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RESEARCH ARTICLE

Day-Ahead Intelligent Energy Management Strategy for Manufacturing Load Participating in Demand Response

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ABSTRACT Flexible resources such as adjustable load widely participate in interaction with power grid, which can effectively promote renewable energy consumption. In previous studies, researchers generally focused on industrial and household users, but usually ignored the manufacturing load. Therefore, in this paper, an day-ahead intelligent energy management strategy for manufacturing load is proposed. Firstly, we analyze the power demand behavior of manufacturing load in detail, and describe the energy flow and material flow of manufacturing load through state task network (STN) method and mixed integer linear programming model. Then, the conditional deep convolution generative adversarial networks (C-DCGAN) algorithm is used to describe the uncertainty of new energy and construct a set of scheduling scenarios. Finally, case study shows that the proposed method can effectively improve the regional renewable energy consumption level and economic benefits of enterprises.

INDEX TERMS Manufacturing load, state task network (STN) method, conditional deep convolution generative adversarial networks (C-DCGAN) algorithm, typical scenario screening method.

I. INTRODUCTION

Under the target of carbon peaking and carbon neutralization, the proportion of traditional fossil energy is decreasing, and the proportion of renewable energy such as wind power is increasing sharply [1]. However, the uncertainty of wind and photovoltaic power has brought great challenges to the safe operation of power system. It is difficult to meet the regulation demand of power system under the high proportion of renewable energy by using only conventional power supply for peak shaving. With the development of intelligent control and Internet of Things technology, demand response (DR) of load side provides an effective way for flexible regulation of power grid and relieving peak load pressure. At present, most relevant researches consider the DR of residential load, commercial load or industrial load [2], [3], [4], realizing the power balance between resources and load, which have achieved good results. In literature [5], an economic technical analysis of the effect of the penetration of electric vehicles in a microgrid is proposed. At the same time, robust stochastic optimization method is used to deal with uncertainty of renewable energy sources and loads. In [6], by guiding the DR of electric vehicles, system operators minimize the peak power demand and improve the safe operation level of the power grid. In [7], researchers focused on small capacity residential load, and develops a mathematical formulation to support a residential-level demand response analogue.

Compared with residential load, the adjustable capacity of industrial load is larger, and the dispatching flexibility and potential are greater. In order to make full use of the resources on the industrial demand side [8], [9], [10], [11] to improve the economy and security of the power system, researchers has studied and implemented many incentive measures. Because the industrial production process cannot

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be interrupted in general, price based DR projects are often used for industrial load, among which the most commonly used is time of use (TOU) price. TOU price guides users to conduct power management spontaneously by giving different electricity prices for different periods of time. Literature [12] pointed out that a reasonable peak valley price can achieve a good effect of peak shaving and valley filling through the analysis of large industrial users. For power grid dispatching, TOU price, as a variable to control the power demand at the user side, will determine the effect of peak shifting and valley filling, thus affecting the system operation cost [13]. The response behavior of load should be taken into account when TOU price is formulated. Users respond to different prices to varying degrees, that is, there is demand elasticity. In the study of time-sharing price for users [14], [15], the correlation between electricity prices in different periods and users' electricity demand is established. Under the TOU price given by the power grid, industrial users can reduce power demand in peak time or transfer demand from peak time to valley time to reduce power demand cost [16], [17]. With the construction and improvement of integrated energy systems, the multi energy flow DR of integrated energy systems has also been widely studied and achieved good results [18], [19].

The research mentioned above mainly focuses on residential load and industrial load, but tend to ignore the DR of manufacturing load. Compared with residential load and commercial load, manufacturing load has the advantages of complete infrastructure, strong willingness to participate in DR [20]. The automation level in the manufacturing enterprise is high, but the adjustment capacity is relatively small, mostly in a few megawatts, represented by automobile production and assembly enterprises, mold processing enterprises, food processing industry, and construction materials industry. In [20], researchers considered the impact of machine tool processing on indoor temperature and humidity, combined with TOU price information, and established a coordinated scheduling model for the entire production line with the goal of minimizing operating costs; [21] incorporates the carbon emission characteristics of cement plants and thermal power units into a low-carbon economic scheduling framework. Literatures [22], [23] analyze the cases of food production plants in detail and refrigerated warehouses participating in DR. In [24], taking a ham storage enterprise in Spain as an example, the internal cooling system includes four types: refrigeration subsystem, storage subsystem, air conditioning subsystem, and drying subsystem. All of the above subsystems can use thermal inertia to control the indoor temperature and humidity within a reasonable range. While reducing production costs, the reduction in greenhouse gas emissions caused by load reduction is also significant.

