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Research on multi-stage optimization planning of power internet of things based on seagull optimization algorithm

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Abstract

The Power Internet of Things (PIoT) is a significant technology for realizing the transformation of future energy systems, with the Integrated Energy System (IES) playing a crucial role in realizing the value of PIoT. Traditional IES planning methods typically focus on a single-stage planning approach and involve complex solution models, often resulting in inefficient equipment configurations and resource wastage. This study proposes a multi-stage IES planning method aimed at enhancing both energy efficiency and the economic performance of IES. The method models the IES based on electric, gas, and thermal buses, considering the coupling, storage, and conversion of multiple energy sources. A range of constraints, such as energy coupling, equipment capacity, and energy purchases, are considered. The planning cycle is divided into multiple stages, and an economic model is developed that accounts for both system investment and operating costs. Given the complexity of the multi-stage planning model, the Seagull Optimization Algorithm (SOA) is introduced to solve the problem. The SOA leverages its strong global and local search capabilities to determine the optimal capacity configuration at each stage. The comparison of the single-stage planning method by a calculation example proves the economic advantage of the multi-stage planning scheme and effectiveness of SOA.

Keywords: Power internet of things (PIoT), Integrated energy system (IES), Multi-stage, Seagull optimization algorithm (SOA), Planning method

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1. Introduction

As the consumption of fossil fuels continues to rise, the challenge of low energy efficiency stemming from the independently planned supply structure of current energy systems has become increasingly pronounced. Effectively enhancing the energy efficiency within the power supply sector has emerged as a critical issue that global energy systems must address. [1], [2]. The development of PIoT technology is considered to be an effective means to alleviate the energy dilemma. Based on Internet thinking, It facilitates the interconnection of devices and the interaction between humans and computers throughout all aspects of the power system, effectively integrating multi-energy systems and enabling hierarchical utilization of energy resources. [3].

IES is the core technology of PIoT technology. IES refers to the energy system that is tightly coupled in the links of energy development, storage, conversion, and utilization to meet the final demand of energy consumers. Different from the traditional energy structure, the reasonably planned IES can make up for the defects of independent planning and decentralized energy system by using the connecting

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relationship among energy systems. As integrated energy technology continues to evolve, the diversity of primary energy supply equipment within Integrated Energy Systems (IES) is expected to increase. Through strategic planning, both energy efficiency and economic viability can be enhanced, while also elevating the level of renewable energy consumption. [4]-[6].

Up till now, there are some works related to the planning of IES. In literature [7], the energy hub model was adopted in solving the above problem of uncertain IES planning structure. In literature [8], taking into account the coupling relationship between the demand side and the energy supply side, an Energy Conversion Interface (ECI) model was developed to streamline the multi-energy network. The Energy Hub model simplifies energy flow processes and provides a more abstract representation of energy transfer, making it suitable for large-scale networks with numerous coupling components. In literature [9], drawing upon the energy flow theory of Combined Cooling, Heating, and Power (CCHP) systems, an energy bus model for electricity and heat was developed to elucidate the energy transfer processes within the system. This bus model effectively illustrates the interconnections among various energy coupling devices and is particularly well-suited for modeling research in small-scale Integrated Energy Systems (IES).

Building upon the established Integrated Energy Systems (IES) model, literature [10] explores the uncertainties associated with distributed renewable energy (DRE) consumption and IES load, investigating the potential for collaborative planning of demand response (DR), distributed generation (DG), and energy storage (ES). Literature [11], [12] for the future high-permeability IES, proposed an IES planning model that considered the application of hydrogen energy. To ensure the reliability of the system, the reliability of key equipment constraints was considered in the planning model. Literature [13] established a multi-objective function model that considered carbon dioxide emissions investment costs as well as the operating costs based on CHP and DG. In literature [14], the improved adaptive genetic algorithm (GA) is applied to provide a solution strategy for IES cross-time scale and multi-dimensional optimization planning, which improved the flexibility of planning scheme. Literature [15] generalized the Benders decomposition (GBD) method and applied it to the hierarchical planning model for optimal multi-energy flow and optimal investment decision, which improved the efficiency of model solving and economy of IES. In literature [16], two meta-heuristic algorithms, Harmony Search and Simulated Annealing, were integrated to develop a hybrid simulated annealing algorithm aimed at addressing the optimization planning problem of hybrid solar/wind energy systems. Compared to the results obtained from individual algorithms, the advantages of the hybrid approach are clearly evident. Literature [17] considered the uncertainty of IES load and DRE, established a staged model using robust optimization ideas, and solved it with algorithm of column and constraint generation.

The aforementioned research has significantly contributed to the advancement of IES planning from the perspectives of IES system modeling, planning methodologies, and solution strategies. But they all ignored the timeliness of IES planning. Most of them determined the load level of the planning area, and carried out one-time equipment planning on the basis of determining the load, ignoring the load changing level which considered the construction changing cycle. So far, many IES projects have been put into operation, but engineering practice shows that the effects of some IES during the operation phase do not reach the expected goals in the planning phase [18], and did not maximize the economic advantages and energy supply characteristics of IES. This is due to the unreasonable configuration of the planned equipment, resulting in a waste of IES overall resources. The reason for this problem is that the initial planning did not fully consider the rationality of the later operation.

In response to above problems, referring to the mature power system planning theory [19]-[21], the idea of dynamic planning is introduced, the time axis factor is added to the planning, and the static planning is redefined as multi-stage planning through the segmentation of the planning cycle. Currently, there is a limited amount of research on the multi-stage planning of IES. Some preliminary studies are as follows, literature [22] takes into account the changes in influencing factors at different stages, such as energy demand, equipment, technical prices, technological improvements, etc., based on long-term and effective flexible multi-stage investment strategies, and establishes a comprehensive energy system flexible multi-stage long-term planning optimization model. Literature [23] aiming at multiple uncertainties, considering the constraints of scenario coverage, cost investment, environment and other constraints of the planning plan, A collaborative stochastic planning model for the multi-stage energy hub and energy network of the IES has been proposed.

Multi-stage planning that incorporates construction sequencing has increasingly emerged as a primary research focus in Integrated Energy Systems (IES) planning This paper establishes mathematical models of energy supply equipment by analyzing the coupling characteristics, including combined heat and power (CHP) systems, photovoltaics, electric boilers, and others. Energy storage equipment is configured in the planning scheme to improve the flexibility of IES to cope with load changes. The IES model is developed based on the principles of unified bus theory. A multi-stage planning model considering investment, operation and maintenance costs is constructed. By utilizing the algorithm's robust global and local search capabilities in conjunction with the operational safety constraints of IES, a Self-Organizing Algorithm (SOA) is introduced to enhance the efficiency and reliability of multi-stage planning solutions. The optimal planning configuration scheme and system economy of each stage are obtained. Multi-stage planning scheme Comparing with single-stage planning scheme, has significant advantages, and the SOA is effective and reliable.

