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Industrial power load scheduling considering demand response

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A B S T R A C T

In the smart grid environment, demand response (DR) program has attracted considerable attention for industrial electricity consumers. There are many optimization problems involved in the DR programs especially the process of industrial power load scheduling. As a friendly interaction between utility companies and industrial electricity consumers, DR program plays an important role in smoothing the load curve, improving the reliability of the power grid and reducing the costs for electricity consumers. In this study, we first introduce some related concepts, including smart grid, Industrial Demand Response and the representations of the industrial production process. Then, the optimal scheduling models for industrial power load in the smart grid environment are presented, and the solving methods of the optimization models are discussed. Finally, the challenges are pointed out and discussed.

Contents

1. Introduction

Low profit margins and increased competitions are pushing

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industrial enterprises to seek ways to improve operational efficiency and reduce energy costs. Meanwhile, the government incentives are also encouraging them to pursue sustainability in operation and energy consumption. With the development of smart grid related technologies, demand response (DR) has drawn ever greater attention from industries (Schulze et al., 2016). The industrial sector currently accounts for about one half of the world's total energy consumption (Agency, 2017), and the implementation of DR could reduce the electricity demand during peak periods which can not only relieve the financial pressure of the investment on the capacity expansion for the utility companies, but also benefit the industrial plants by reducing the electricity costs (Tang et al., 2011).

DR is a form of voluntary load shedding in response to financial incentives offered by the utility (Vardakas et al., 2014), which is a decision process combing the involved manpower, materials facilities and so on. It is an effective way to keep the supply and demand balanced during the peak periods. From the perspective of industrial plants, decision makers should find the optimal scheduling of the industrial power load. In the face of process data in the plants increasing explosively, the decision makers have to turn to the high-performance computer for the large-scale optimization problems. With the prosperity of Big Data, data-driven optimal models could turn data to smart decisions, making the DR more intelligent. DR could cover various participators from different fields, such as residential (Roh and Lee, 2016), commercial (Yao et al., 2015), and industrial sectors (Mohagheghi and Raji, 2014), and amounts of industrial plants coming from different industries, which brings greater challenges in modelling of the industrial power load scheduling. With the progress of smart grid, advanced technologies, such as microgrid (MG), Virtual Power Plant (Zhang et al., 2017a), must be taken into consideration in the modelling process. Moreover, the industrial plants must take the responsibility to protect the environment actively due to the greenhouse gases emissions, around 30% CO_2 emissions produced by the industrial sector (Dyer et al., 2008). These aspects enrich the connotation of DR. As DR is considered as a virtual power resource, it should be utilized properly to make its utility maximum.

Optimization problems are one of the most common and primary problems in both scientific research and engineering practice (Cui et al., 2017). According to the objective function, the scheduling models could be divided into two groups, single-objective and multi-objective scheduling models of industrial power load. The single-objective optimal models usually chose the overall costs minimization as their objective without compromising system production during the period of DR program (Li and Hong, 2016). As for the multi-objective models, they are divided into two groups by the theory applied, optimality theory and game theory (Choobineh and Mohagheghi, 2016a). The former seeks for the individual optimization combing the microgrid, the assets and environmental concerns, while the latter aim to reach the social optimization with multiple utility companies and multiple industrial electricity consumers.

The objective of this study are to summarize the models and solving methods in the current studies, which focused on the power load scheduling problems in the industrial plants. Combing with DR program, this study also presents the related concepts on how to conduct DR programs in the industrial plants. Industrial plants range from discrete manufacturing industry to process industry, consisting of iron industry, meat industry, electrolytic industry and so on. The remainder of this study is structured as follows. A brief introduction of smart grid, Industrial Demand Response as well as representations of industrial production processes are described in Section 2. Then, the optimization mathematical models of industrial power load scheduling, both single-objective and multi-objective, are reviewed in Section 3. In Section 4, the solving methods are discussed with the two parts, categories of the models and optimization solution methods. Finally, the conclusions are drawn in Section 5.

2. Related concepts

The emerging technologies in power system bring many new challenges to the power load scheduling problems. Some of the emerging technologies and concepts are discussed in this section.