Therefore, adjusting manufacturing load is a feasible idea to ensure the reliable and economic operation of the power system. On the other hand, economic dispatch of power systems often involves many uncertainties. In terms of uncertainty analysis methods, [25] introduces analysis methods such as stochastic programming, robust optimization, and interval programming. Reference [26] summarizes data driven uncertain scheduling methods, and introduces methods for solving stochastic decision-making problems in power systems such as multi scenario analysis and risk constraint methods. Currently, scenario generation, chance constraint, and robust optimization methods are still the main methods for solving uncertain models.

However, there are still some challenges. Firstly, the mathematical model of manufacturing load is very complex. Different from industrial load and residents load, the manufacturing load model contains many logical constraints, and energy flow and material flow need to be considered at the same time. Secondly, when formulating the day-ahead energy management strategy, it is necessary to consider the uncertainty of both source and load. Although the multi-scenario stochastic optimization method can well describe the uncertainty, it also brings a heavy computational burden.

In order to solve the above issues, this paper proposes a day-ahead intelligent energy management strategy for manufacturing load participating in DR. The contribution of this paper can be summarized as follow:

(1). Firstly, the complex production process in manufacturing industry involves a coupling relationship between energy flow and material flow, and its production task scheduling is essentially an NP-hard problem. Current optimization algorithms can only handle small-scale NP-hard problems. To solve this problem, the STN method is adapted to describe the production process of manufacturing load. Based on STN method, the production process is decoupled into independent status nodes and task nodes. Then, MILP model is used to describe the power demand behavior of manufacturing load;

(2). Secondly, this paper uses conditional deep convolution generative adversarial networks (C-DCGAN) algorithm to construct typical day-ahead scenario sets. A stochastic optimization method based on scenario generation used in this paper can reduce computational complexity while avoiding conservative decisions.

The remainder of the paper is organized as follows. First, the intelligent operation framework of manufacturing load is given in section II. Then, in section III, the mathematical model of manufacturing load is given by STN method, which can well describe the relationship between materials and energy flow in the production process. In section IV, the structure and working principle of the C-DCGAN model are introduced in detail. Finally, the feasibility of the proposed method is verified by case study.

II. INTELLIGENT OPERATION FRAMEWORK OF MANUFACTURING LOAD

Figure. 1 shows the intelligent operation framework of manufacturing load. Compared with residential and industrial load, the power demand of manufacturing load is more complex. Due to such factors as the type of electrical equipment, production process, and yield requirements, there is a large difference in power demand among different manufacturing load. Conditional manufacturing load can use renewable energy generation system to realize partial self-sufficiency of electric energy, and even can transmit excess electric energy to the power system, which is also a DR resource for the power system. For such manufacturing load, the intelligent operation framework designed in this paper covers renewable power generation management and power utilization optimization dispatching, taking into account relevant power purchase and sale decisions when participating in DR.

In the intelligent operation framework, the ways to obtain electric energy include from external power grid and on-site renewable energy. The power demand mainly includes the power for production equipment and basic load. Power demand of production equipment refers to the power demand of equipment to perform various production tasks, which is also the main power load of manufacturing users.

The intelligent operation framework integrates renewable energy power generation management of manufacturing load, power dispatching of production equipment, and power purchase and sale decision-making functions. According to the price signal, yield planning, production constraint and other information provided by the DR planning, the framework effectively realizes the power prediction of renewable energy, production task scheduling, and makes power purchase and sale decisions with the goal of minimizing total costs.

In order to reduce the electricity expenditure, manufacturing users can optimize the power demand mode through intelligent operation framework to participate in the DR planning provided. DR is mainly divided into price based DR and incentive DR. The price based DR includes time of use price and real-time electricity price. Users are fully willing to respond to changes in retail electricity price and adjust electricity demand accordingly. In the incentive DR, the user can sign a contract about interruptible load with the power company to negotiate and determine the corresponding compensation.

In this paper, manufacturing load participates in price based DR. The intelligent operation framework considers the price signal provided by power grid, and develops the power demand strategy with the goal of saving total operation cost. Under this scheme, the production task can be scheduled according to the power demand and electricity price signal. On the premise of meeting various production constraints, the production tasks in the peak electricity price period can be transferred to the low electricity price period. On the other hand, users can flexibly transfer power demand according to the price signal to increase the consumption of renewable energy, which can also be seen as load reduction for power system. If the output of renewable energy exceeds the power demand of manufacturing load, users can sell electricity to power grids and obtain economic benefits [27].