2. IES modelling

2.1. Typical energy coupling unit model

1) CHP

The CHP system serves as the central component of energy coupling equipment within IES, converting natural gas into both electricity and thermal energy. The model and constraints are:

$$\begin{gathered} Q_{st}^{CHP} = G_{st}^{CHP}\eta^{Q,CHP} \\ P_{st}^{CHP} = G_{st}^{CHP}\eta^{P,CHP} \\ \bar{Q}_{min}^{CHP} \le Q_{st}^{CHP} \le \bar{Q}_{max}^{CHP} \end{gathered} \tag{1}$$

Where Q_{st}^{CHP} is the heat supplying power of CHP planned in IES at time t of scene S; P_{st}^{CHP} is the electric supplying power of CHP planned in IES at time t of scene S; G_{st}^{CHP} is the natural gas supplying power of CHP planned in IES at time t of scene S; $\eta^{Q,CHP}$ is CHP conversion efficiency between gas and heat; $\eta^{P,CHP}$ is CHP conversion efficiency between gas and electric; $\bar{Q}_{min}^{CHP}$ is lower limit of CHP operating power; $\bar{Q}_{max}^{CHP}$ is upper limit of CHP operating power.

2) photovoltaic

Many factors related to photovoltaic (PV) power generation, including sunlight, temperature, and equipment operating status. This paper assumes that when PV adopts the MPPT control strategy, the model and constraints are:

$$\begin{gathered} P_{st}^{PV} = P_{E,C}^{STC}G^{AC}[1+k(T_C - T_r)]/G_{E,C}^{STC} \\ 0 \le P_{st}^{PV} \le \bar{P}_{max}^{PV} \end{gathered} \tag{2}$$

Where P_{st}^{PV} is power supplying of PV planned in IES at time t of scene S; $P_{E,C}^{STC}$ is the power supply under standard experimental conditions; G^{AC} is the illumination intensity; $G_{E,C}^{STC}$ represents the illumination under standardized experimental conditions.; The temperature coefficient is expressed by k; T_C is operating temperature of PV; T_r is the reference value; $\bar{P}_{max}^{PV}$ is the maximum output of PV.

3) heat pump

The heat pump (HP) system functions as a conversion device for electrothermal coupling within the system It consumes electric energy and upgrades the heat energy from low quality to high quality to meet the heating demand of IES. The model and constraints are:

$$\begin{gathered} Q_{st}^{HP} = P_{st}^{HP}COP^{HP} \\ 0 \le Q_{st}^{HP} \le \bar{Q}_{max}^{HP} \end{gathered} \tag{3}$$

Where Q_{st}^{HP} is the heat supplying power of HP planned in IES at time t of scene S; P_{st}^{HP} is the electric power supplied to HP planned in IES at time t of scene S; COP^{HP} is HP conversion efficiency; $\bar{Q}_{max}^{HP}$ is upper limit of HP operating power.

4) gas boiler

The gas boiler (GB) burns externally purchased natural gas to supply heat to IES. The model and constraints are:

$$\begin{gathered} Q_{st}^{GB} = G_{st}^{GB}\eta^{GB} \\ 0 \le Q_{st}^{GB} \le \bar{Q}_{max}^{GB} \end{gathered} \tag{4}$$

Where Q_{st}^{GB} is the heat supplying power of GB planned in IES at time t of scene S; G_{st}^{GB} is the natural gas supplied to GB planned in IES at time t of scene S; η^{GB} is the gas-to-heat conversion efficiency of GB; $\bar{Q}_{max}^{GB}$ is the upper limit of heating power for GB.

5) electric boiler

The electric boiler (EB) serves as an electric-heat conversion device within IES. The model and constraints are:

$$\begin{gathered} Q_{st}^{EB} = P_{st}^{EB}\eta^{EB} \\ 0 \le Q_{st}^{EB} \le \bar{Q}_{st}^{EB} \end{gathered} \tag{5}$$

Where Q_{st}^{EB} is the heat supplying power of GB planned in IES at time t of scene S; P_{st}^{EB} is the electric power supplied to GB planned in IES at time t of scene S; η^{EB} is EB conversion efficiency between electric and gas; $\bar{Q}_{max}^{EB}$ is upper limit of EB operating power.

6) energy storage device

To strengthen flexibility of IES, thermal energy storage (HS) facility and electric energy storage (ES) facility are planned in this paper to cope with the load changes of IES. The two energy storage mechanisms are similar. All need to meet the following constraints:

$$\begin{gathered} 0 \le P_{charge} \le P_{charge,max} \\ 0 \le P_{discharge} \le P_{discharge,max} \\ SOC(t+\Delta t) = SOC(t) + \\ \frac{(\eta_{charge}P_{charge}(t)\Delta t - P_{discharge}(t)\Delta t/\eta_{discharge})}{W_{capacity}} \\ SOC_{min} \le SOC(t) \le SOC_{max} \\ P_{charge}(t)P_{discharge}(t) = 0 \\ SOC(0) = SOC(T) \end{gathered} \tag{6}$$

Where P_{charge} is the charging input power of energy storage equipment; $P_{discharge}$ is the discharging output power of energy storage equipment; $P_{charge,max}$ is upper operating limit of energy storage power; $P_{discharge,max}$ is upper operating limit of discharge power; $W_{capacity}$ is the planned capacity of energy storage equipment; η_{charge} is the efficiency of the equipment when charging. $\eta_{discharge}$ is the efficiency of the equipment when discharging; $SOC(t)$ is the charging state of equipment at time t; SOC_{max} is the maximum state of charge; SOC_{min} is the minimum state of charge; $SOC(0)$ and $SOC(T)$ are the state of charge at the beginning and the end of operation.

The models can be expressed as:

ES model:

$$\begin{aligned} W_{st}^{ES} &= (1-\eta^{loss,ES})W_{s(t-1)}^{ES} \\ &-(P^{ES,out}/\eta^{ES,out} - P^{ES,in}\eta^{ES,in})\Delta T \end{aligned} \tag{7}$$

Where W_{st}^{ES} is the capacity of ES planned in IES at time t of scene S; $W_{s(t-1)}^{ES}$ is the capacity of ES planned in IES at time $t-1$ of scene S; $\eta^{loss,ES}$ is ES self-discharge loss rate; $\eta^{ES,in}$ is the input charging efficiency; $\eta^{ES,out}$ is the output discharging efficiency; $P^{ES,in}$ is the input charging of ES; $P^{ES,out}$ is the output discharging of ES.