2.1. Smart grid

The United States and some European countries proposed the concept (Fang et al., 2012), that the smart grid is a modern electrical infrastructure system through which information and electricity between utility companies and electricity consumers could communicate. At present, lots of countries has taken smart grid into account as one of their national strategies, and a variety of studies around smart grid have already been conducted in China (Wu et al., 2011), Turkey (Colak et al., 2014) and many other countries, which will be discussed in the following section. Smart grid is generally an intelligent power grid system (Zhou et al., 2014) which integrates the energy flow and information flow by advanced information technology, sensor technology, automatic control technology and scientific management methods etc. Smart grid technologies enable the interaction between utility companies and electricity consumers, give the power system ability to balance the electricity supply and demand, and reduce the power load peak and off-peak difference (Tsoukalas and Gao, 2008). Smart grid technologies achieve the curtailment of the investment on the capacity expansion, make the intelligent scheduling of the industrial power load available and accelerate the development of the renewable resources for cleaner electricity (Blarke and Jenkins, 2013).

Smart grid is a power grid including intelligent substation, intelligent distribution network, smart meters, smart appliances, renewable energy resources, intelligent power generation system and energy storage system (Fang et al., 2012), which is of great significance for industrial sector. These technologies make the precise control of electricity operation feasible. Industrial electricity consumers could utilize the smart grid technologies to build the microgrid to ensure the stability of the production output (Mohagheghi and Raji, 2014). Due to the emerging technologies, less pollution would come true during the power generation and production process. The electricity for industrial consumers would be cleaner and more green. Smart grid technology can also provide the electricity consumers with the opportunity to realize the interaction between utility companies and electricity consumers, which also give them both additional benefit. Meanwhile how to achieve the optimal scheduling of the industrial power load would be another challenge faced with the industrial electricity consumers.

Industrial power load in the smart grid also have the characteristics different from the residential, and commercial sectors'. Smart grid technologies push the industrial power load to keep the pace with their development, which makes the industrial power load more suitable for the constraints of the industrial production process. In the real industrial plants, the production must meet these requirements, that delivering products on time, flexible production, fault tolerance, measurable energy consumption (Chang et al., 2007) etc. Specially the smart grid technologies attached the controllability and high level of automation (Gholian et al., 2013) to industrial power load enabling them could participate in the DR programs (Siano, 2014).

2.2. Industrial Demand Response (IDR)

Demand response is a solution to the electricity demand side management, aiming to reduce or shift the electricity usage during peak periods, which means making effort to smooth the load curve and decrease the difference between peak and off-peak power load, which stretches limits of the power grid (Strasser et al., 2015). Demand response is more a resource that could balance electricity supply and demand in the power system than a method enabling the shift of power load (Rahimi and Ipakchi, 2010). DR programs would be categorized into two groups according to the different conducting measures, incentive-based DR and price-based DR.

Incentive-based DR includes the following programs. Direct load control (DLC), the load directly controlled by utility companies, would be shut down or shifted to the low consumption operation state during the DR event. Interruptible/curtailable rates means that the predefined curtailment of electricity supply would be conducted by utility companies when electricity consumers respond the DR event signals. Emergency demand response programs is that electricity consumers voluntarily respond to emergency DR event signals. Capacity market programs mean that electricity consumers provide the surplus electricity to the utility companies when electricity demand beyond the installed capacity. And the last one is demand bidding programs that electricity consumers exchange the curtailment of the electricity consumption for revenue in the form of power load curtailment bidding.

The sequent group is the price-based DR. Time-of-use rate (TOU) is extremely common in daily life, which provides a static price schedule by utility companies according to peak and off-peak periods. Critical peak pricing (CPP) is a less predetermined variant of TOU. And real-time pricing (RTP) is a dynamic price mechanism reflecting the real-time cost of electricity.

The North American Energy Standards Board has defined the timing for a DR event (Coe et al., 2010). Due to the similarity, IDR event also consists of three stages as shown in Fig. 1. The first stage is that the utility companies deliver the DR signal to the electricity consumers. Due to the dynamics of the industrial power load, it takes a certain amount of time (ramp period) because that plants still need response time to make the load scheduling plan and complete the DR deployment. Furthermore, the electricity demand would be reduced to the requested levels through optimizing the scheduling of industrial power load (El-Metwally et al., 2009). From the perspective of the industrial sector, many industrial plants would switch to the backup generator units to reduce the economic loss brought by participating in the DR program. The second stage is the implement of IDR event, plants must keep the requested level until receiving the IDR release signal. The last stage is the recovery period, and the IDR event will come to an end till the plants come back to the pervious operating level.

