Bi-Level Multi-Objective Optimal Design of Integrated Energy System Under Low-Carbon Background

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ABSTRACT The integrated energy system can realize the coupling and complementation of various energy sources such as cold, heat and electricity, and plays an important role in the consumption of renewable energy. This paper proposes a bi-level optimal design method for integrated energy system from both economic and carbon emissions aspects. The upper model aims at maximizing the system economy and optimizes the selection and capacity allocation of renewable energy power generation, storage and conversion equipment to meet the demands in the region. The lower model aims at maximizing the environment-protection performance and minimizes the system’s carbon emissions. Since the lower model contains binary variables to characterize trading states and charging and discharging states, the model cannot be transformed into a mathematical program with equilibrium constraints. To effectively handle this problem, the reformulation and decomposition method is adopted. Case studies show that this bi-level model can effectively consider the influence of the objective function in the lower model on the optimal capacity configuration in the upper model, avoid the influence of different objective weights when the multi-objective model is converted to the single-objective model, and obtain the global optimal solution.

INDEX TERMS Integrated energy system, bi-level planning method, multi-objective, low carbon.

I. INTRODUCTION

With human society’s development, the contradiction between energy demand and the living environment is becoming more and more serious. How to improve the energy utilization efficiency and explore renewable energy is a common concern of all countries around the world [1], [2]. With the characteristics of high renewable energy integration and low carbon emissions, the integrated energy system (IES) has attracted more and more attention and research [3]. In the IES, devices with different functions, such as achieving energy co-production, conversion, and storage, are integrated together to supply electricity, heat, and cooling power for terminals [4]. Since the IES contains multiple uncertainties raised by renewables and terminals, selecting the most suitable co-generation, conversion, and storage devices to achieve economical and reliable energy supply is the key to the planning and design of the multi-energy system [5], [6].

With the integration of various technologies, the planning process of the IES needs to base on the actual demands. For instance, to handle the uncertainties caused by multi-source and multi-load, the authors of [7] proposed a bi-level planning model for IES with flexible means consist of energy storage and demand response. Considering the expensive investment cost of electric storage devices, the authors of [8] proposed an optimal planning method for islanded IES incorporating solar and biogas energy. This model can use the complementarity nature of solar and biogas energy to reduce electric storage devices equipped in the IES. Based on Energy Hub theory, the authors of [9] proposes a data-driven two-stage planning model for energy hubs connected by multi-carrier energy networks. The authors of [10] proposed an expansion planning model for integrated power and heating systems under a market environment. In the model solution, the model
considering the interactions of DHSCOs, GENCOs, and ISO is handled based on decentralized decision-making processes. In addition, there are also some studies that carry out IES planning from the perspective of public utilities [11], grid auxiliary services [12], and latitude differences [13].

There have been some researches on multi-objective optimization [14]–[17]. For instance, literature [18] proposes a two-stage mixed-integer linear programming approach for the regional IES planning, with the objective to achieve the distributed renewable integration. Under a low-carbon environment, the authors of [19] proposed a bi-level expansion planning model of IES using a decentralized approach, and the low-carbon constraints affect both the planning approaches for different levels of IES. Considering both carbon emissions and economy, the authors of [20] proposed a unit commitment for power systems, and then uses multi-objective evolutionary algorithms to solve the problem. The multi-objective optimal planning for active distribution networks (ADN) integrated with electric vehicles is proposed in [21], with the objectives of both the investment costs and energy losses in ADN and traffic flows. From the above research, we can conclude that the principle of multi-objective solution mainly includes the conversion of multiple objectives into single objective, or the application of different levels or stages. However, when converting the multi-objective function into a single objective function, the optimization result is greatly affected by the objective weight, which is generally set artificially and often not intelligent and accurate enough. When using the bi-level frameworks to cope with the multi-objective problems, the modeling of the lower level is generally convex to solve effectively. Considering the inconsistency between economics and environmental benefits, a multi-objective planning method for a district-level IES is proposed in [22], and the dual theory is applied to make the objectives to be optimized simultaneously. However, if the model has binary variables that characterize the interactive states, it will cause the model to be non-convex. Under this scenario, the strong duality theory is not applicable to transform the maximum problems into minimum problems, and thus the multi-objective planning model cannot be optimized simultaneously.