HS model:

$$\begin{aligned} W_{st}^{HS} &= (1-\eta^{loss,HS})W_{s(t-1)}^{HS} \\ &-(Q^{HS,out}/\eta^{HS,out} - Q^{HS,in}\eta^{HS,in})\Delta T \end{aligned} \tag{8}$$

Where W_{st}^{HS} is the capacity of HS planned in IES at time t of scene S; $W_{s(t-1)}^{HS}$ is the capacity of HS planned in IES at time $t-1$ of scene S; $\eta^{loss,HS}$ is HS self-heating loss rate; $\eta^{HS,in}$ is the input charging efficiency of heat; $\eta^{HS,out}$ is the output discharging efficiency of heat; $Q^{HS,in}$ is the input charging of HS; $Q^{HS,out}$ is the output discharging of HS.

2.2 IES model based on unified bus

After analyzing and modeling the coupling unit model of IES, in order to describe the coupling relationship of each part more vividly, the unified bus modeling theory is adopted to model the IES as a whole, as shown in Figure 1. Taking the actual situation of IES and the coupling relationship of energy equipment as consideration factors, the mutual coupling connection is established through the thermal bus, the natural gas bus and the electric bus. "The constraints for power balance are outlined as follows:

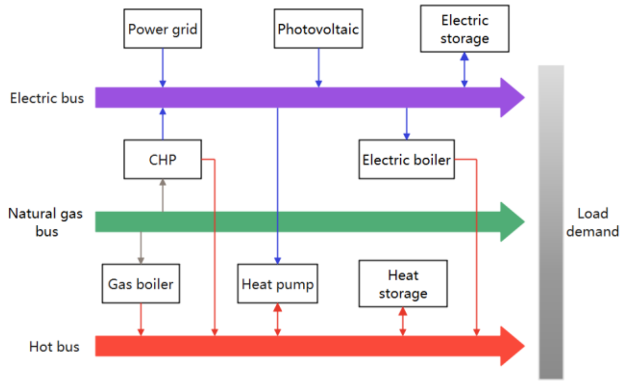

Figure 1. Unified bus-bar structure model of IES

1) Constraint of Power Balance on Electric Bus

$$P_{st}^{grid} + P_{st}^{CHP} + P_{st}^{PV} + P_{st}^{ES,out} - P_{st}^{ES,in} - P_{st}^{EB} - P_{st}^{HP} = P_{st}^{load} \tag{9}$$

Where P_{st}^{grid} is the power supplied by grid to IES at time t of scene S; $P_{st}^{ES,in}$ is the input charging power of ES planned in IES at time t of scene S; $P_{st}^{ES,out}$ is the output discharging power of ES planned in IES at time t of scene S; P_{st}^{load} is electric load of IES at time t of scene S.

2) Constraint of Power Balance on thermal Bus

$$Q_{st}^{HP} + Q_{st}^{CHP} + Q_{st}^{EB} + Q_{st}^{GB} + Q_{st}^{HS,out} - Q_{st}^{HS,in} = Q_{st}^{load} \tag{10}$$

Where $Q_{st}^{HS,out}$ is the output discharging power of HS planned in IES at time t of scene S; $Q_{st}^{HS,in}$ is the input charging power of HS planned in IES at time t of scene S; Q_{st}^{load} is heat load of IES at time t of scene S.[23]

3) Constraint of Power Balance on Gas Bus

$$G_{st}^{gas} = G_{st}^{GB} + G_{st}^{CHP} \tag{11}$$

Where G_{st}^{gas} is the natural gas supplying power from natural gas grid to IES at time t of scene S.

3.Multi-stage planning model of IES

3.1 Multi-stage planning scheme of IES

The IES planning method should be closely linked with the development of the planned area. Considering that the IES planning scheme has the characteristics of long cycle and the need for the overall development of the system, this paper introduces the idea of multi-stage planning into IES planning and divides IES planning into multiple stages according to the development mode of regional load. Through multi-stage planning, the multi energy equipment coupling system in IES can match with the planned load development, so as to avoid excessive investment and idle equipment at the beginning of planning, insufficient equipment capacity and high external energy purchase cost at the end of planning. The comprehensive energy system multi-stage planning scheme comprehensively considers all the economic costs of each planning stage, and solves it through the seagull algorithm to obtain the most economical multi-stage planning configuration scheme. The planning process of the Integrated Energy Systems (IES) is segmented into multiple stages, referred to as S .

$$S=[S_1,S_2,\ldots,S_i,\ldots S_N] \tag{12}$$

Where S_i represents the i-th planning cycle.

The specific planning ideas are illustrated in figure 2.