To gain a better understanding, a schematic diagram of manufacturing load participating in DR is given as Figure. 2. The whole process of participating in DR can be described as follows: first, the enterprise receives the electricity price signal from the grid side; enterprise decision-makers consider

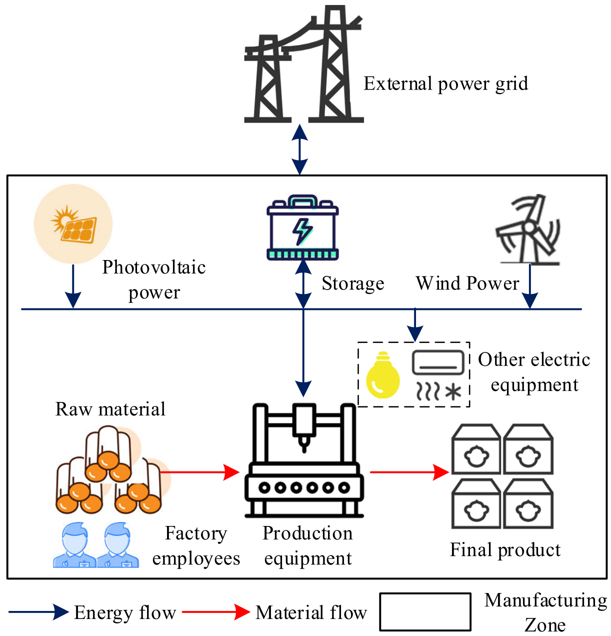

FIGURE 1. Intelligent operation framework of manufacturing load.

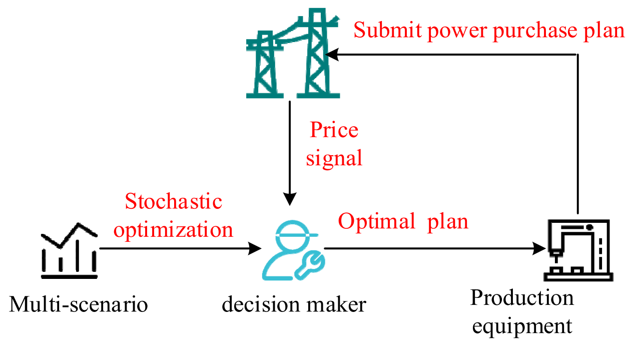

FIGURE 2. Schematic diagram of manufacturing load participating in demand response.

the predicted output of renewable energy in the factory, and use C-DCGAN method to generate some scheduling scenarios; finally, with the goal of minimizing the system operation cost under several selected scenarios, the day-ahead optimal production plan is formulated to reduce the conservatism of traditional method on the premise of meeting the production tasks of the enterprise.

III. MATHEMATICAL MODEL OF MANUFACTURING LOAD

Establishing mathematical models of various production equipment in the factory is the basis for realizing intelligent energy management. The state task network (STN) can be used to describe the manufacturing production process, and the power demand model of production equipment can be established by combining the STN with the power of equipment for production tasks [28]. Meanwhile, the optimal scheduling model of production equipment can be built after the power demand of equipment for each production task is included. In detail, STN includes two types of nodes: status node and task node. The status node indicates the material stock in the production process, such as raw materials, middle products, or final products; the task node can describe a manufacturing task or a combination of several manufacturing tasks. For example, a task node can describe a production line or a piece of equipment on a production line. Task nodes can be further divided into fixed tasks and flexible tasks. Fixed tasks mean that the production rate of each period is fixed and equipment cannot be dispatched freely. Flexible tasks mean that the power demand behavior of equipment can be adjusted in different periods to respond to the electricity price signal. It should be noted that the modeling in this article is based on certain assumptions and simplifications. In practice, it is difficult to accurately control the working status of each device, especially when there are many devices within the enterprise. This paper assumes that some devices are centrally scheduled rather than distributed scheduled. In addition, another feasible strategy is to assume that the number of products produced by each task in a single period is an integer, which can avoid frequent start and stop of production tasks.

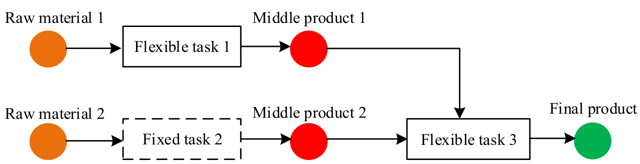

FIGURE 3. STN based production process.

Figure. 3 shows an example of using STN to describe the production process. Flexible task 3 processes middle product 1 and middle product 2 to obtain final products. Flexible task 1 converts raw material 1 into middle products 1. In task 1, the power demand of equipment in each period can be adjusted according to the electricity price signal. During the peak period of electricity price, operator reduce the power demand of the equipment in task 1 by producing at a lower production rate; during the period of low electricity price, operator can increase the power demand of the equipment in task 1, and save the total operation cost as much as possible while meeting the production requirements and production constraints.

The status node parameters include the initial quantity, upper and lower storage limit of the material. The consumption and production of materials should meet the material balance constraints, and the material quantity should meet the storage constraints.