Therefore, this paper proposes a bi-level multi-objective optimal design of regional integrated energy system (RIES), with the considerations of economics and carbon emissions. The main contributions are listed as follows:

1) We propose a bi-level multi-objective optimal design of integrated energy system considering both economic and environmental benefits.

2) In the model solution, the reformulation and decomposition method is used to deal with the non-convex problem of the model caused by the introduction of 0-1 state variables. Then, the bi-level multi-objective model can be solved efficiently and quickly.

Moreover, this model allows the introduction of binary variables in the lower level, which is essential for characterizing the operating state of the system. Firstly, we introduce the structure of the RIES; secondly, we describe the bi-level multi-objective programming model. Whereafter, the solution strategy is given. Finally, case studies are implemented to verify the superiority and effectiveness of the method. Case studies are given in Section IV, and Section V concludes this paper.

II. STRUCTURE OF RIES

FIGURE 1 shows the structure of the RIES. The RIES includes wind turbines (WT), gas turbines (GT), gas boilers (GB), batteries (BT), thermal storage tanks (TT), absorption chiller (AC), and heat pumps (HP). Additionally, the RIES can trade with the upper active distributed networks (ADN) and natural gas networks (NGN). Based on Energy Hub, the integrated input-output relationships are shown in the following:

\[ p_{st}^{G+/-} = p_{st}^{G} + p_{st}^{WT} + p_{st}^{BT} - p_{st}^{HP} = p_{st}^{E} \]  
\[ \lambda_{st}^G p_{st}^{GT} + \lambda_{st}^H p_{st}^{GB} + \lambda_{st}^T p_{st}^{TT} + \alpha_{st} \eta_{st}^{HP-H} p_{st}^{HP} - p_{st}^{TT} - p_{st}^{AC} = p_{st}^{H} \]  
\[ \eta_{st}^{AC} p_{st}^{AC} + (1 - \alpha_{st}) \eta_{st}^{HP-C} p_{st}^{HP} = p_{st}^{C} \]  
\[ p_{st}^{GT} / p_{st}^{GB} / p_{st}^{AC} = p_{st}^{GAS} \]

where \( p_{st}^{G+/-} \) indicates the purchased/sold electric power between RIES and ADN in scenario \( s \) at time \( t \). \( p_{st}^{E} \) means the output electric power of GT. \( p_{st}^{WT} \) is the output electric power of WT in scenario \( s \) at time \( t \). \( p_{st}^{BT+/-} \) is the charging/discharging power of BT in scenario \( s \) at time \( t \). \( p_{st}^{HP} \) is the input power of HP in scenario \( s \) at time \( t \). \( p_{st}^{TT+/-} \) means output heat power of GB in scenario \( s \) at time \( t \). \( p_{st}^{TT+/-} \) means the charging/releasing thermal power of TT in scenario \( s \) at time \( t \). \( p_{st}^{AC} \) is the input thermal power of AC in scenario \( s \) at time \( t \). \( p_{st}^{GAS} \) represents the purchased gas power by RMES in scenario \( s \) at time \( t \). \( p_{st}^{E} / p_{st}^{H} / p_{st}^{C} \) represents the output electric/heat/cooling power of RMES in scenario \( s \) at time \( t \), respectively. In addition, \( \eta_{st}^{HP-H/C} \) represents the heating/cooling efficiency of HP, \( \alpha_{st} \) represents the scheduling factor of HP to supply heating or cooling power in scenario \( s \) at time \( t \). \( \eta_{st}^{AC} \) represents the efficiency of AC, \( \eta_{st}^{GB} \) represents the energy efficiency of GB, \( \lambda_{st}^G \) represents the power generation efficiency of GT, and \( \lambda_{st}^H \) represents the
heat-to-electricity ratio of GT. Equations (1)-(3) are the balance equations of electric power, heating power, and cold power in the RMES, and equation (4) represents the gas flow balance within the RIES.