According to the load importance in the plant-level, there are 3 types of power load in the industrial plants. Important load needs interruptible electricity supply. Controllable load sometimes could be reduced or cut off electricity if necessary. The curtailable load could be cut off the electricity supply anytime, namely this kind of load will not cause interruption for production process. IDR program aims to smooth the load curve by scheduling the aforementioned load, which can benefit for both utility companies and industrial plants. Its impact to the power load curve could be divided into three categories, i.e., load shedding or load curtailment, load shifting and load shaping (Tang et al., 2011).

Load shedding or load curtailment is that the industrial plants shut down the load or switch the load to low electricity consumption pattern in order to reduce the electricity demand during the peak periods. The time of load shedding is usually less than 1 h. Load shifting means that power load is shifted from peak period to off-peak period. Load shaping is the impact of the DR program which constantly fine-tunes the electricity demand in real time to adjust to fluctuations but it is not widely used at present. The implement measures consist of Vehicle to Grid (V2G) system, microgrid and power generator and renewable energy technologies. In the superposition of three kinds of results, the load curve will become smooth and stable, and more towards an ideal one.

The studies on policy making considering DR programs have been concentrated, such as the price policy, optimal price models from the supply side (Greening, 2010). From the perspective of demand side, while so many prior studies focused on price-based DR in the residential and commercial sectors, a few studied the industrial sector before the impact of IDR become more and more

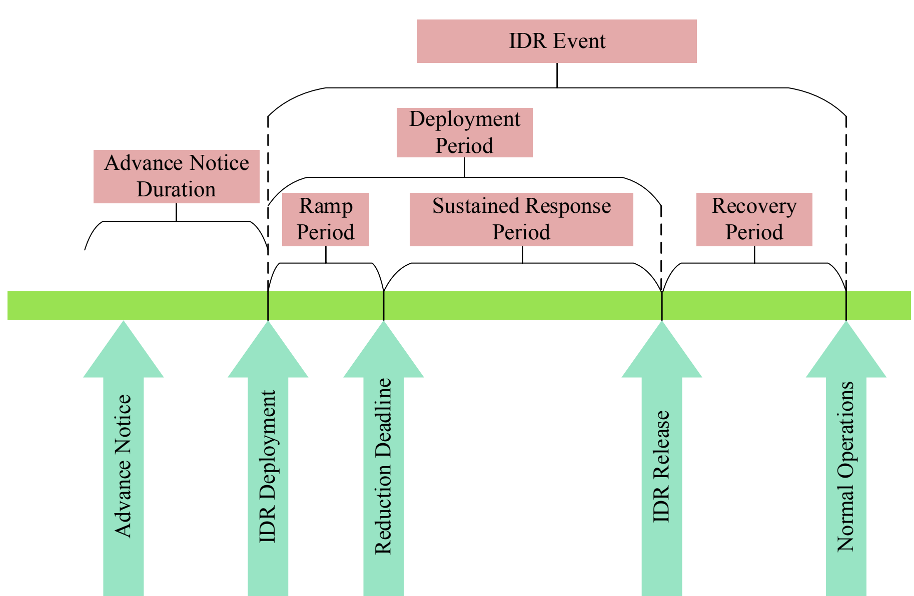

Fig. 1. The chronological steps of an IDR event.

prominent. Gholian et al. (2013) proposed an automated DR scheme for oil refineries which superior to the manual DR. Li and Hong (2016) focused on the real-time demand bidding in discrete manufacturing facilities and automatically generated optimal load reduction bids with adjusted production and energy plans. Baboli et al. (2012) concluded that customers' reactions to price-based DR significantly differed to their reactions to incentive-based DR, and incentive-based DR was found to have greater impact on customers' behavior. While the existing studies for industrial sector still mainly focused on the price driven DR (Wang and Li, 2013), studies for the incentive driven DR still have a long way to go, for example a single machine model (Chao and Chen, 2005) needs to be improved for better applicability. As the awareness of environment protection received more and more attention, the DR program should also make effort to balance the economic interests and environmental benefits.