(1) Material balance constraints

$$S_{i,t+1} = S_{i,t} + h(\sum_{j \in G_i} g_{i,j,t} - \sum_{j \in C_i} c_{i,j,t}) \tag{1}$$

Here, $S_{i,t}$ is the material stock of status node i at time t; $g_{i,j,t}$ and $c_{i,j,t}$ are the yield and consumption rate of status node i in task j at time t; G_i and C_i are the task sets connected with node i to produce and consume the materials of this node.

(2) Material stock constraints

$$S_i^{\min} \le S_{i,t} \le S_i^{\max} \tag{2}$$

Here, $S_i^{\min}$ and $S_i^{\max}$ represent the lower and upper limit of the material storage quantity in the status node i. In addition, operators usually require the daily yield of products to reach a certain value S_i^{op}, so the corresponding status node i also needs to meet the yield constraints (3):

$$S_{i,n+1} - S_{i,1} \ge S_i^{op} \tag{3}$$

There are m operating conditions for a given task node j, where the power demand corresponding to condition k is $p_{j,k}$, the number of workers required is $w_{j,k}$, and the consumption rate of material i is $\alpha_{i,j,k}$, the yield rate of material i is $\beta_{i,j,k}$. The 0-1 variable $Z_{i,j,k}$ represents the operation state corresponding to the working condition k of task j at time t. State variable $Z_{i,j,k}$ take 1/0 to indicate that task node j operates /does not operate at working condition k at time t. In this way, the consumed power of task node j at time t can be calculated as follows:

$$P_{j,t} = \sum_{k=1}^{m} Z_{j,k,t} p_{j,k} \tag{4}$$

Meanwhile, the sum of power demand of all tasks is the power demand of production equipment:

$$P_t^p = \sum_{j=1}^{N} P_{j,t} \tag{5}$$

Here, P_t^p is the power demand of production equipment at time t; N is the total number of task nodes. The number of workers $W_{j,t}$, material consumption rate $c_{i,j,t}$ and yield rate $g_{i,j,t}$ in task node j at time t can be calculated respectively according to the following formula (6):

$$\begin{aligned} W_{j,t} &= \sum_{k=1}^{m} Z_{j,k,t} w_{j,k} \\ c_{i,j,t} &= \sum_{k=1}^{m} Z_{j,k,t} a_{i,j,k} \\ g_{i,j,t} &= \sum_{k=1}^{m} Z_{j,k,t} \beta_{i,j,k} \end{aligned} \tag{6}$$

(3) State constraints of flexible task nodes

$$0 \le \sum_{k=1}^{m} Z_{j,k,t} \le 1 \tag{7}$$

It should be noted that constraint (7) is used to ensure that the schedulable task j at time t is only in one operating condition.

(4) Worker quantity constraints

$$0 \le W_{j,t} \le W_{j,t}^{\max} \tag{8}$$

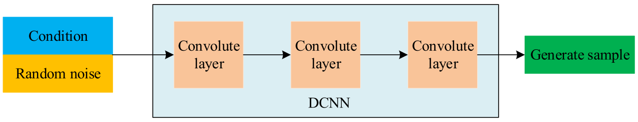

FIGURE 4. **The structure of the generator in the C-DCGAN model.**

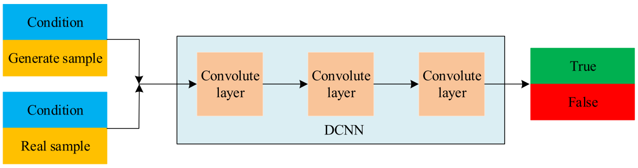

FIGURE 5. **The structures of the discriminator in the C-DCGAN model.**

Here, $W_{j,t}^{\max}$ is the upper limit of the number of workers that task j can engage in production at time t.

Finally, the objective of the optimal scheduling of manufacturing plants is to minimize the maximum operating cost. As shown in (9), the objective function is composed of three parts, in which the operation cost of manufacturing enterprise is represented by F_{op}, the labor cost is represented by F_{man}, and the revenue from electricity sales is represented by F_{sell}. It should be noted that this paper mainly considers the manufacturing load (production equipment) and associated renewable generation and operation costs.

$$\min(F_{op} + F_{man} - F_{sell}) \tag{9}$$

IV. DAY-AHEAD SCHEDULING SCENARIO GENERATION METHOD AND TYPICAL SCENARIO SCREENING METHOD

It is difficult for traditional statistical methods to generate scenarios to fully describe the uncertainty of new energy and load. In this paper, the conditional deep convolution generating network (C-DCGAN) algorithm is used to describe the uncertainty of new energy and construct a set of scheduling scenarios.

As one of the commonly used deep learning network structures, deep convolution neural network (DCNN) can accurately analyze the correlation between sampling data points and local input information, and mine the local information characteristics of input data [29], [30]. Combined with the time vertical similarity of renewable energy generation data, DCNN can effectively describe the mapping relationship between scenario data by mining local information features. Therefore, this paper adopts the C-DCGAN model with DCNN as the main network structure to realize the migration of scenario data. The structures of the generator and discriminator in the C-DCGAN model are shown in Figure. 4 and Figure. 5 respectively.