**III. BI-LEVEL PLANNING MODEL**

The upper-level planning model aims at minimizing the system total cost, which consists of the annual investment cost, annual operation and maintenance cost, annual purchase cost of natural gas, and annual interaction cost with the grid in the integrated energy system. The lower-level model minimizes the annual carbon emissions. The objective functions and constraints are as follows:

\[
\text{min}(C_{\text{INVESTMENT}} + C_{\text{OPERATION}}) \tag{5}
\]

\[
C_{\text{INVESTMENT}} = \begin{bmatrix} f_{GT}^x c_{GT}^x x_{GT} + f_{GB}^x (c_{GB}^x x_{GB} + f_{BT}^x c_{BT}^x x_{BT} + f_{TT}^x c_{TT}^x x_{TT}) \\
+f_{AC}^x c_{AC}^x x_{AC} + f_{HP}^x (c_{HP}^x x_{HP} + f_{WT}^x c_{WT}^x x_{WT}) \\
+f_{GB}^x (c_{GB}^x x_{GB} + f_{BT}^x c_{BT}^x x_{BT} + f_{TT}^x c_{TT}^x x_{TT}) \end{bmatrix} \tag{6}
\]

\[
\text{C_{OPERATION}} = 365 \sum_{s \in S} w(s) \left( \sum_{t \in T} \left( \xi^x_{st} + \xi^G_{st} + \chi w_s \right) \Delta t \right) \tag{7}
\]

\[
\text{s.t.} 0 \leq x^x \leq C_{\text{max}}^x \tag{8}
\]

\[
\text{min} \left( 365 \sum_{s \in S} w(s) \left( \sum_{t \in T} \frac{v_{GT}^x p_{GT}^x + v_{GB}^x p_{GB}^x}{\eta_{GT}^x} \right) \Delta t \right) \tag{9}
\]

\[
0 \leq P_{st}^x \leq x^x \tag{10}
\]

\[
0 \leq P_{st}^{WT} \leq \rho_{st}^{WT} x_{st}^{WT} \tag{11}
\]

\[
0 \leq P_{st}^{GB} \leq \tilde{\xi}^{G+} + \tilde{\xi}^{G-} \tag{12}
\]

\[
0 \leq P_{st}^{BT+} \leq \xi_{st}^{BT+} + \tilde{\xi}^{BT+} \tag{14}
\]

\[
0 \leq P_{st}^{BT-} \leq \xi_{st}^{BT-} + \tilde{\xi}^{BT-} \tag{15}
\]

\[
0 \leq P_{st}^{TT+} \leq \xi_{st}^{TT+} + \tilde{\xi}^{TT+} \tag{16}
\]

\[
0 \leq P_{st}^{TT-} \leq \xi_{st}^{TT-} + \tilde{\xi}^{TT-} \tag{17}
\]

\[
\text{Soc}_{\text{MIN}}^{BT} \leq \text{Soc}_{\text{MIN}}^{BT} \leq \text{Soc}_{\text{MAX}}^{BT} \tag{18}
\]

\[
\text{Soc}_{\text{MIN}}^{TT} \leq \text{Soc}_{\text{MIN}}^{TT} \leq \text{Soc}_{\text{MAX}}^{TT} \tag{21}
\]

\[
\text{Soc}_{\text{MIN}}^{TT} = \text{Soc}_{\text{MIN}}^{TT} + \left( Q_{st}^{TT+} - Q_{st}^{TT-} \right) \Delta t \tag{22}
\]