2.3. Representations of industrial production process

With the scaling up of the production, the production complexity brings greater challenges to the industrial process representation. The traditional flowsheet representation and recipe networks, the early two process representation, are simple and understood, but ambiguities usually come with them due to the growing complexity of industrial production process. For example, though the recipe networks have the ability to describe the serial processing structures, they often involve ambiguities when applied to the ones whose ingredients are complex. Take the industrial production process described in Fig. 2 (Kondili et al., 1993) as an example. It is not clear whether task 1 produces two different products as the inputs of task 2 and task 3 respectively or only one product for both task 2 and task 3. Kondili et al. (1993) proposed the state-task network (STN), and introduced it as a unified representation of industrial production process, which brought great convenience to develop general algorithms for optimal solution to the scheduling problem. STN consists of two types of nodes, task node and state node, with task nodes denoted by rectangles and state nodes denoted by circles. Fig. 3 (Kondili et al., 1993) shows a STN, which erases the ambiguity as the discussed one corresponding to Fig. 2. Task nodes indicate the operation in the industrial process, and state nodes indicate the feed, intermediate and final product in Fig. 3. Barbosa-Póvoa and Macchietto (1994) proposed resource-task network (RTN) and enriched it in this reference (Barbosa-Póvoa and Pantelides, 1997), denoting that main characteristic of the RTN representation is the entirely uniform description and characterization of all available production resources. These representations previously were used in the field of scheduling, such as short-term scheduling (Maravelias and Grossmann, 2003), mid-term scheduling (Casola et al., 2016), multipurpose batch operations in polymer plant (Shah et al., 1996), in computational study (Lin and Floudas, 2001) and in chemical engineering (Maravelias, 2005). Also Su et al. (2008) and Nyberg (2016) proposed the extended STN to keep pace with the progress of scheduling

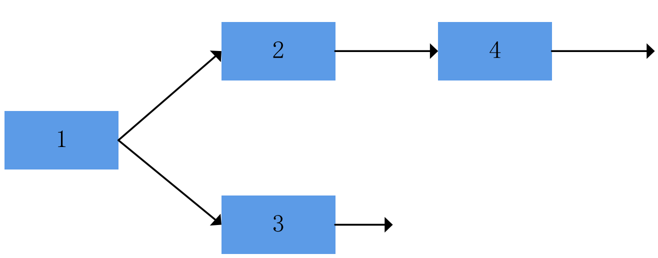

Fig. 2. Recipe network representation of production process.

problems.

In the production process, buffers of production lines play a significant role as a temporary inventory. The buffer could store the intermediate or final product, which improves the faults tolerant capacity under the unexpected circumstances. For example, the upstream buffer could help upstream machine get rid of 'blockage' state due to sudden breakdown of downstream machine. That is the reason why many scholars introduced the buffers in the scheduling research field, which developed the machine-buffer representation to describe the industrial process (Jia et al., 2016). Different from STN, machine-buffer representation consists of machine nodes and buffer nodes. Generally, machine nodes are denoted by rectangles and buffer nodes are denoted by circles. Fig. 4 shows the structure of a discrete manufacturing assembly system (Li and Hong, 2016). The intermediate produced by the machines would be stored in the buffers temporarily for the downstream machines' production. M_{i1} to M_{in} represent the machines in the ith production line, and M_{01} to M_{0m} constitute the assembly line. The final products are stored in the B_{0m}.

The representations do not only eliminate the ambiguity but also provide great convenience to the modelling process. As DR draw greater attention from the industrial plants, more and more optimal scheduling problems of industrial power load are modeled based on the above representations (Castro et al., 2009), even some scholars created extended representations (Ding and Hong, 2013) to adjust the specific industries or problems. Some production sequence constrains would be clear by the pleasant representations.

