC for generating cooling power. WH provides 74.6% of the heat energy absorbed by AC. In Case 4, since there is no cooling load in the system, AC is not involved in the system's energy dispatch, and the thermal energy absorbed by AC is 0. The thermal power generated by each device is mainly used to provide thermal power to the user side. Since there is a high demand for thermal power, the HS releases the thermal energy only at 1:00.

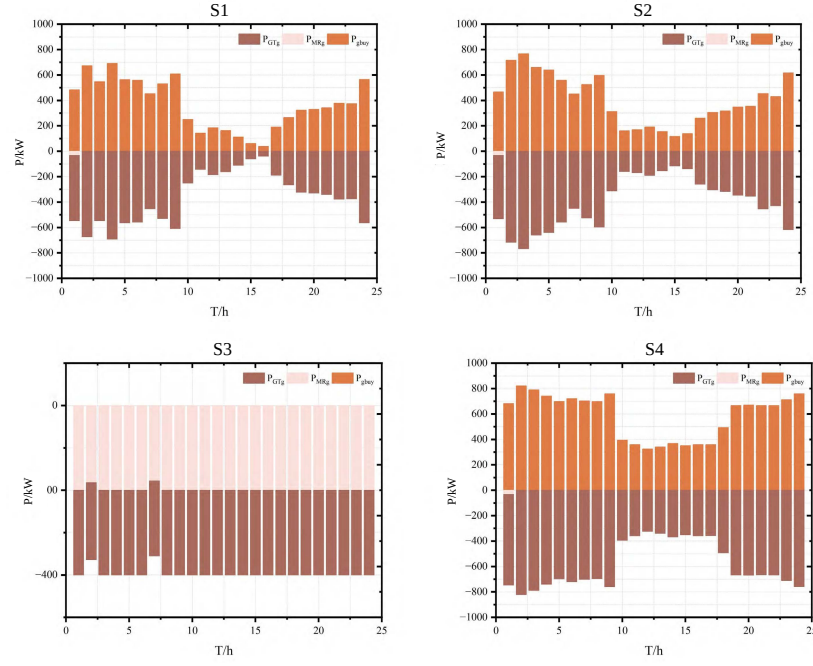


Fig. 14: Natural gas output in each case.

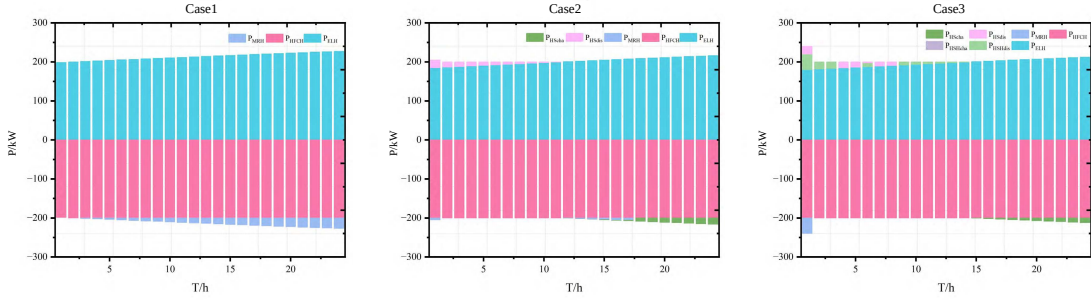


Fig. 15: Hydrogen dispatch results for each Case under Scenario 1.

methane reactor to synthesize natural gas for use. In Scenario 4, the hydrogen produced by the electrolyzer is correspondingly increased by 0.3% compared to Scenarios 1 and 2 because the demand for the cold load is zero, and the electric refrigeration plant is not involved in the output. Scenario 3 is compared to Scenario 1 as there is no hydrogen storage system in Scenario 1, so the excess hydrogen energy in the system can only be distributed in real-time to the hydrogen fuel cell and the methane reactor, and the excess power cannot be stored for use in times of low renewable energy output. In comparison to Case 3 and Case 2, since Case 2 incorporates hydrogen storage only in the intraday phase, the excess hydrogen energy can be stored in the intraday phase when the renewable energy output is high and then released to supply the system in the phase when the electricity price is high. However, in Case 2, due to the lack of a seasonal hydrogen storage device, in response to seasonal differences in renewable energy output in different scenarios, the hydrogen stored in the abundant energy scenario cannot be supplied to the system in the depleted energy scenario, resulting in the system having to purchase additional electricity from the grid to be utilized in the depleted energy scenario during periods of high electricity prices. As a result, the cost of purchasing electricity in Case 3 increased by an average of 0.58% and 0.13% compared to Cases 1 and 2. In Case 3, the renewable energy output in Scenarios 1 and 2 is high, so the HSH is mainly used to store the excess hydrogen energy to supply for use in Scenarios 3 and 4. In Scenario 3, from 3:00-7:00 and 15:00-17:00, the hydrogen produced by the electrolyzer alone is not enough to support the system, so the hydrogen storage tank outputs hydrogen energy to supply the system. In Scenario 3, from 8:00-14:00 and 18:00-24:00, the hydrogen produced by the electrolyzer is sufficient to support the system, so the excess hydrogen is stored in the hydrogen storage tank. In Scenario 4, from 1:00-8:00, the electrolyzer produces enough hydrogen to supply the system, so the excess hydrogen is stored in the hydrogen storage tank. From 9:00-16:00, the electrolyzer produces all the hydrogen to supply the users, and the tank neither stores nor releases hydrogen. From 17:00-24:00, the electrolyzer does not produce enough hydrogen to supply the users, so the tank releases hydrogen to supply the users. The storage tank releases hydrogen energy for use by the user.

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