As shown in Figure. 4, with the real data as the condition y, after splicing with the random noise z, the input generator enables the convolution layer of C-DCGAN to effectively analyze the local information characteristics of the input data. Convolution layer, as the basic structure of C-DCGAN, usually contains multiple convolution cores, which enables C-DCGAN to extract complex data features more comprehensively and quickly. The kernel in the convolution layer is convolved with the input characteristics of the layer. The function relation obtained by combining the convolution result with the corresponding convolution kernel is the output of the convolution kernel. The result of condition y and random noise z through convolution kernel is shown in equation (10)-(11).

$$m_{yp} = f(w' y_{p:p+g-1} + b') \tag{10}$$
$$m_{zp} = f(w' z_{p:p+g-1} + b') \tag{11}$$

Here, m_{yp} and m_{zp} respectively represent the p-th feature of conditional y and random noise z through convolution calculation; $f(\cdot)$ is the activation function set for the convolution layer; w' and b' respectively represent the weight and deviation corresponding to each convolution kernel; the window size of convolution kernel is g; y_p, z_p are the p-th input of the characteristics y, z, x and $G(z)$.

Each convolution layer is provided with multiple convolution kernels to perform the convolution operation on the original data, so that different convolution kernels will be given different weights in the adjustment. Multiple convolution kernels will extract features from the data in the same area, and finally all features of the convolution layer will be spliced into one feature, which is the output feature of the convolution layer. The convolution layer output feature of the generator is shown in equation (12).

$$M_G = f(m_{yp:1}, L, m_{yp:n-g+1}, m_{zp:1}, L, m_{zp:n-g+1}) \tag{12}$$

According to equation (12), after the convolution operation, the output characteristics of the convolution layer can represent the mapping relationship between the source power data y and the random noise z. Through multi-layer convolution calculation, the convolution layer features extracted from the source power data y and random noise z are continuously refined, and finally the generated sample data $G(z)$ is output.

Similarly, as shown in Figure. 5, take the source power data as the condition y, respectively splice with the generated sample $G(z)$ and the historical sample x, and input the discriminator. The results of the convolution kernel of the historical sample x and the generated sample $G(z)$ are shown in formula (13)-(14) respectively.

$$M_G = f(m_{yp:1}, L, m_{yp:n-g+1}, m_{zp:1}, L, m_{zp:n-g+1}) \tag{13}$$
$$m_{zp} = f(w' z_{p:p+g-1} + b') \tag{14}$$

Here, m_{xp} and m_{zp} respectively represent the p-th feature of the convolution calculation of the historical sample x and generated sample $G(z)$; x_p, z_p are the p-th input of characteristics x, $G(z)$.

After multiple convolution kernels are calculated, the output characteristics M_{D1} and M_{D2} of generated data $G(z)$ and history sample x through discriminator convolution layer are shown in formula (15) and (16) respectively.

$$M_{D1} = f(m_{yp:1}, L, m_{yp:n-g+1}, m_{Gp:1}, L, m_{Gp:n-g+1}) \tag{15}$$
$$M_{D2} = f(m_{yp:1}, L, m_{yp:n-g+1}, m_{xp:1}, L, m_{xp:n-g+1}) \tag{16}$$

TABLE 1. TOU price and electricity selling price.

Period	TOU price	Electricity selling price
0:00-5:00	0.05344	0.1
6:00-9:00	0.19946	0.1
10:00-11:00	0.08500	0.1
12:00-12:00	0.19946	0.1

Meanwhile, the output characteristics of the convolution layer can respectively represent the mapping relationship between the source power data y, historical data x, and the generated power data $G(z)$ of renewable energy. The discriminator continuously refines the convolution layer features extracted from the generated data $G(z)$, data x and data y through multi-layer convolution calculation, and finally outputs the classification results. Finally, the generator after training can convolve the random noise according to the mapping relationship to generate the corresponding power data of renewable energy.

When too many scenarios are generated, the computational burden will also increase. For the scenario set generated by C-DCGAN, we can use the typical scenario screening method to select representative scenarios [31], [32].

V. CASE STUDY

In this paper, an automobile seat manufacturing factory is used for a case study to illustrate the proposed intelligent power management method. The total scheduling period considered in this article is 12 hours, because decision makers choose certain periods of the day to participate in demand response scheduling. According to the current situation in China, most enterprises only schedule work tasks at certain times of the day, rather than all day. In additional, the scheduling interval considered in this article is 1h. If a scheduling cycle with a longer interval is adopted, it can effectively reduce the difficulty of solving the problem. In this paper, power grid uses TOU price to guide the manufacturing load to participate in the demand response, and adopts the unified price for the redundant renewable energy power generation. Table. 1 shows the price data of TOU price and unified price. The production process of the plant is shown in Figure. 6, and the parameters of each status node and task node are shown in Table. 3 to Table. 8 in appendix. Generator and discriminator hyperparametric information is given in Table. 9 in appendix. The number of car seats to be produced during the scheduling period is 800. The test case is carried out by a desktop computer with MATLAB 2016a and the CPLEX solver installed. The computer is configured with a Win-10 Pro operating system, Intel i5-7300HQ and 8G memory.