3. Optimal scheduling models of industrial power load

With the development of technology, especially the smart grid technology and manufacturing technology, how to model DR power load scheduling problems entered the scholars' awareness. The barriers of modelling DR programs in industrial plants described by Mckane et al. (2008) could be divided into two aspects. The first one is that modelling DR problems should consider the interdependencies among machines in production lines, which attaches the complexity of mathematical models. In the other aspect, it is impossible to design a universal model for the DR program. Specialized optimal scheduling models of industrial power load cover the industrial refrigerated warehouses (Ma et al., 2015), the cement industry (Olsen et al., 2010), the meat industry (Alcázar-Ortega et al., 2012). The models are categorized into single-objective models and multi-objective models on the basis of optimal objectives. Mixed integer linear programing (MILP) is a common method for this problem. No matter single or multi-objective models, MILP has excellent performance in the modelling process.

3.1. Single-objective models

With long term developments of single-objective models, they have the feature that solving methods are relatively mature and have been widely applied in the industrial power load scheduling problems considering the DR program. There are two types of basic unit in the scheduling problems, the schedulable one and the non-schedulable one. The aim of the models is to satisfy the uninterruptible electricity supply for the non-schedulable ones and make the scheduling plan for the schedulable ones. On the basis of categories of schedulable units, the single-objective models in the existing studies could be divided into three groups, industrial facilities scheduling models, HVAC system involved scheduling models s and buffers involved scheduling models.

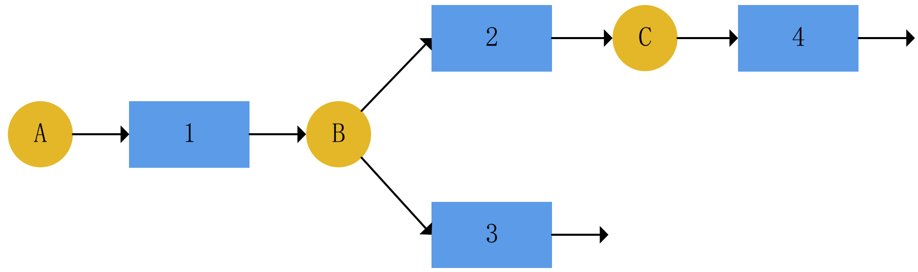

Fig. 3. State-task network representation of production process.

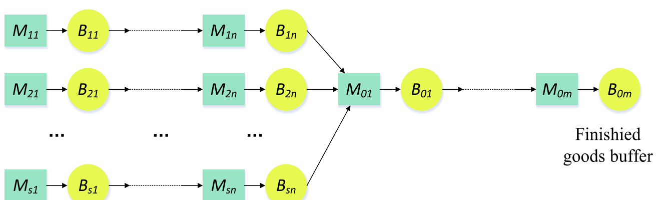

Fig. 4. A discrete manufacturing assembly system with n machines and n-1 buffers.

3.1.1. Industrial facilities scheduling models

Industrial facilities are one type of schedulable units during the DR event. In the smart grid environment, according to the characteristics of facilities and industrial production processes, the facilities would be shut down or switch to a low electricity consumption pattern and standby distributed energy resources (DERs) could be turned on to meet the load requirements during the DR event.

In the industrial plants, such as the steel industry, automobile industry and chemical industry, the facilities are categorized into schedulable facility and non-schedulable facility on the basis of whether the facility could execute the scheduling of DR event (Mohagheghi and Raji, 2014). Ding et al. (2014) classified tasks as non-schedulable tasks (NSTs) and schedulable tasks (STs), and proposed a STN model for DR in industrial facilities. Different from the representation of STN, the proposed model presents the task nodes in the form of non-schedulable task and schedulable task, and the state node in form of feed, intermediate and final product. Meanwhile the utility, the equipment and the energy management system involved in the DR event were taken into account. A production process expressed by the STN model for DR is shown in Fig. 5 and the elements defined for the model are also listed in the right part.

In the industrial facility scheduling models, each schedulable facility has several operating states, indicating that this schedulable facility could run at several powers, such as full operation, ready for operation, and turned-off (Li and Kara, 2011), and once the operating state of schedulable facility is determined, the information involved the power, runtime, electricity consumption and other detailed operating information would be specified. STs are scheduled to operate on the operating states with low electricity consumption when the electricity price is high and are scheduled to operate on the operating state with high electricity consumption when the price is low under the premise of satisfying the market demand. In this way, the electricity demand of industrial production processes could be shifted from peak demand periods to off-peak periods. While some studies took electricity price into account, the DR program could be divided into day-ahead, real-time and price forecasting DR programs. For example, Conejo et al. (2010) focused on modelling the real-time DR problem, and Huang et al. (2017) proposed the energy management scheme based on forecasted price, which are different from the previous studies.

