Two-stage Planning of Integrated Energy System Considering Investment Flexibility

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Abstract. The Integrated Energy System (IES) can optimize the utilization of various forms of energy and effectively alleviate the problems of energy exhaustion and environmental pollution. A two-stage planning model of IES that considers the uncertainty of renewable energy and the flexibility of investment is proposed in this paper. The planning period is divided into two stages in terms of varying degrees of uncertainty based on Monte Carlo simulation. In terms of economic, technical, and environmental performance, the two-stage planning method is proved to be better than conventional single planning method. The proposed algorithm shows the superiority of multi-stage planning. In addition, it can be used for the planners to comprehensively analyze and compare the optimal decision-making schemes generated by different combinations of weight factors.

1. Introduction
As a significant research direction of the Energy Internet, the Integrated Energy System (IES) can take full account of the synergistic complementarity of different forms of energy in the process of energy production, transmission, distribution, transformation, storage and consumption [1-3]. The planning of IES is to determine the optimal decision-making scheme according to the prediction results of multiple kinds of loads, renewable energy and the existing energy network in the planning duration, so as to minimize the construction and operational costs of IES on the premise of meeting the requirements of energy demand, safety and reliability.

The planning of IES is a complicated mathematic programming problem with multi-objective, complex constraints, nonlinearity, randomness and uncertainty, which essentially belongs to a non-deterministic NP-hard problem [4]. Reference [5] pointed out that the planning of IES, to a great extent, is impacted by a large number of uncertain and unquantifiable factors. In [6], a model of combined heat and power generation system including power network and gas pipeline network was constructed based on the theory of energy concentrator, and the proposed hybrid power flow algorithm is applicable to the calculation of IES power flow. Reference [7] studied the operation mode of “source-network-load-storage” coordinated optimization and summarizes the key technologies of IES coordinated optimization. Reference [8] proposed an active distribution network planning model that includes expansion of substation, CCHP system, gas boiler, central air conditioning and so on.

The flexibility of the IES in the planning stage can be divided into operational flexibility and investment flexibility. At present, the related researches are still at its preliminary stage, and mainly focuses on the operational flexibility [9]. Operational flexibility emphasizes whether the system has...
the following four merits: adaptability to different load characteristics of cooling, heat and electricity load, peak shaving ability for the fluctuations of the renewable energy output, balancing capability among multiple energy types, and ability to improve the entire system efficiency [1]. Compared with the operational flexibility, the investment flexibility concerns about how to construct the whole system stage by stage according to the phased nature of IES construction. The key of the multi-stage programming model is to coordinate and optimize the configuration scheme of each stage to achieve the goal of overall optimization. Referring to relevant studies on the investment flexibility of power generation in the power market [10], the investment flexibility of IES planning needs to take account of the uncertainty of renewable energy output and cooling, heat and electricity load, as well as the choice of investment time.

A two-stage IES planning method considering investment flexibility is proposed in this paper. Considering the long-term uncertainty of the renewable energy output and load forecasting, this method divides the entire planning process into two stages. The system objective function is the weighted sum of the objective function of each stage. By Pareto optimality, the sensitivity of optimization results to the combinations of weight factors is analyzed.

2. Two-stage planning model

2.1. Structure

The IES can provide diverse types of energy, such as cooling, heat and electricity, so the equipment in IES is diversified and the operational characteristics are complex. The key equipment can be divided into two categories: power units and auxiliary equipment. Figure 1 demonstrates the structure of IES and the coupling relationship among the equipment. It includes a gas turbine (GT), a gas boiler (GB), a battery (BT), a thermal storage tank (TST), an electric chiller (EC) and an absorption chiller (AC). The input energy sources consist of electricity and gas; the output energy comprises electricity, cooling and heat.