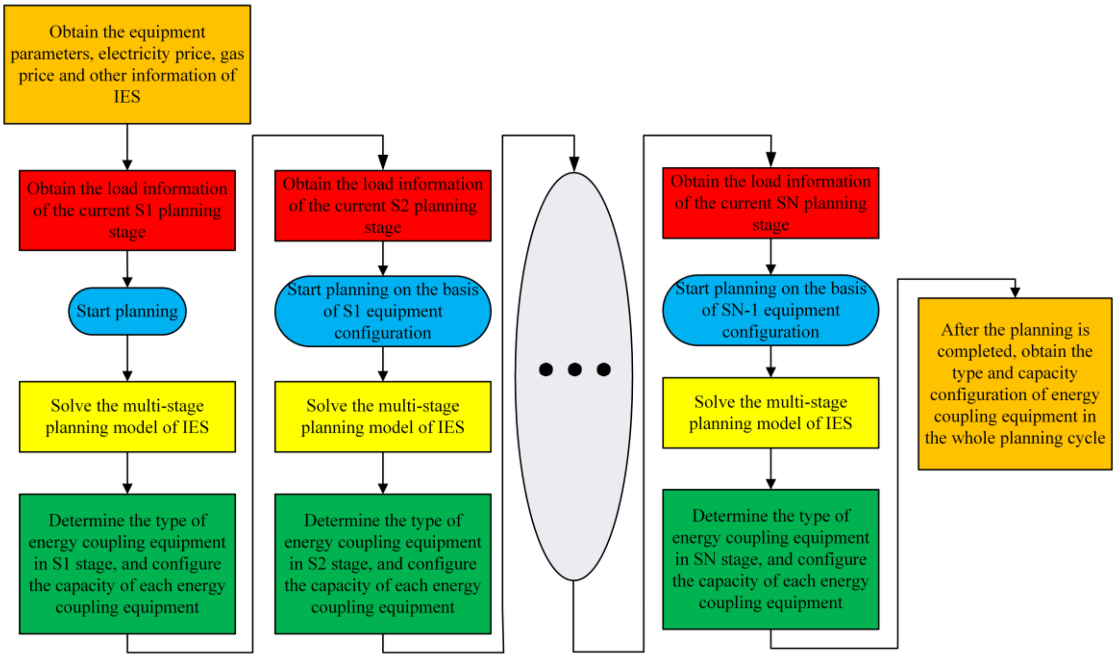

Figure 2. Multi-stage IES planning scheme

3.2 Objective Function

Taking into account the configuration of heat, electricity, and gas coupling equipment within the system, this paper presents an economic model that encompasses the entire planning cycle According to the different thermal and electrical load ratios and the planning cycle operation conditions of the system, the seagull optimization algorithm is employed to determine the capacity of each coupling unit. aiming at the optimal planning cycle economy considering the annual investment, operation and maintenance costs.

$$\text{Minimize}[\sum_{i=1}^{N}(C_{inv}^{i}+C_{ope}^{i})] \tag{13}$$

$$C_{inv}^{i}=\frac{r(1+r)^n}{(1+r)^n-1}\times\begin{pmatrix}P_{cap,CHP/PV/HP/GB/EB/ES/HS}^{i}\\ \times C_{CHP/PV/HP/GB/EB/ES/HS}\end{pmatrix} \tag{14}$$

$$C_{ope}^{i}=\sum_{k=1}^{3}[D_s^k\times\sum_{t=1}^{24}(C_{st}^{fuel,i}+C_{st}^{ele,t}+C_{st}^{om,i})] \tag{15}$$

$$C_{st}^{fuel.i}=(G_{st}^{CHP,i}+G_{st}^{GB,i})\times C_{st}^{gas,i} \tag{16}$$

$$C_{st}^{ele,i}=P_{st}^{grid,i}\times C_{st}^{grid,i} \tag{17}$$

$$C_{st}^{om,i}=\begin{pmatrix}P_{st,CHP/PV/HP/GB/EB/ES/HS}^{i}\\ \times C_{ope,CHP/PV/HP/GB/EB/ES/HS}\end{pmatrix} \tag{18}$$

Where N is the quantity of planning stages; C_{inv}^{i} is investment equivalent cost of planned equipment in planning stage i ; C_{ope}^{i} is the cost for operation and maintenance of IES in planning stage i ; $P_{cap,CHP/PV/HP/GB/EB/ES/HS}^{i}$ is the planned capacity of CHP/PV/HP/GB/EB/ES/HS in planning stage i ; $C_{CHP/PV/HP/GB/EB/ES/HS}$ is the unit capacity investment cost of CHP/PV/HP/GB/EB/ES/HS; The equipment present value coefficient is r ; The life of the planned equipment is represented by n ; D_s^k is the quantity of days in k typical days in condition S ; $C_{st}^{fuel,i}$ is investment of IES in buying fuel in planning stage i at moment t of condition S ; $C_{st}^{ele,i}$ is investment of IES in buying electricity in planning stage i at moment t of condition S ; $C_{st}^{om,i}$ is the cost for operation and maintenance of planned energy coupling equipment in planning stage i at moment t of condition S ; $P^{i}_{st,CHP/PV/HP/GB/EB/ES/HS}$ is the output power of CHP/PV/HP/GB/EB/ES/HS in planning stage i at moment t of condition S ; $C^{gas,i}_{st}$ is the price of natural gas consumed by IES in planning stage i at moment t of condition S ; $C^{grid,i}_{st}$ is the price of electric consumed by IES in planning stage i at moment t of condition S .

3.3 Constraints

1) Power Constraint Balance

Overall, it is essential to adhere to the constraints of power balance., such as equation (9), (10), (11).

2) Equipment Operation Constraints

Each device needs to satisfy equation (1-6) and its own operating constraints.

3) External Energy Purchase Constraints

In IES, the purchase of electric energy and natural gas from outside needs to meet the following constraints:

$$0 \le P^{grid,i}_{st} \le \bar{P}^{grid}_{max} \tag{19}$$

$$0 \le G^{gas,i}_{st} \le \bar{G}^{gas}_{max} \tag{20}$$

Where $\bar{P}^{grid}_{max}$ is the maximum power purchase between IES and grid. $\bar{G}^{gas}_{max}$ is the maximum gas purchase between IES and natural gas grid.

4. Seagull optimization algorithm and solution strategy

IES planning is a nonlinear and multi-constrained optimization problem. As a heuristic algorithm, the Seagull Optimization Algorithm (SOA) exhibits characteristics of rapid convergence., strong local search capability, and easy implementation [24]. The SOA continuously updates the positions of seagulls and records the optimal position by simulating the natural migration and foraging behaviors of seagulls, and searches for global and local optimal solutions through iterative calculations.

Migration and aggressive behavior are the key characteristics of seagulls. Migration refers to the seasonal movement of seagulls from one location to another, obtaining energy by searching for abundant food. During migration, seagulls fly in groups to minimize the risk of collisions with one another., the initial positions of seagulls are different. In a group, seagulls keep changing positions, flying in the direction of the best-positioned seagull. When seagulls migrate, the seagull groups make a natural spiral movement to hunt fish and shrimp.

The optimization criterion of this paper is to minimize the comprehensive objective function value of IES planning model, and to develop a rational combined configuration capacity for energy coupling equipment within the IES multi-stage planning model established in this paper., the process of seagull migration corresponds to the process of finding the global search corresponding to the solution planning model 1;the fitness function is employed to calculate the position of each individual seagull, which reflects the value of the objective function within the planning model; the attack process of the seagull corresponds to the local search procedure in solving the planning model.

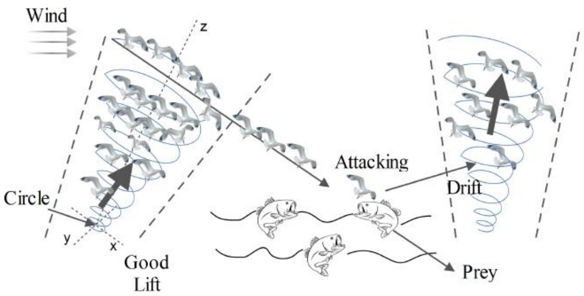

Figure 3. Schematic diagram of seagull migration and attack mode

These two behavioral expressions are shown in figure 3 [25], these correspond respectively to the global search capability and local search capability. By integrating the relationship between the algorithm and the planning model, the SOA is employed to address the multi-stage planning model.