A. ANALYSIS OF THE SCHEDULING RESULTS

Figure. 7 shows the wind and solar power data generated by the original and C-DCGAN models. Compared with the original wind and solar power data shown in subgraphs (a) and (c), the wind and solar power data generated by the C-DCGAN model can well depict the volatility of renewable

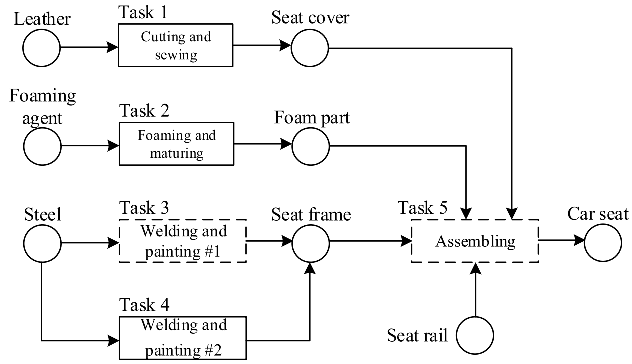

FIGURE 6. The production process of the automobile seat manufacturing factory.

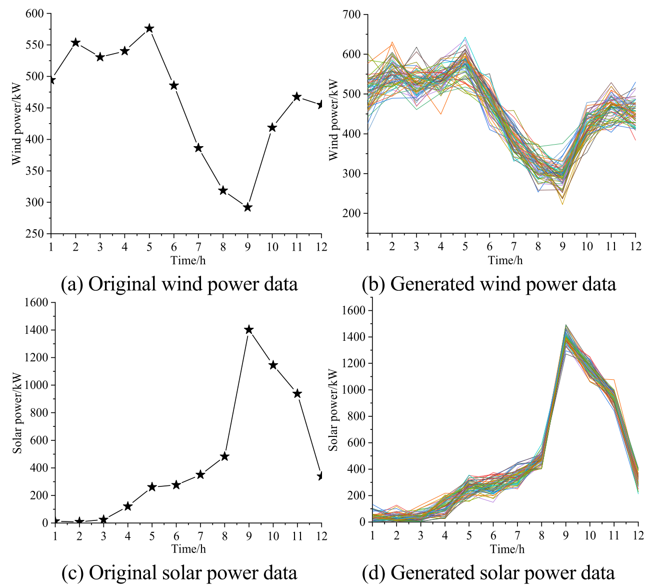

FIGURE 7. Original and generated data set.

energy output, and the generated data set is consistent with the original data in trend. Therefore, according to the data set generated, operators can be well guided to specify the day-ahead intelligent energy management strategy of manufacturing load.

Figure. 8 shows the electricity buy and sell quantity of manufacturing industry enterprise. In general, enterprise mainly purchases electricity from 1:00 to 9:00, which is mainly caused by the following two reasons: first, the solar power is very small during this period, and it is difficult to meet the production power demand of manufacturing load only relying on wind power. In addition, according to the electricity price information, the electricity price in this period is cheap. In order to reduce the operation cost, the enterprise will increase the electricity consumption in this low electricity price period. From 9:00 to 12:00, due to good lighting conditions and increased solar power, the manufacturing load cannot fully consume renewable energy, and the surplus energy is sold to the power grid to increase the enterprise's

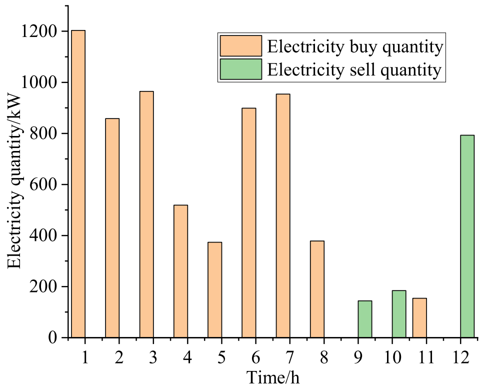

FIGURE 8. Electricity buy and sell quantity of manufacturing industry enterprise.