![Diagram of the IES model.](image)

2.2. Objective function

Considering that the construction of IES should be done in stages, the proposed model divided the whole planning duration into two stages. The system planning duration is set to 20 years, the first stage is the first 5 years and the second stage is the next 15 years. The planners can make optimal investment decisions according to demand changes and varying prediction accuracy of different investment stages, which demonstrates the investment flexibility of the IES. The objective function includes two sub-objective functions. Each one consists of four parts: the cost of system initial investment, the operational cost, the gas cost, and the cost of electricity purchased from the grid.
\[
\begin{align*}
\min f &= \omega_1 \cdot f_1 + \omega_2 \cdot f_2 \\
&= C_{ac1} + C_{ac2} + C_{om1} + C_{om2} \\
f_2 &= C_{ac2} + C_{ac3} + C_{om2} + C_{om3} \\
\omega_1 + \omega_2 = 1 \\
0.5 \leq \omega_1 \leq 0.8
\end{align*}
\]

Where: \( f \) denotes the total objective function of IES system; \( f_1 \) and \( f_2 \) are the objective function of the first and the second stage; \( C_{ac1} \) and \( C_{ac2} \) are the system initial investment cost of the two stages, respectively; \( C_{om1} \) and \( C_{om2} \) are the operational cost of the two stages, respectively; \( C_{gas1} \) and \( C_{gas2} \) are the gas cost of the two stages, respectively; \( C_{grid1} \) and \( C_{grid2} \) are the cost of electricity bought from the grid of the two stages, respectively; \( \omega_1 \) and \( \omega_2 \) are the weight factors of the two stages, respectively; The multi-objective weight factors are usually set flexibly by the planners according to the actual situation. In this paper, the determining principle of \( \omega_1 \) and \( \omega_2 \) is \( 0.5 \leq \omega_1 \leq 0.8, \omega_1 + \omega_2 = 1 \). It should be noted that \( C_{om1}, C_{om2} \) and \( C_{grid2} \) contain two parts respectively, including the equipment installment cost in the first and second stage.

2.3. Constraints.

a) Bus balance: The constraints of bus balance are expressed as (2), where: \( P_{GT,t}, P_{BT,t}, P_{PV,t}, \) and \( P_{grid,t} \) are severally the output electrical power of gas turbine, battery, photovoltaic (PV) and the electricity bought from the grid in interval \( t \); \( Q_{TST,t} \) and \( Q_{GR,t} \) are the output heat power of thermal storage tank and gas boiler in interval \( t \); \( Q_{AC,t} \) and \( Q_{EC,t} \) are the output cooling power of absorption chiller and electric chiller in interval \( t \); \( L_{E,t}, L_{H,t} \) and \( L_{C,t} \) are the electricity, heat and cooling load in interval \( t \); \( \eta_{GT} \) denotes the efficiency of gas turbine; \( COP_{AC} \) and \( COP_{EC} \) are the refrigeration coefficients of absorption chiller and electric chiller.

\[
\begin{align*}
P_{ac1} + P_{ac2} + P_{ac3} + P_{ac4} &= L_{e,t} + Q_{ac1} / COP_{AC} \\
&= L_{e,t} + Q_{ac1} / COP_{AC}. \\
P_{ac1} \cdot (1 - \eta_{ac}) / \eta_{ac} + Q_{ac1} + Q_{ac2} &= L_{h,t} + Q_{ac1} / COP_{AC}. \\
Q_{ac1} + Q_{ac2} &= L_{c,t}.
\end{align*}
\]

b) Limit of electricity purchased from the grid: The constraints of the electrical power purchased from the main network is expressed as (3), where \( P_{grid}^{min} \) and \( P_{grid}^{max} \) are the minimum and maximum electricity IES can purchase from the grid.

\[
P_{grid}^{min} \leq P_{grid,t} \leq P_{grid}^{max}
\]

c) Operational limits of devices: The devices operation constraints are demonstrated as (4), where: \( P_{GT}^{min} \) and \( P_{GT}^{max} \) are the minimum and maximum output electrical power of gas turbine; \( Q_{GB}^{min} \) and \( Q_{GB}^{max} \) are the upper and lower limits of the output heat power of gas boiler; \( Q_{AC}^{min} \) and \( Q_{AC}^{max} \) are the upper and lower output cooling power of absorption chiller; \( Q_{AC}^{min} \) and \( Q_{AC}^{max} \) are the upper and lower output cooling power of electric chiller.