4.1 Definition of seagull population

The planning capacity of each energy coupling facility is considered as the position of the individual seagull, provided that the output limits of each energy coupling facility are satisfied., the electric, heat, and gas power balance constraints of the operation in IES and system energy purchase constraints are satisfied.

4.2 Migration (global search)

The SOA simulates the migration process of seagull, which corresponds to the solution process of the optimal value of the objective function of IES planning model. And the migration process of seagull is shown in figure 4. In this process, seagulls need to meet the following conditions:

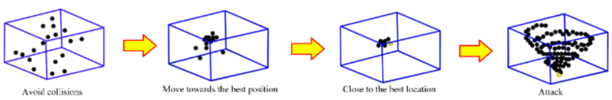

Figure 4. The migration process of seagull

1) Avoid Collision:

Variable A is introduced to avoid the collision between each individual in the seagull population, to improve the accuracy of IES planning. Calculate new search agent location, that is, the possible optimal solution of the planning model.

$$C_s(t) = A \times P_s(t) \tag{21}$$

Where $C_s(t)$ suggests that the search agent positioned here does not encounter conflicts with other agents. $P_s(t)$ specifies the position of the active search agent during the iteration and delineates its activities within the defined spatial search area.

$$A = f_c - [t \times (f_c / Max_{iteration})] \tag{22}$$

Where the frequency of A is linearly regulated by , resulting in a linear decrease from 2 to 0; this defines the range for the number of iterations t is 0 to $Max_{iteration}$, with integer increments.

2) Move towards the best position:

Upon successfully avoiding collisions and conflicts with neighboring agents, the search agent advances toward the optimal position., that is, it starts looking for the optimal solution of the multi-stage planning model.

$$M_s(t) = B \times [P_{bs}(t) - P_s(t)] \tag{23}$$

Where $M_s(t)$ represents the direction of moving from the search agent position to the best position; $P_{bs}(t)$ represents the best position for the seagull, that is, the optimal solution of the planning model. B is a random quantity, used to balance the relationship between local and global.

$$B = 2 \times A^2 \times r_d \tag{24}$$

Where the value range of r_d is a random quantity from 0 to 1.

3) Close to the best location:

Finally, seagulls will fly to the best position and reach a new position, which is the optimal solution of the model.

$$D_s(t) = |C_s(t) - M_s(t)| \tag{25}$$

Where $D_s(t)$ is the new position of the seagull.

4.3 Attack (local search)

The angle and velocity of the seagull attacking prey correspond to the speed of solving the optimal value of IES planning model. During the migration process, the optimal height of the attack is maintained through the relationship between the movement of the wings and the weight of the body. Upon locating the prey, the seagull engages in a spiral attack by adjusting its angle and velocity. The motion behavior of seagulls in three-dimensional space is articulated as follows:

$$x = \cos\theta \times r \tag{26}$$

$$y = \sin\theta \times r \tag{27}$$

$$z = \theta \times r \tag{28}$$

$$r = e^{\theta v} \times u \tag{29}$$

Where r represents the radius of the seagulls' attack spiral; θ randomly takes an angle from 0 to 2π; u and v are set constants.

After calculation, the attack position of the seagull can be obtained as:

$$P_s(t) = P_{bs}(t) + D_s(t) \times x \times z \times y \tag{30}$$

Where $P_s(t)$ is the attack position of seagull.

4.4 Restriction condition processing when seagull population in updated

This paper addresses the power constraints associated with the capacity allocation of planning cycle economic equipment, taking into account annual investment, operational, and maintenance costs. Due to the mutual restriction among the planned equipment capacity, system operating power and total load demand, the fitness value of seagull population should not only consider the output limit of the planned equipment operation, but also add the penalty function as a component. During the execution of SOA, the fitness value of seagull population is verified with the constraint conditions of the multi-objective programming model of IES. If it is not satisfied, the fitness value of the seagull population is given a larger value.

4.5 Solution process

1) Main Solution Steps

For the multi-stage IES planning model established in section III, the SOA is used for optimization calculations The specific steps are outlined as follows:

(1) Configure the parameters A, $Max_{iteration}$, B, u, f_c and v in SOA

(2) Seagull population initialization, that is to meet all the constraints of the safe operation of IES

(3) While ($t < Max_{iteration}$)

(4) {

(5) Use the established multi-stage IES planning model to calculate the possible solutions represented by each seagull

(6) r_d takes the random quantity in (0,1)

(7) θ takes the random quantity in [0, 2π]

(8) Calculate D_s using equation (25)

(9) Use equation (30) to calculate P_s

(10) Introduce a penalty function to determine whether P_s meets the constraints of the multi-objective planning model of IES

(11) Update fitness value and the best seagull position

(12) }

(13) Obtain the optimal position of the seagull, output the optimal value of the planning model and the multi-stage planning scheme

(14) End

2) The process of calculating the possible optimal solution ($P_s(t)$) of the model

(1) for i=1 to n

(2) {

(3) Use the planning optimization model to calculate the possible optimal solution for each seagull

(4) }

(5) Update fitness value and the best seagull position

(6) Output the best fitness value of seagull, that is, the optimal solution of the planning optimization model

(7) End

3) he procedure for updating the optimal position of the seagull and the corresponding solution of the planning model.

(1) for i=1 to n

(2) {

(3) If the fitness value of seagull (i) is less than the optimal value of the planning model

(4) {

(5) Replace the optimal value of the planning model for the fitness value associated with the seagull. (i)

(6) Replace the optimal value of the planning model with the position of the seagull (i)

(7) }

(8) }

(9) Output model optimal value and optimal position

(10) End the program

The main solution steps are shown in Figure 5.