The mathematical formation of industrial facilities scheduling model for DR is based on a discrete time representation and the time horizon of interest is split into several intervals of equal duration (Labrik, 2014). Events, such as changes in the scheduling of the facilities, only occur at the interval boundaries.

Minimizing the overall energy cost of industrial facilities is the immediate intention for industrial plants participating in the DR program. The objective function is defined to minimize the overall energy cost, by rescheduling the load, satisfying the industry constraints. The objective usually includes the power purchase cost, operating cost of microgrid, start-up and shut-down cost of generators and the revenue loss due to responding the DR event (Babu and Ashok, 2008). The cost is presented as Equ. (1), and the revenue is usually denoted as Equ. (2).

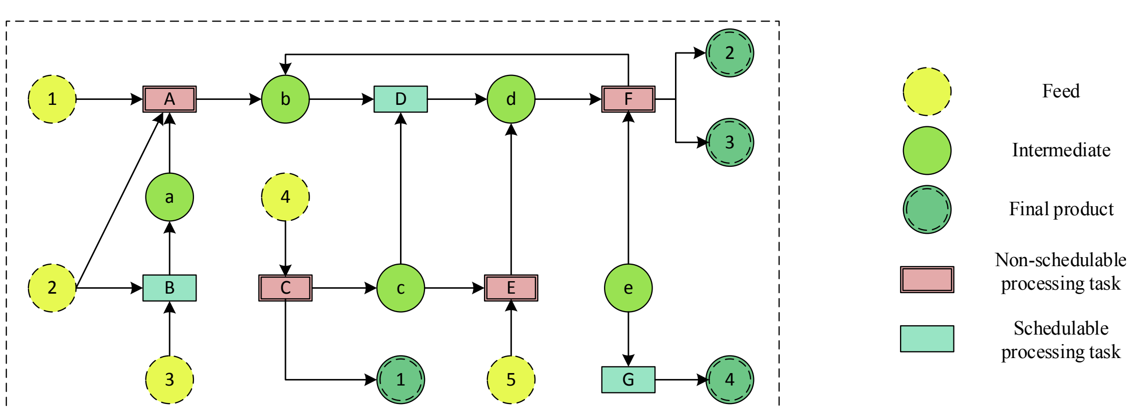

Fig. 5. A production process expressed by the STN model for DR.

$$Cost = \sum_t P_t^{pur} \cdot E_{t,pur} - \sum_t P_t^{sell} \cdot E_{t,sell} + \sum_g^G C(g) + \sum_g^G C(su_g) + \sum_g^G C(sd_g) \tag{1}$$

$$Revenue = \sum_p \sum_t output(t,p) \cdot profit(p) - Cost \tag{2}$$

where P_t^{pur} and P_t^{sell} are the electricity purchased from and sold to the grid at interval t, respectively. $E_{t,pur}$ and $E_{t,sell}$ are the electricity price for purchasing and selling respectively. The cost of generators, $C(g)$, such as the operation cost of micro gas turbine, diesel generator and etc. (Wang et al., 2015), which could also refer to the study (Zhang et al., 2017b). The last two items in (1) are the start-up and shout-down cost of each generator. In Equ. (2), $output(t,p)$ and $profit(p)$ are the output and profit of the production p, respectively.

The industrial production process constrains, energy storage constrains, energy generation constrains and electricity purchasing or selling constrains constitute the model constrains. The industrial production process constrains consist of material balance, electricity balance and operating constraints of the STs. Energy storage could purchase and store electricity from utility when the price is low, and utilize the stored energy during peak periods or DR event. Energy generation facilities provide electricity and supply it to the tasks in the process or even sell the surplus to the utility in exchange of revenue. The models scheduling the industrial facilities could be applied in discrete manufacturing plants (Ding et al., 2014) and also help process industry, such as electrolytic process industries (Babu and Ashok, 2008), build the facilities scheduling models. Though the research objective focused on the residential DR program, which is presented by Cortés-Arcos et al. (2017), there are still lots of advantages should be learnt. For example, the impressive boxplot diagrams and Gantt charts showed the convergence of the applied algorithms and production sequence constrains clearly.