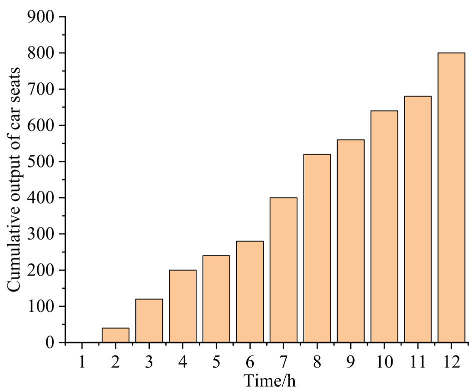

FIGURE 9. Cumulative output of car seats in manufacturing industry enterprise.

income. Figures. 9 and 10 show the cumulative output of the enterprise and the power demand of each task node, respectively. As shown in Figure. 9, through the intelligent energy management strategy, the final output of car seats is 800, which meets the seat production requirements. While completing the production task, the consumption level of renewable energy in the region is improved to achieve a win-win situation for the power grid and the load side. It can be clearly seen from Figure. 10 that the power of each task node responds to the scheduling instructions in an orderly manner. Among them, power of welding and painting #1 remains unchanged. This is because welding and painting #1 is a fixed task, which only has two working states: operation and stopping, so its scheduling flexibility is slightly poor.

B. CALCULATION EFFICIENCY ANALYSIS

The optimization model proposed in this paper is essentially a multi-scenario stochastic optimization problem. Figure. 11 shows the relationship between the total calculation time and the number of selected scenarios. It is not difficult to find that the total solution time is approximately linear with the number of selected scenarios. On the other hand, the scanning time of typical scenarios is controlled within 2 s, which shows the high efficiency of the proposed algorithm. In conclusion, the method proposed in this paper can significantly reduce the calculation burden and meet the needs of practical engineering applications.

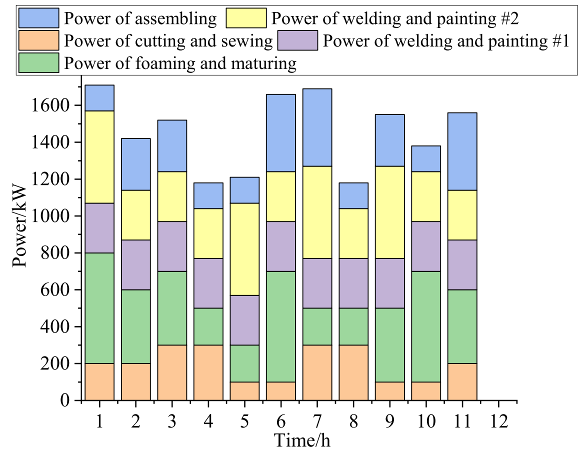

FIGURE 10. Power of each task node.

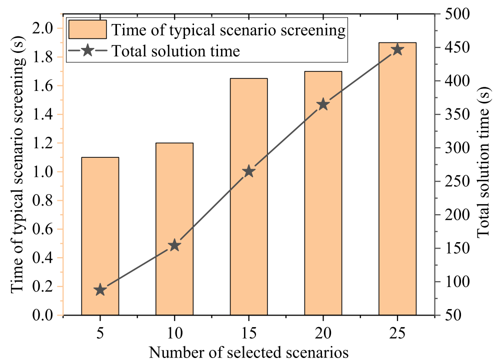

FIGURE 11. Solution time of the proposed algorithm.

TABLE 2. Comparision results between different methods.

Method	Computational time/s	Total operation cost/$
The proposed method	287.5	1324.7
Robust method used in [33]	37.5	1542.8
Fuzzy chance constraint method used in [34]	42.6	1426.9
Stochastic optimization method used in [35]	314.5	1421.4

In this paper, the stochastic optimization method based on scenario is mainly used to deal with uncertainty. Common methods to deal with uncertainty include fuzzy chance constraint method, robust method and stochastic optimization method generated by other scenarios. This paper compares the results obtained by different methods form the two aspects of computational time and conservatism. The results are given in Table. 2.

Here, robust method uses a box model to characterize the uncertainty of renewable energy output. The fuzzy chance constraint method uses triangular fuzzy parameters to describe the uncertainty. As shown in Table 2, the

TABLE 3. Paramaters of various state nodes.

State nodes	Lower storage limit	Upper storage limit
Leather	65	1000
Foam raw material	36	600
Steel	1	50
Seat cover	120	340
Foam part	120	420
Seat frame	120	420
Seat rail	120	1600
Car seat	500	2000

TABLE 4. The paramaters of tasks 1.

Task node	Operating conditions	Power/kW	Number of workers	Leather consumption rate (piece/hour)	Seat cover production rate (piece/hour)
Cutting and sewing	1	0	0	0	0
	2	100	20	20	40
	3	200	40	45	90
	4	300	60	65	130

TABLE 5. The paramaters of tasks 2.