where \( C_{\text{INVESTMENT}} \) and \( C_{\text{OPERATION}} \) are the annual investment cost and annual operation cost of RMES, which is the sum of annual investment costs of GT, GB, BT, TT, AC, HP and WT. \( f^x = \frac{\theta x_t}{(1+\theta)^t-1} \) and \( N^x \) are the recovery factor and lifetime of device \( x \), which denotes GT, GB, BT, TT, AC, HP and WT, respectively. \( \theta \) is the discount rate. \( c^x \) and \( \chi \) is the unit investment cost and capacity of device \( x \). In (7), \( w(s) \) represents the share of scenario \( s \) in the whole year and imposes the sum of \( w(s) \) equals 1. \( c_{st}^{GB}/c_{st}^{GT}/c_{st}^{AC}/c_{st}^{HP}/c_{st}^{WT}/c_{st}^{BT}/c_{st}^{TT} \) is the unit O&M costs of the corresponding devices, \( c_{st}^{GB} \) is the unit cost of purchasing natural gas, and \( c_{st}^{G/-} \) is the unit purchased/sold electricity costs in scenario \( s \) at time \( t \), respectively. In addition, \( S \) and \( N \) respectively represent the set of operating scenarios and scheduling periods. Formula (8) limits the optimal investment capacity of each device less than the maximum capacity \( C_{\text{max}}^x \). Formula (9) shows the objective in the lower-level model, which minimizing the carbon emissions of RIES. \( v_{GT}^x/g_{GT}^x \) is the corresponding carbon emission coefficients by GT/GB/upper grid, respectively. Formula (10) means that the maximum operating power of each equipment should not be greater than the installed capacity of the corresponding equipment. Formula (11) gives that the output of WT is not greater than the maximum output power, and \( \rho_{st}^{WT} \) is the power output of 1-kW WT in scenario \( s \) at time \( t \). Formula (12)-(13) limits the maximum buying/selling power with the grid. Formulas (14)-(17) represent the charging and discharging power constraints of BT and TT, respectively. Formulas (18)-(20) constraint the storage level of BT and keep the beginning and ending states the same in a typical day cycle. The similarity is true for TT, as shown in Formulas (21)-(23). Formula (24) is the power balance constraint of electricity, heating, and cooling power within the RIES.

**IV. SOLUTION STRATEGY**

Generally, the bi-level planning model can be transform into mathematical programs with equilibrium constraints (MPEC) model [23], [24] for one-time solution based on duality theory or Karush–Kuhn–Tucker conditions. When facing the bi-level max-min problems, the column-and-constraint generation algorithm [25], [26] and Benders decomposition algorithm [27], [28] can transform the max-min problem into single level max problem to solve. However, this process still requires the inner layer model to be convex. In this work, the lower-level model introduces plenty of 0-1 variables to characterize the interactive states, so it cannot be directly converted to the MPEC model. To this end, we apply the reformulation and decomposition method [29], which can first deal with the 0-1 variables to keep the model convex in an iterative situation. For clarity, we write the above problem in the following
matrix form:

\[
\begin{aligned}
\min_{x,y,z} & \quad a^T x + b^T y \\
\text{s.t.} & \quad Ax \leq d, \quad y, z \in \mathbb{R}^n \\
\end{aligned}
\]

where \( x \) is the investment capacity variable in the upper-level model, \( y \) and \( z \) are the continuous and binary variables in the lower-level model. \( A, C, E, F, G, a, b, c, d, e, \) and \( f \) are all coefficient matrix.

Firstly, the above problems are decomposed into a main problem and two sub-problems. The main problem is described as follows:

\[
\begin{aligned}
\min_{x,y,z} & \quad a^T x + b^T y \\
\text{s.t.} & \quad Ax \leq d, \quad Cy = e, \quad Ey + Fz = f - Gx, \quad \text{and} \\
& \quad c^T y \leq (z^{(l)} F^T y + 0) (l), \\
& \quad E^T \lambda^{(l)} + F^T y (l) + c = 0, \quad \lambda^{(l)} \geq 0, \quad 1 \leq l \leq m
\end{aligned}
\]

(25)

where \( \lambda \) and \( \nu \) are the dual variables corresponding to the equality and inequality constraints of the lower model in (25). The constraints include equality constraints and inequality constraints of the lower model in (25). The lower boundary is \( \min_{x,y,z} a^T x + b^T y \) which is obtained by solving the main problem in each iteration \( m \).