Facilities would breakdown at any time during the production process, whose consequence could influence the sequent procedures with no doubt (Choobineh and Mohagheghi, 2015). If the breakdown occurring during the DR event, the cost of participating in the DR program would increase immensely. For better feasibility and applicability, the probability is introduced to the scheduling models. We assume the random variables of machine's lifetime, repair time for considering the incidents thoroughly to make the optimal scheduling. In this study, Sun and Li (2014) estimated the potential capacity of power demand reduction during the period of demand response event for the real time demand response. Markov Decision Process was used to model the complex interaction between the adopted demand control actions and the system state evolutions.

3.1.2. HVAC system involved scheduling models

Different from the industrial facilities, the HVAC system is not directly involved in the production process. But we could see that the manufacturing system and HVAC system are both the top energy consumers in the industrial plants (Brundage et al., 2013). Therefore the studies of DR scheduling problem for the two systems is of crucial importance. Most existing studies for these two systems are conducted separately. The studies from the manufacturing system's perspective are listed in the last part 3.1.1.

In general, the models on IDR considering combined manufacturing and HVAC system have not attracted much attention. From the perspective of HVAC systems, a great number of studies have been conducted to reduce the overall electricity cost and power demand of commercial (Beil et al., 2016), residential buildings (Nguyen and Aiello, 2013) and strategy evaluation (Katipamula and Lu, 2006) during peak periods. Still there are some scholars setting the integrated electricity DR model combining the manufacturing system and HVAC system (Sun et al., 2016). As for HVAC systems of industrial plants, some prior studies concentrating on the HVAC design considering industrial process have been implemented to identify the desired size, appropriate capability in building design (Liu et al., 2012) and control strategy of HVAC system (Liao et al., 2012). In some specific industrial processes, temperature plays a vital role in the quality and quantity of the output, even the inappropriate temperature may cause safety problems. The operating states of HVAC system have a close association with ambient temperature. All factors influencing HVAC performance (i.e., outdoor temperature and the required HVAC load) contribute to the quantity how much energy is needed to add or remove one unit of heat by the HVAC system (Sun et al., 2016).

Minimizing the energy consumption costs (Erickson and Cerpa, 2010) is the main optimal objective of the IDR model integrating the manufacturing facilities and HAVC system. The energy consumption is the electricity consumption of industrial facilities and HVAC system on the basis of day-ahead or real-time electricity price, power limitation, ambient temperature in the scheduling horizon. The cost of HVAC system is presented in Equ. (3). The difference between indoor temperature and the set temperature has a dramatic impact on the cost.

$$Cost_{HVAC} = \sum_t k \cdot |TemI_t - TemS_t| \tag{3}$$

where $TemI_t$ is the indoor temperature, $TemS_t$ is the set temperature, and k is the heat capacity ($kWh_{/^\circ F}$).

The models must satisfy the indoor temperature ranging from the upper and lower bound of acceptable indoor temperature, production throughput surpassing the production target in the planning horizon and so forth.

3.1.3. Industrial buffer involved scheduling models

In the production process, buffers always come with the machines, which provide the interim warehouse for intermediate products and coordinate the production progress of the machines with different takt times. Although the buffers are not really industrial power load, their impact in the scheduling problems could not be ignored. So many studies are conducted around the buffers. The goals of load curtailment or shifting could come true through utilizing temporary inventory control to coordinate the production process and building temporary buffers to adjust the various takt time due to the shutdown of machines.

Each buffer built in plants has its own capacity. It is clear that buffers are on machines' heels from machine-buffer representation discussed above, and store the upstream machine's output and provide the input for the downstream machine. The state space of machine and buffer would give great convenience to build constrains involved the buffers. The production process would be much clear through the detailed definition of state space. Buffer has 3 states, which are full, empty and in-between, on the basis of the relationship between stock and capacity. Li and Meerkov (2009) defined the state space of machine, operation, blockage, starvation, and breakdown according to the states of upstream and downstream buffer and machine, namely the production sequence constrains. The proposed demand bidding scheme in (Li and Hong, 2016) presented the structure of a discrete manufacturing assembly system, which is shown in Fig. 6. Each machine in the figure is marked with power and cycle time, and each buffer is marked with its capacity, which makes the production process and detailed parameters so clear. We could also see that some machines are arranged in parallel to increase the production capacity of some specific process.