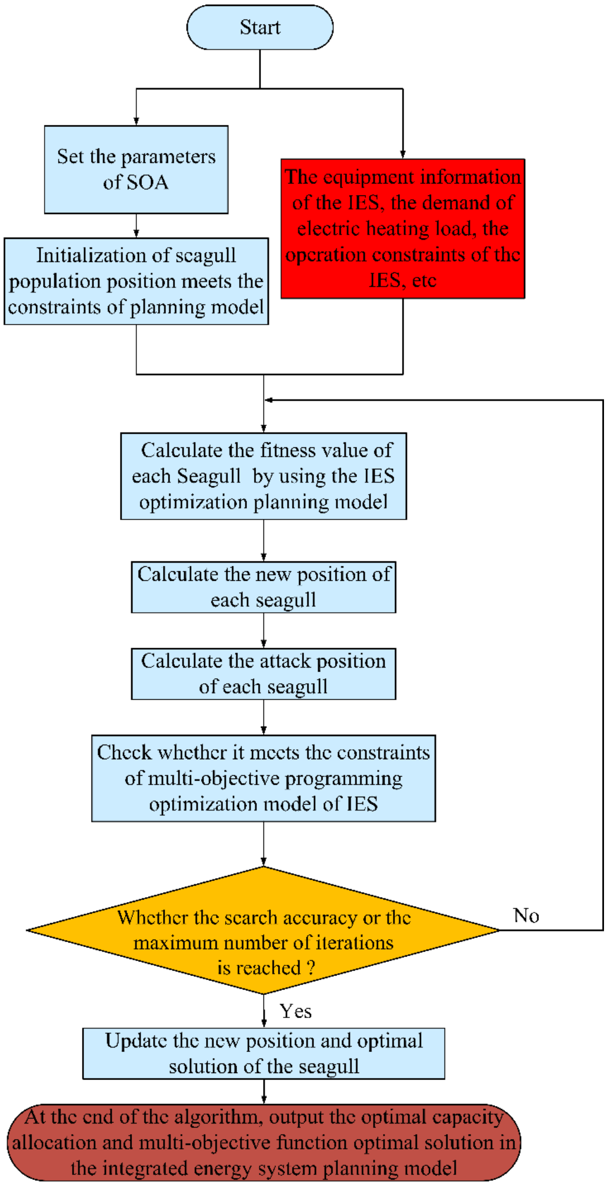

Figure 5. Flow chart of seagull algorithm

5 Case analysis

This paper utilizes an industrial park in northern China as a case study for analysis. The energy consumption of users within the park is concentrated, primarily encompassing electric load demand, thermal load demand, and gas load demand. "It is presumed that the planning period extends over 15 years, with a relatively rapid initial load growth rate, a moderate medium-term growth rate, and a gradual stabilization of the later load levels. The planning cycle is segmented into three stages: S1, S2, and S3, with durations of 3 years, 5 years, and 7 years respectively. Planning information is illustrated in Figure 6.

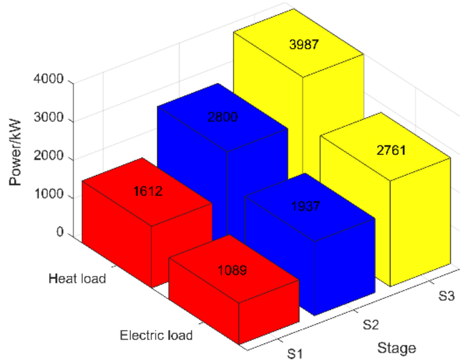

Figure 6. Electricity and heat load demand information diagram at various planning stages

The candidate equipment types at each stage include PV, CHP, HP, EB, GB, ES and HS. The relevant parameters are shown in Table 1 [26],[27].

Table 1. Multi-Energy coupling equipment parameter information

Equipment	Parameters	Value
PV	Investment cost Operation and maintenance cost	9000￥/kW 0.04￥/kW
CHP	Investment cost Maintenance cost/Operation cost Gas-heat conversion efficiency Gas-electric conversion efficiency Life	8000￥/kW 0.05￥/kW 0.45 0.3 25Years
HP	Investment cost Maintenance cost/Operation cost Electric heating energy efficiency ratio Life	3000￥/kW 0.03￥/kW 3.8 25Years
GB	Investment cost Maintenance cost/Operation cost Gas-heat conversion efficiency Life	1000￥/kW 0.03￥/kW 0.95 25Years
EB	Investment cost Maintenance cost/Operation cost Electricity-heat conversion efficiency Life	1000￥/kW 0.04￥/kW 0.95 25Years
ES	Investment cost Maintenance cost/Operation cost Maximum charging / discharging efficiency Life	750￥/kW 0.03￥/kW 25% 20Years
HS	Investment cost Maintenance cost/Operation cost Maximum charging / discharging efficiency Life	40￥/kW 0.03￥/kW 40% 20Years

This paper utilizes data from typical days in summer, transitional seasons, and winter to accurately represent the actual conditions of the park. The electricity/heat/photovoltaic output curves of each typical day (take the standard unit value) are shown in Figures 7, 8, and 9, respectively. The park implements a moment-of-use electricity pricing structure, as depicted in Figure 10. The fixed rate for natural gas is 2.75 ￥/m³, and its lower heating value is 9.7 kWh/m³.. After conversion, the natural gas price is 0.28￥/kWh. The discount rate is 8%.

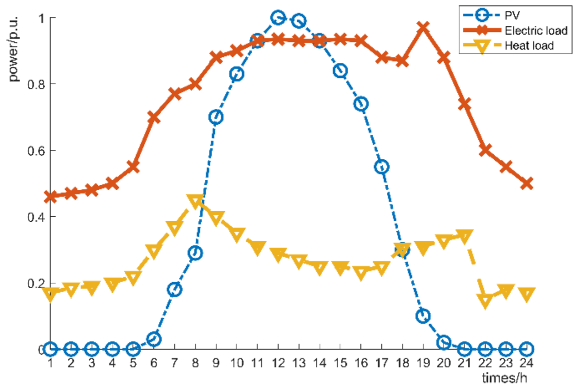

Figure 7. Typical days (summer)

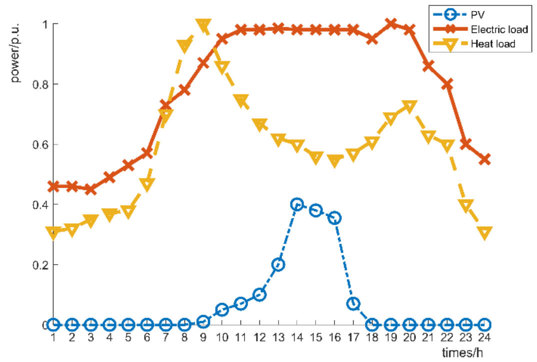

Figure 8. Typical days (winter)