The Sub-question 1 is described as follows:

\[
\begin{aligned}
\nu(x^*) = & \quad \min_{y,z} c^T y \\
\text{s.t.} & \quad Cy = e, \quad Ey + Fz = f - Gx^*
\end{aligned}
\]

(27)

where \( x^* \) is the upper-level investment variable optimized from the main problem (26), which is taken as a known quantity into the sub-problem 1 to solve the lower-level objective function.

The Sub-question 2 is described as follows:

\[
\begin{aligned}
\psi(x^*) = & \quad \min_{y,z} b^T y \\
\text{s.t.} & \quad c^T y \leq \nu(x^*), \quad Cy = e, \quad Ey + Fz = f - Gx^*
\end{aligned}
\]

(28)

Sub-problem 2 is used to solve the annual operating cost in the upper model and obtain the upper boundary value of the model.

The specific solution process given in FIGURE 2 is as follows:

**Step 0:** Initialize: Set the lower boundary \( LB = -\infty \), the upper boundary \( UB = +\infty \), the number of iterations \( n = 1 \), and the convergence condition \( \epsilon_{\text{down}} = 0.01 \);

**Step 1:** Solve the main problem, obtain \( x^* \) and update the lower boundary \( LB = a^T x + b^T y \);

**Step 2:** Based on \( x^* \), solve the Sub-problem 1 and obtain \( \nu(x^*) \);

**Step 3:** With \( \nu(x^*) \), solve the Sub-problem 2 and obtain 0-1 state binary \( z^* \);

**Step 4:** If UB-LB \( \leq \epsilon_{\text{down}} \), return \( x^{sr+1} \) and stop the loop; otherwise, go to Step 5;

**Step 5:** Add the following constraints to the main problem, update \( m = m + 1 \), and return to Step 1.

\[
\begin{aligned}
c^T y \leq (z^{(l)} F^T y + 0) (l), & \quad E^T \lambda^{(l)} + F^T y (l) + c = 0, \quad \lambda^{(l)} \geq 0
\end{aligned}
\]

(29)

The main problem is a complementary program that can be converted into a regular MIP by linearizing using big-M method. Then, this algorithm dynamically provides stronger lower (from the main problem) bounds and upper (from sub-problems) until the difference between bounds is not larger than the convergence condition \( \epsilon_{\text{down}} \). The convergence proof can be seen in [30].

**V. RESULTS**

In this section, we use the RIES shown in FIGURE 1 to perform the case studies, to verify the robust planning and design method of RIES that considers the temporal-correlation proposed in this article. Three typical days representing summer, transition season, and winter are selected. Each typical day contains 24 time periods. Since the optimization results of each typical day are independent, we integrate them into 72 time periods. The data is shown in FIGURE 1. In addition, Table 1-2 shows the unit investment costs of various equipment and related prices and equipment parameters [18], [31], [32].

**VI. COMPARATIVE ANALYSIS OF OPTIMIZATION RESULTS**

The optimal results are shown in Table 3, based on the data and parameters above. Case 1 only considers the economics...
TABLE 1. Parameters of system and equipment.

| Device | Efficiency | Unit investment cost (¥/kW) |
|--------|------------|-------------------------------|
| GT     | 0.07 x 1.5 | 13870                         |
| GB     | 0.9        | 2000                          |
| AT     | 1.2        | 1228                          |
| HP     | 0.07 x 1.2 | 3870                          |
| BT     | 0.9        | 90                            |
| TT     | 0.9        | 90                            |
| BT     | -          | 16070                         |

TABLE 2. Parameter of price.

| Parameter | Price (¥/kWh) | Time (h) |
|-----------|---------------|----------|
| $C_{\text{gas}}$ | 0.345 | 00:00-24:00 |
| $C_{\text{w}}$   | 0.01  | 00:00-24:00 |
| $C_{\text{e}}$   | 0.45  | 00:00-24:00 |
| $C_{\text{o}}$   | 0.47  | 00:00-08:00 |
| $C_{\text{o}}$   | 1.05  | 08:00-12:00, 17:00-21:00 |
| $C_{\text{o}}$   | 0.75  | 12:00-13:00, 21:00-00:00 |

TABLE 3. Optimal results.