\[
\begin{align*}
P_{GT}^{min} &\leq P_{GT,t} \leq P_{GT}^{max} \\
Q_{GB}^{min} &\leq Q_{GB,t} \leq Q_{GB}^{max} \\
Q_{AC}^{min} &\leq Q_{AC,t} \leq Q_{AC}^{max} \\
Q_{AC}^{min} &\leq Q_{AC,t} \leq Q_{AC}^{max}
\end{align*}
\]

d) Battery: The battery constraints are expressed as (5), where: \( \mu_{BT,loss} \) represents the energy loss rate of battery; \( \eta_{BT,c} \) and \( \eta_{BT,d} \) are the charge and discharge efficiency of battery; \( \gamma_{BT,c} \) and \( \gamma_{BT,d} \) are the upper charge and discharge rate of battery; \( U_{BT,c,t} \) and \( U_{BT,d,t} \) are state variables of battery in interval \( t \); \( W_{BT,t}^{min} \) represents the storage status of the battery in interval \( t \); \( W_{BT}^{min} \) and \( W_{BT}^{max} \) are top and bottom limits of battery capacity, respectively.
\[ W_{c,t} = W_{c,t-1} \cdot (1 - \mu_{c,t}) + (P_{c,t-1} \cdot \eta_{c,t-1} - P_{d,t-1} / \eta_{d,t-1}) \cdot \Delta t \]
\[ 0 \leq U_{c,t-1} \cdot P_{c,t-1} \leq \gamma_{c} \cdot W_{c,t-1} \]
\[ 0 \leq U_{d,t-1} \cdot P_{d,t-1} \leq \gamma_{d} \cdot W_{d,t-1} \]
\[ W_{c,t} \leq W_{c,max} \leq W_{c,min} \]
\[ U_{c,t-1} + U_{d,t-1} \leq 1 \]  \( (5) \)

\( e) \) Thermal storage tank: The thermal storage tank constraints are expressed as (6), where: \( \mu_{TST,loss} \) represents the energy loss rate of thermal storage tank; \( \eta_{TST,c} \) and \( \eta_{TST,d} \) represents storing and releasing efficiency of thermal storage tank; \( \gamma_{TST,c} \) and \( \gamma_{TST,d} \) are the maximum store and release rate of thermal storage tank; \( U_{TST,c,t} \) and \( U_{TST,d,t} \) are state variables of store and release of battery in interval \( t \); \( W_{TST,t} \) represents the storage status of the thermal storage tank in interval \( t \); \( W_{TST,min} \) and \( W_{TST,max} \) are top and bottom limits of thermal storage tank capacity, respectively.

\[ W_{c,t} = W_{c,t-1} \cdot (1 - \mu_{c,t}) + (P_{c,t-1} \cdot \eta_{c,t-1} - P_{d,t-1} / \eta_{d,t-1}) \cdot \Delta t \]
\[ 0 \leq U_{c,t-1} \cdot P_{c,t-1} \leq \gamma_{c} \cdot W_{c,t-1} \]
\[ 0 \leq U_{d,t-1} \cdot P_{d,t-1} \leq \gamma_{d} \cdot W_{d,t-1} \]
\[ W_{c,t} \leq W_{c,max} \leq W_{c,min} \]
\[ U_{c,t-1} + U_{d,t-1} \leq 1 \]  \( (6) \)

2.4. Monte Carlo Simulation.
Monte Carlo method is usually taken to process multiple variables at the same time [11]. In this paper, the uncertain parameters of the model are PV output and demand side multi-loads. The algorithm process of this paper is divided into internal and external layers: the internal layer solves the IES planning problem, obtains the optimal configuration results of the system and calculates the evaluation index values of the system; the external layer is Monte Carlo simulation, and the probabilistic characteristics of the target function are obtained.

The target variable values characterize the economy with total annual cost, characterize energy efficiency with primary energy ratio (PER), and characterize environmental performance with annual CO\(_2\) emission (\( E_{CO2} \)). The mean value is taken as the estimated value of the target variable. The flow diagram of the algorithm is shown in figure 2.

**Figure 2.** The base load and PV output curve of three typical days.
3. Case study

In this section, two cases are constructed to demonstrate the advantages of the proposed two-stage planning model, in terms of the economic, technical, and environmental performances.

3.1. Configuration of the Case System

The example in this paper refers to a district located in the heart of the Beijing-Tianjin-Hebei region. According to the regional characteristics and current energy consumption rules of the district, 3 typical days in summer, winter and transition seasons are selected to represent the annual load and PV output characteristics. The days of each typical day are 100, 125 and 140, respectively. Each typical day is divided into 24 periods and the time interval is 1 h, then there are 72 periods in the whole year. With the development of the district, the demand of cold, heat and electricity increases, and it is roughly considered that the base load in the second stage is twice as much as that in the first stage. Figure 3(a)-(d) show three typical daily base load curve and three typical daily PV base output curve of the first stage respectively.