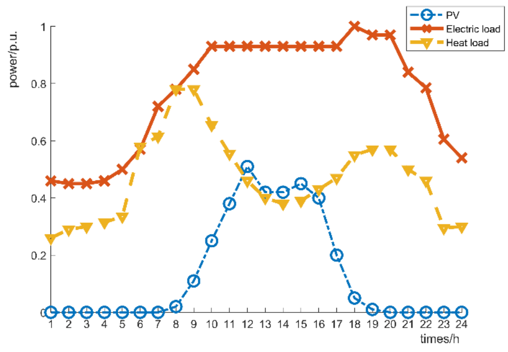

Figure 9. Typical days of the transition season

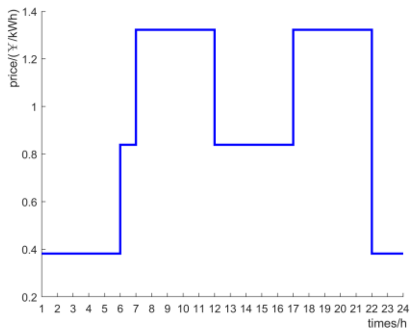

Figure 10. Moment-of-use electricity price curve

Table 2. Configuration results of multi-energy coupling equipment in each planning stage

Equipment/kW	PV		CHP		HP		ES		HS		GB		EB	
Stage	I	II	I	II	I	II	I	II	I	II	I	II	I	II
S1	1430	2150	755	1515	755	1270	2035	2855	1905	3645	0	50	0	50
S2	830	0	555	0	565	0	700	0	1430	0	0	0	0	0
S3	850	0	555	0	400	0	0	0	180	0	0	0	0	0
Total	3110	2150	1865	1515	1720	1270	2735	2855	3575	3645	0	50	0	50

To assess the efficacy of the multi-stage planning approach and the SOA strategy presented in this paper, a calculation example is established with two scenarios for comparison:

Condition I: The IES planning is segmented into multiple stages, utilizing both the multi-stage planning model and SOA to derive the optimal configuration scheme for each stage.

Condition II: In contrast, without employing multi-stage planning for IES, a general system planning scheme is derived solely from the initial phase of planning. The configuration results of multi-energy coupling equipment in each planning stage are shown in table 2.

Set SOA according to the information provided in the following table:

Table 3. SOA algorithm configuration information

Parameters	Value
Population size	50
iterations quantity(max)	1000
f_c	2
u	1
v	1
A	Controlled by f_c
B	Randomly controlled by A

5.1 Analysis of planning and configuration results

The planning schemes of Condition I and Condition II are solved, and the configuration types and parameters of system equipment in each stage are obtained, as shown in Table 3. In terms of equipment selection, Condition I is not configured with EB and GB, while Condition II is configured with a small amount of EB and GB. Until the planning is completed, the capacity of PV, CHP, HP as well as other primary energy supply apparatus in Condition I is higher than that in Condition II, while the total configuration capacity of ES, HS and other energy storage equipment is lower than that in Condition II.

5.2 Seagull algorithm and economic analysis

As shown in Figure 11, it reflects the variation in the seagull population corresponding to the increase in the number of iterations. The Figure 11 shows that the SOA iteration can stabilize convergence after about 420 iterations. The convergence process is faster and the jitter is smaller. Figure 12 presents a comparison of the full planning cycle economics between Condition I and Condition II. It is evident that the overall planning cycle cost for Condition I is lower than that of Condition II, resulting in savings of approximately 5.7 million yuan in investment costs.

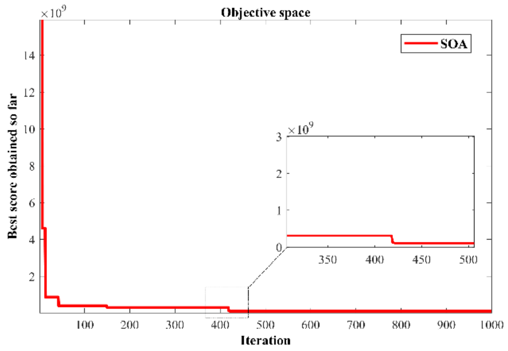

Figure 11. Multi-stage objective function changes with iterations quantity

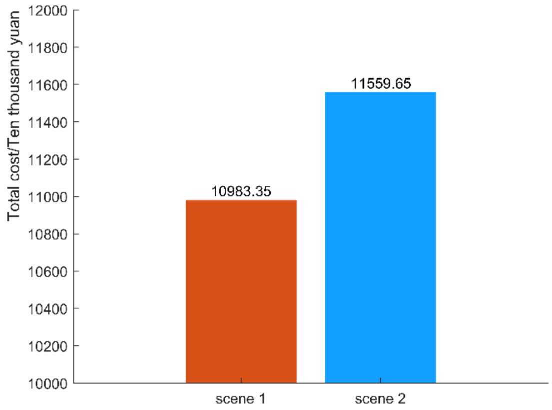

Figure 12. Economic comparison of the whole planning cycle

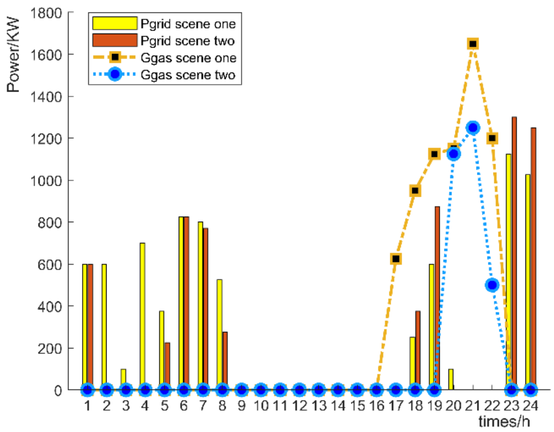

Figure 13. Typical daily energy purchase in S1 summer

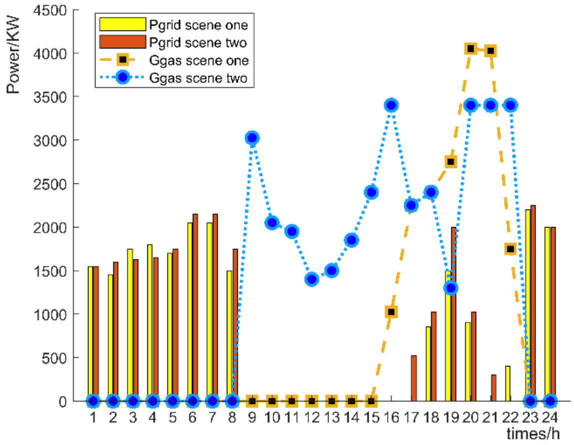

Figure 14. Typical daily energy purchase in S3 summer

In stage S1, Condition I avoids the waste of capacity and idle equipment caused by advanced construction and large equipment capacity configuration in Condition II. At the same moment, as shown in Figure 13, Condition I needs to purchase more electric energy and natural gas from outside than Condition II, consequently, the annual operating cost is elevated. However, the increased annual operating cost in Condition I is counterbalanced by the savings in equipment investment costs, resulting in nearly equivalent annual operating costs for both Condition I and Condition II.