Task node	Operating conditions	Power/kW	Number of workers	Foam raw material consumption rate (piece/hour)	Foam part production rate (piece/hour)
Foaming and maturing	1	0	0	0	0
	2	200	5	12	50
	3	400	10	24	100
	4	600	15	36	150

method proposed in this article needs to calculate the optimal solution under multiple scenarios, so its calculation time is longer. However, multiple scenarios describe uncertainty more accurately, so the total operating cost is minimal, which can effectively reduce the conservatism of decision-making. By comparison, robust method and fuzzy chance constraint method essentially only need to calculate one scenario, so their calculation time is very small, but the results tend to be conservative, resulting in an increase in total operating costs. Compared with the literature [36], there are several differences: (1). The objects of scheduling are different: this paper focuses on the load side, i.e., manufacturing enterprises, with the lowest production cost as the objective function; [36] focuses on the power system side, with the lowest generation cost as the objective function; (2). The methods of problem solving are different: in this paper, the scheduling model is modeled using MILP using the STN method, which can be directly solved using commercial solvers; mathematical model in [36] can be solved using multi-objective and multi-stage optimization algorithms.

VI. CONCLUSION

For manufacturing industry enterprise with renewable energy generation and demand response capabilities, this paper designs an intelligent power demand management model. First, the energy management architecture including different types of power demand is constructed. Then, the power consumed model based on STN method are respectively introduced, which can accurately describe the relationship between material flow and energy flow. On this basis, an intelligent power demand optimization model for manufacturing load with the objective of minimizing the operation cost is given. The calculation results of the case study show that the intelligent energy management model can properly describe the load demand in each period of the actual manufacturing production process, flexibly adjust the power demand of various types of equipment under the guidance of the price signal, and optimize the system load curve profile while reducing the total power demand cost, thus improving the economy and security of power system operation.

Meanwhile, through the analysis of calculation examples, the algorithm proposed in this paper has high calculation efficiency. Compared with the traditional algorithm, it significantly reduces the calculation burden. The total calculation time is controlled within hundreds of seconds, meeting the needs of practical engineering applications. Finally, for large-scale enterprises, the scale of this optimization problem can become very large, especially with the sharp increasing of the 0-1 variables involved, resulting in great difficulty in solving the problem. How to design more efficient solution algorithms is also potential research direction in the future.

APPENDIX

See Tables 3–9.

TABLE 6. The paramaters of tasks 3.

Task node	Operating conditions	Power/kW	Number of workers	Steel consumption rate (piece/hour)	Seat frame production rate (piece/hour)
Welding and painting #1	1	0	0	0	0
	2	270	10	0.75	30

TABLE 7. The paramaters of tasks 4.

Task node	Operating conditions	Power/kW	Number of workers	Steel consumption rate (piece/hour)	Seat frame production rate (piece/hour)
Welding and painting #2	1	0	0	0	0
	2	270	10	0.75	30
	3	500	15	1.5	56

TABLE 8. The paramaters of tasks 5.

Task node	Operating conditions	Power/kW	Number of workers	Seat cover consumption rate (piece / hour)	Foam part consumption rate (piece / hour)	Seat frame consumption rate (piece / hour)	Seat rail consumption rate (piece / hour)	Car seat consumption rate (piece / hour)
Assembling	1	0	0	0	0	0	0	0
	2	140	20	40	40	40	40	40
	3	280	40	80	80	80	80	80
	4	420	60	120	120	120	120	120

TABLE 9. Generator and discriminator hyper parametric in formation.

Structure	Layer	Name	Parameter
Generator	Layer -1	2D convolution layer	Number of input channels: 3 Number of convolution kernels: 32 Convolutional kernel size: 3*3 Activation function: LeakyReLU(0.2)
	Layer -2	2D convolution layer	Number of input channels: 32 Number of convolution kernels: 64 Convolutional kernel size: 3*3 Activation function: LeakyReLU(0.2)
	Layer -3	2D convolution layer	Number of input channels: 64 Number of convolution kernels: 4 Convolutional kernel size: 3*3 Activation function: ReLU
Discriminator	Input layer	2D convolution layer	Number of input channels: 3 Number of convolution kernels: 32 Convolutional kernel size: 3*3 Activation function: LeakyReLU(0.2)
	Layer -1	2D convolution layer	Number of input channels: 32 Number of convolution kernels: 64 Convolutional kernel size: 3*3 Activation function: LeakyReLU(0.2)
	Layer -2	2D convolution layer	Number of input channels: 64 Number of convolution kernels: 128 Convolutional kernel size: 3*3 Activation function: LeakyReLU(0.2)
	Layer -3	2D convolution layer	Number of input channels: 128 Number of convolution kernels: 256 Convolutional kernel size: 3*3 Activation function: LeakyReLU(0.2)
	Layer -4	2D convolution layer	Number of input channels: 256 Number of convolution kernels: 16 Convolutional kernel size: 3*3 Activation function: LeakyReLU(0.2)
	Output layer	Full connectivity layer	Output latitude: 1*1

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