![Figure 3. The flow diagram of the Monte Carlo simulation.](image)

In this paper, the probability distribution of uncertain parameters of IES is deduced by investigating the historical data of PV power generation and multi-loads in the area where the district is located. Besides, relevant experience is taken into account. It is considered that $C_e$ (electricity load coefficient), $C_h$ (heat load coefficient), $C_c$ (cooling load coefficient) and $C_{PV}$ (PV output coefficient) are all subject to Normal distribution [12]. Taking into account the increase of the uncertainty of the long-term PV output and load forecasting, the standard deviation of the uncertain parameters of the PV output and load forecasting in the second stage is set to double that of the first stage. Table 1 shows the specific distribution characteristics of these uncertain parameters.
Table 1. Probability characteristics of uncertain parameters.

| Uncertain Parameters | Distribution Pattern | Probability Characteristic |
|----------------------|-----------------------|----------------------------|
|                      |                       | Mean Value | Standard Deviation |
| $C_{e1}$             | Normal distribution   | 1          | 0.2               |
| $C_{e2}$             | Normal distribution   | 1          | 0.2               |
| $C_{c1}$             | Normal distribution   | 1          | 0.2               |
| $C_{c2}$             | Normal distribution   | 1          | 0.4               |
| $C_{PV1}$            | Normal distribution   | 1          | 0.025             |
| $C_{PV2}$            | Normal distribution   | 1          | 0.05              |

In this paper, the sample number is taken as 1000. Figure 4 shows the frequency distribution of the random variables $C_{e1}$. It can be seen from figure 4 that the histogram of random parameter sampling results is close to the probability density function curve of Normal distribution. Therefore, 1000 sampling times are enough to make the sampling results conform to the distribution characteristics of various uncertain parameters.

Figure 4. The sampling result of $C_{e1}$.

In order to demonstrate the advantages of multi-stage planning, two cases are set up in this paper. Case 1 is single-stage planning for IES, without taking account of tri-generation technology or stage differences. Case 2 is the two-stage planning of IES. On the basis of case 1, the development of the district and the increase of uncertainty of load forecasting in the second stage are considered in Case 2.

In this paper, the model is debugged on Intel 32-bit machine, running on the platform of MATLAB, and the optimization solution tool is CPLEX. The optimized object is the investment capacity of two-stage equipment and the optimal objective is to achieve the overall economic optimization.

3.2. Results and discussion

3.2.1. Results. Table 2 shows the optimal configuration results for two cases. It should be noted that averages are taken as the estimated value of the evaluation indicators.
Table 2. Optimal configuration results of two cases.

| Optimal configuration results | Case1: Single stage planning of IES | Case 2: two-stage planning of IES (ω1=0.50) |
|-----------------------------|-----------------------------------|------------------------------------------|
|                             | the first stage | the second stage                        |
| \( f(10^8¥) \)             | 6.3832          | 3.2483                                   |
| \( C_{inf}(10^8¥) \)       | 6.0490          | 3.0821                                   |
| \( C_{om}(10^6¥) \)        | 11.394          | 4.7539                                   |
| \( C_{gas}(10^8¥) \)       | 20.465          | 10.9128                                  |
| \( C_{grid}(10^6¥) \)      | 1.5581          | 0.9582                                   |
| \( PER(\%) \)              | 80.78           | 81.23                                    |
| \( E_{CO2}(10^7kg) \)      | 1.76            | 1.21                                     |
| \( GT(10^6kW) \)           | 7.4601          | 4.1949                                   |
| \( PV(10^3kW) \)           | 4.5139          | 4.5970                                   |
| \( BT(10^5kWh) \)          | 1.2445          | 1.1956                                   |
| \( TST(kWh) \)             | 0               | 0                                        |
| \( AC(10^6kW) \)           | 10.270          | 2.4467                                   |
| \( EC(10^4kW) \)           | 5.7074          | 3.5135                                   |
| \( GB(10^3kW) \)           | 4.5645          | 2.6045                                   |

According to table 2, the annual cost of each type of single-stage planning is higher than that of two-stage planning. Because of not considering the stage difference of mid-long term forecasting, the optimal allocation of the initial investment in equipment capacity needs to meet the biggest multi-loads of the whole planning period. However, the district construction should be in stages. The load demand of the early planning stage is low, which causes equipment idle for a long time. Hence additional operational costs are generated and the equipment service life is wasted. Besides, \( PER \) of Case 2 is 0.45% higher than that of Case 1 while \( E_{CO2} \) of Case 2 is 5,500,000kg lower than that of Case 1. To sum up, the performance of the two-stage planning method from the economic, technical, and environmental viewpoints is better than conventional single planning method.