| Case | GT (MW) | GB (MW) | BT (MW) | TT (MW) | HP (MW) | AT (MW) | WT (MW) | Annual investment cost (¥/kW) | Annual operating cost (¥/kW) | Annual cost (¥/kW) | Carbon emissions (x10^6 kg) |
|------|---------|---------|---------|---------|---------|---------|---------|-----------------------------|-----------------------------|---------------------|------------------------|
| 1    | 4       | 4       | 2       | 6       | 0       | 6       | 6       | 17.2                        | 15.7                        | 33.0                | 5.12                   |
| 2    | 4       | 4       | 2       | 6       | 0       | 6       | 6       | 17.0                        | 16.7                        | 33.7                | 3.81                   |

of the upper-level model without considering the carbon emissions at the lower level; Case 2 considers both economics and carbon emissions via the proposed bi-level planning model. It can be seen from Table 3 that compared with Case 1, Case 2 is equipped with fewer gas boilers, so its investment cost is less than Case 1, but the operating cost of Case 2 is greater than Case 1, and the total cost is higher than Case 1. This is due to the lower level taking into account the carbon emissions, which makes the system economics have declined. In the carbon emission indicators, the annual carbon emissions of Case 1 are $5.12 \times 10^6$ kg, while the annual carbon emissions of Case 2 have been reduced to $3.81 \times 10^6$ kg. By comparison, it can be found that the annual carbon emissions of the system can be effectively reduced.

A. OPERATION SCENARIO ANALYSIS

FIGURE 4-5 shows the electric power balances in Cases 1-2, respectively. It can be seen from the figure that the electrical load on different typical days has obvious seasonality. Among them, the load demand on the typical day of summer is the largest, and the most amount of electricity is purchased from the upper grid. In different typical days, the output of the wind turbine is mainly concentrated in the period of 0:00-5:00 and 18:00-24:00, and the output is relatively small at noon. The gas turbine mainly produces power during the peak period of energy consumption, which is highly complementary to the WT. The battery is mainly charged at 0:00-5:00 and 18:00-24:00 in a typical day, and discharged at 8:00-12:00, to achieve peak shaving and valley filling. In addition, in Case 2, the electricity purchased from the grid at moments 2, 27, 42, 47, and 56 was significantly less than that in Case 1, but the role of the battery has gradually increased. This is because we set the carbon emission factor for power purchase from the grid to 0.785 kg/kWh. In order to reduce carbon emissions, the power purchase from the grid is reduced.

FIGURE 6-7 shows the thermal power balances in Cases 1-2, respectively. For the convenience of presentation,
we convert the summer cooling load to thermal load. It can be seen from the figure that the thermal power required in Cases 1 and 2 is mainly produced by gas turbines. GB are mainly operated on typical winter days to meet the peak heat demand when the residual heat generated by the GT is insufficient. The output of the GB in Case 2 was significantly lower than that in Case 1, but the role of the TT was further enhanced. In order to reduce annual carbon emissions, the system’s natural gas consumption is gradually reduced, since the natural gas carbon emission coefficient set in this paper is 0.19 kg/kWh. Through comparison, it can be found that the bi-level model proposed in this paper can effectively consider both system economy and carbon emissions, making the optimal configuration of the RIES more in line with actual requirements. Considering that the carbon trading market is not yet fully mature, unreasonable setting of carbon trading fees will make the system economics too large or too small. However, this bi-level planning model proposed another way to handle the multi-objective problems.

VII. CONCLUSION

This paper proposes a bi-level multi-objective planning method for the regional integrated energy system (RIES) that considers both economy and carbon emissions. The upper-level model takes system economy as the goal, optimizes equipment configuration capacity, and satisfies cooling, heating, and electricity demands within this region. The lower level model aims to minimize the carbon emissions of the system. Finally, the R&D method is used to effectively solve the model. The results show that the bi-level programming model can effectively consider both system economy and carbon emissions, making the optimal configuration of the RIES more in line with actual requirements. Considering that the carbon trading market is not yet fully mature, unreasonable setting of carbon trading fees will make the system economics too large or too small. However, this bi-level planning model proposed another way to handle the multi-objective problems.

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