In stage S3, as shown in Figure 14, Condition II purchase more electric energy and natural gas from the outside than Condition I, and the annual operating cost is greatly increased. This is because the equipment capacity planned in Condition II cannot meet the growing energy demand of IES at this moment. Although the equipment investment cost of Condition I is higher, it saves a relatively high annual operating cost, so the annual operating cost of Condition I is less than that of Condition II.

In summary, Condition I has better operation economy than Condition II. Through multi-stage planning, it not only avoids the waste of resources caused by advanced investment, but also meets the growing load demand, and improves the economy of the whole planning cycle.

5.3 Comparative analysis of equipment operation

In stage S1, Condition II has the problem of redundant equipment capacity and low output of some equipment. Figures 15-18 illustrate the output diagrams of various power coupling equipment during typical summer and transitional season days, thereby reflecting the performance of these facilities as shown in Table 1, the CHP configuration capacity of Condition I is about one-half that of Condition II, and the ES configuration capacity is about two-thirds of Condition II.

However, on a typical summer day, the operating power of ES in Condition I is slightly smaller than in Condition II, and the CHP output is higher than in Condition II. On a typical day of the transition season, the energy charged and discharged by the ES system, as well as the output from the CHP system in Condition I, are greater than those observed in Condition II.; In addition, the GB and EB output of Condition II has always been 0, which has been abandoned. It shows that Condition II has the problem of idle equipment due to capacity redundancy.

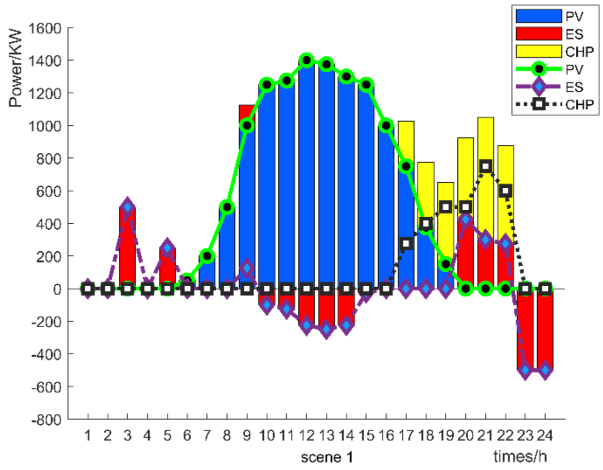

Figure 15. Part of the output diagram of power coupling equipment on a typical summer day in Condition I

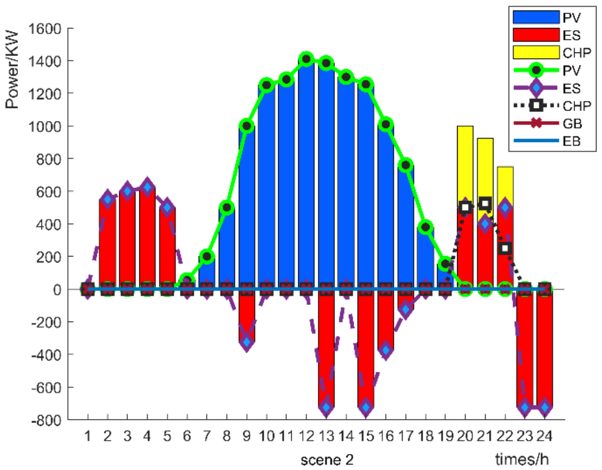

Figure 16. Part of the output diagram of power coupling equipment on a typical summer day in Condition II

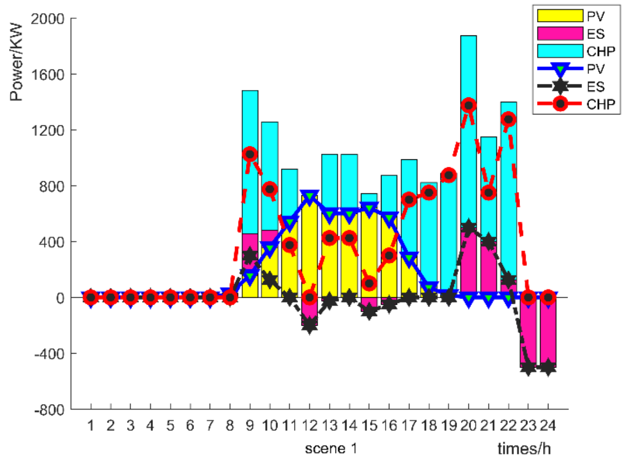

Figure 17. Part of the output diagram of power coupling equipment on a typical day during the transition season in Condition I

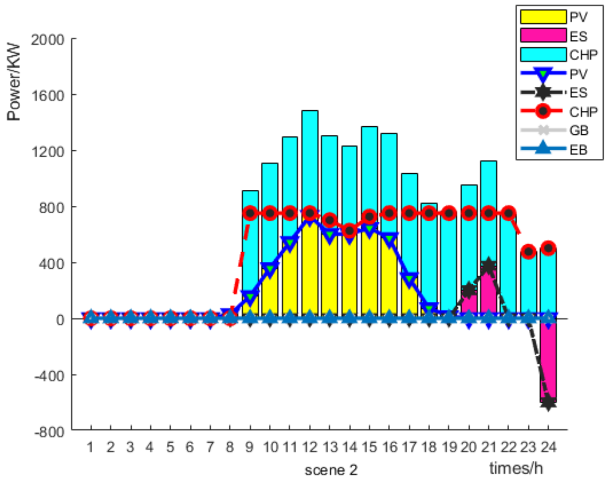

Figure 18. Part of the output diagram of power coupling equipment on a typical day during the transition season in condition ii

6. Conclusion

This study proposes a multi-stage planning methodology for Integrated Energy Systems (IES) aimed at mitigating equipment idleness caused by premature investments and capacity redundancies during the initial phases of IES operation, as well as reducing elevated operational costs stemming from inadequate equipment capacity and increased external energy procurement in later stages. The multi-stage planning model segments the planning cycle into several distinct stages, establishing a series of constraints including multi-energy coupling, equipment capacity, and energy purchasing to derive economic indicators and capacity configuration data for each stage. Given the complexity inherent in this multi-stage planning model, this paper employs a Self-Organizing Algorithm (SOA) with robust global and local optimization capabilities to address the formulated model. The findings substantiate the efficacy of both the proposed multi-stage planning approach and SOA.

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