In combination with table 2, the scheme in which \( \omega_1 \) equals to 0.50 is taken as an example to explain the difference in installation capacity and component costs in the two stages.

3.2.2 Discussion. a) Equipment capacity expansion: In addition to the thermal storage tank, electric chiller and gas boiler, the installation capacity of other equipment in the second stage has increased compared with that in the first stage. The expansion capacity of gas turbine, battery and PV is approximately the same as the respective installation capacity of the first stage, which conforms to the assumption that the base load of the second stage is doubled on the basis of the first stage. The expansion capacity of the absorption chiller is about double that of the installed capacity of the first stage, but the electric chiller does not need capacity expansion. The recovery of waste heat from the gas turbine can satisfy the needs of heating power as well as cooling power, so the heat storage tank and gas boiler need not be further invested.

b) Component costs: Each cost of the second stage is greater than that of the first stage. The system initial investment cost of the second stage is slightly higher than that of the first stage. Although the second stage has equipment that does not need capacity expansion, the unit investment cost of gas turbine and absorption chiller that needs capacity expansion is much higher than that of other
equipment that need small capacity expansion. In addition to the equipment expanded in the second stage, the equipment installed in the first stage also needs to be operated and maintained in the second stage, and the operating and maintenance costs of each equipment unit are similar. The operating and maintenance costs of the second stage are approximately the double of that in the first stage. The increase of gas cost in the second stage is the same as that in the first stage. Compared with the first stage, the annual electricity purchase cost of the second stage increases. On the one hand, electricity load increases; on the other hand, because IES adopts the operation mode of ordering power by heat, the shortage of power output of gas turbine is made up by main grid.

c) Investment flexibility analysis on Pareto Front curve: Solving multi-objective optimization problem is actually an attempt to find as many Pareto optimal solutions as possible. The corresponding values had better distribute uniformly on the Pareto Front. In order to distribute the value of the objective function as evenly as possible, 15 groups of \((\omega_1, \omega_2)\) are selected. The corresponding Pareto Front curve is made according to the simulation results, which is shown in figure 5.

In figure 5, \(\omega_1\) corresponding to 15 points from right to left increases successively, and the change range is \([0.5, 0.8]\). With the increase of \(\omega_1\), \(f_1\) decreases and \(f_2\) increases. It is because that the larger the weight factor is, the corresponding sub-target is of more importance, that is, it is more important to minimize the sub-target. The different combinations of \(\omega_1\) and \(\omega_2\) represent different degrees of emphasis in the decision-making process.

In order to further analyze the influence of the value of weight factors on the optimization result of the system, 30 groups \((\omega_1, \omega_2)\) are re-taken and \(\omega_1\) in the range \([0.5, 0.8]\) uniformly increases, with the step length of 0.1. Figure 6 represents the relevant Pareto Front curve.

![Figure 5. The Pareto Front curve of IES two-stage planning.](image)

![Figure 6. The Pareto Front curve of IES two-stage planning ((\(\omega_1, \omega_2\) changes uniformly).](image)
As Figure. 6 shows, with the uniform change of \( (\omega_1, \omega_2) \), the relation curve of \( f_1 \) and \( f_2 \) presents the characteristic of locally dense and locally sparse. The points corresponding to \( (\omega_1, \omega_2) \) between \((0.56, 0.44)\) and \((0.79, 0.21)\) are the densest ones, that is, the optimization results are less sensitive to weight factors within the range. The points corresponding to \( (\omega_1, \omega_2) \) between \((0.50, 0.50)\) and \((0.49, 0.51)\) are the sparsest ones, that is, the optimization results are more sensitive to weight factors within the range. Reference [13] pointed out that in the same Pareto non-inferior-rank, the sparser individuals should be retained in the evolutionary selection process. When setting the combination of weight factors to choose the optimal decision-making scheme, the locally sparse points in Pareto Front should be paid more attention. In actual investment cases, the determination of the multi-stage weight factors is usually flexibly set by the planners according to the actual situation. The proposed algorithm shows the superiority of multi-stage planning and reflects the investment flexibility of IES planning.

4. Conclusion

A two-stage planning model of IES considering the uncertainty of renewable energy output and demand side multi-loads, the flexibility of investment is established in this paper. The method of Monte Carlo simulation adopted in this model demonstrates the superiority of multi-stage planning from the several viewpoints and researches the investment flexibility of IES planning. Moreover, the proposed model can be used for the planners to comprehensively analyze and compare the optimal decision-making schemes generated by different weight factors combinations.

However, the specific reasons for the locally dense and locally sparse characteristic of the Pareto Front curve have not been analyzed in depth. Explaining the characteristic with L2 norm related theory is one of the research directions.

In addition, the multi-stage planning of IES can be divided into more detailed periods to exploit the coordinated complementarity of different districts.

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References

[1] W Gu, Z Wu, R Bo, et al. “Modeling, planning and optimal energy management of combined cooling, heating and power microgrid: A review,” *International Journal of Electrical Power & Energy Systems*, vol. 54, no. 1, pp. 26-37, 2014.

[2] W Gu, J Wang, S Lu, et al. “Optimal operation for integrated energy system considering thermal inertia of district heating network and buildings,” *Applied Energy*, vol. 199, pp. 234-246, 2017.

[3] H Sun, Z Pan, and Q Guo. “Energy internet: concept, architecture and frontier outlook,” *Automation of Electric Power Systems*, vol. 39, no. 19, pp. 1-8, 2015.

[4] HJ Jia, D Wang, XD Xu, and XD Yu, “Research on Some Key Problems Related to Integrated Energy Systems,” *Automation of Electric Power Systems*, vol. 39, no. 7, pp. 198-207, 2015.

[5] L Cheng, J Zhang, RL Huang, CP Wang, and H Tian, “Case analysis of multi-scenario planning based on multi-energy complementation for integrated energy system,” *Electric Power Automation Equipment*, vol. 37, no. 6, pp. 282-287, 2017.

[6] L Guo, W Liu, J Cai, et al. “A two-stage optimal planning and design method for combined cooling, heat and power microgrid system,” *Energy Conversion and Management*, vol. 74, no. 10, pp. 433-445, 2013.

[7] L Zeng, YQ Yang, DN Liu, et al. “‘Generation-Grid-Load-Storage’ Coordinative Optimal Operation Mode of Energy Internet and Key Technologies,” *Power System Technology*, vol. 40, no. 1, pp. 114-124, 2016.

[8] XW Shen, YD Han, SZ Zhu, et al.  “Comprehensive power-supply planning for active distribution system considering cooling, heating and power load balance,” *Journal of Power Systems and Clean Energy*, vol. 3, no. 4, pp. 485-493, 2015.
[9] Lannoye E, Flynn D, and O'Malley M. “Evaluation of Power System Flexibility,” *IEEE Transactions on Power Systems*, vol. 27, no. 2, pp. 922-931, 2012.

[10] M Zeng, K Tian, F Yan, S Xue, and J Dong, “Analysis on Investment Decision of Power Generation Project in Electricity Market Considering Flexible Tactics,” *Power System Technology*, vol. 34, no. 11, pp. 151-155, 2010.

[11] XS Zhang, XL Guo, and LF Yi, “Analysis of marginal cost of power generation based on Monte Carlo simulation,” *Power System Protection and Control*, vol. 39, no. 14, pp. 21-25, 2011.

[12] Y Yang, SJ Zhang, YH Xiao, XQ Xiao, and WM Kan, “Application of Monte Carlo Method in Uncertainty Evaluation for Cogeneration Systems,” *Proceedings of the CSEE*, vol. 33, no. 2, pp. 16-23, 2013.

[13] M Zeng, YQ Yang, HW Xiang, LH Wang, and B Zeng, “Optimal dispatch model based on coordination between ‘generation-grid-load-energy storage’ and demand-side resource,” *Electric Power Automation Equipment*, vol. 36, no. 2, pp. 102-111, 2016.