For better participating in the DR program without compromising output of production, a novel method is proposed to decrease the loss due to DR program. The temporary inventory strategy is proposed for no interrupts during the DR event. The temporary buffers would be built on critical path of production process (Sun et al., 2014). When some machines are shut down to respond the DR signal during peak periods, the downstream machines could get the materials from the upstream temporary buffers to continue the production process, which minimize the revenue loss due to participating in the DR program. The "just-for-peak" buffer inventory proposed by Fernandez et al. (2013), is shown in the Fig. 7. J_i denotes the ith "just-for-peak" buffer inventory, built during off-peak durations ahead of DR events.

Hence, upstream machine could be shut down during the DR event, and downstream machines could utilize the intermediate stored in the "just-for-peak" buffer inventory to keep the production process without being influenced. Let k_i be a set of binary variables to denote the on-off states of machine M_i. If $k_i = 0$, it means the ith machine is turned off, and else is turned on. Building policies for "just-for-peak" buffer inventory would be clear under different circumstances. They are discussed as follows.

If $k_i = 0$ and $k_{i+1} = 1$, the "Just-for-Peak" buffer inventory of buffer J_i needs to be built during the off-peak period T, since the adjacent upstream machine of buffer B_i will be turned off and the adjacent downstream machine of buffer B_i has to utilize the "Just-for-Peak" inventory to maintain production during the peak period. In the other cases, the "just-for-peak" buffer inventory of buffer J_i does not need to be built.

The novel "just-for-peak" strategy's research objective is to identify the optimal building policies of the "just-for-peak" buffer inventory and corresponding load management actions during the peak period. However this research does not consider the random failures during peak periods, otherwise the whole scheduling plan would be nonsense and the limitation of this method is that the feasible actions of load management are only limited to a few machines due to the throughput constraint. And Sun et al. (2014) improved the above method by considering the tradeoff between the penalty due to production loss and the benefit resulted from energy savings, and thus more load management options are available.

The building process of "just-for-peak" buffer is shown in the

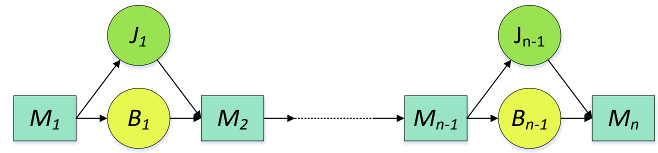

Fig. 7. Architecture of DR energy management scheme for industrial facilities.

Fig. 8 (Fernandez et al., 2013).

As for the optimization objective considering the buffers, the objective function could be built from the two aspects, maximizing the revenue and minimizing the overall cost. The revenue come from the profit of products and the loss due to conducting the demand reduction during the DR event. The optimal scheduling plan must include the building policy if buffer inventory is to be built. The cost of building temporary buffer is shown in Equ. (4).

$$Cost_T = \sum_{i=1}^{n-1} h_i \left[\frac{\left(J_i^T\right)^2 (1 - k_i) k_{i+1} (a_i + c_i)}{2 a_i c_i (T + t_p)} \right] \tag{4}$$

where a_i is the assumed linear accumulation rate for "just-for-peak" inventory built up in J_i during the off-peak periods without the impact on system throughput. c_i is the consumption rate of "just-for-peak" inventory in J_i during the peak periods when demand reduction is implemented. J_i^T is the target unit of "just-for-peak" inventory accumulated in J_i that can ensure the production of the corresponding downstream machine not to be influenced when the upstream machine is turned off for peak demand reduction. T is the building time of "just-for-peak" buffer J_i.

So the objective should include the holding cost of the buffers inventory, total energy consumption and the revenue losses caused by DR event. The models considering buffer must satisfy the constrains of buffer capacity. Other constrains is the same as the constrains discussed in the 3.1.1, such as the process constrains, energy storage constrains, power balance constrains and so forth.

3.2. Multi-objective models

In contrast to single-objective models, multi-objective models are more practical but more complex. Although multi-objective models have a late start, their theory and solving methods have gained huge development in recent years. In comparison to the single-objective function, overall energy cost minimization or revenue maximization, multi-objective models could analyze the

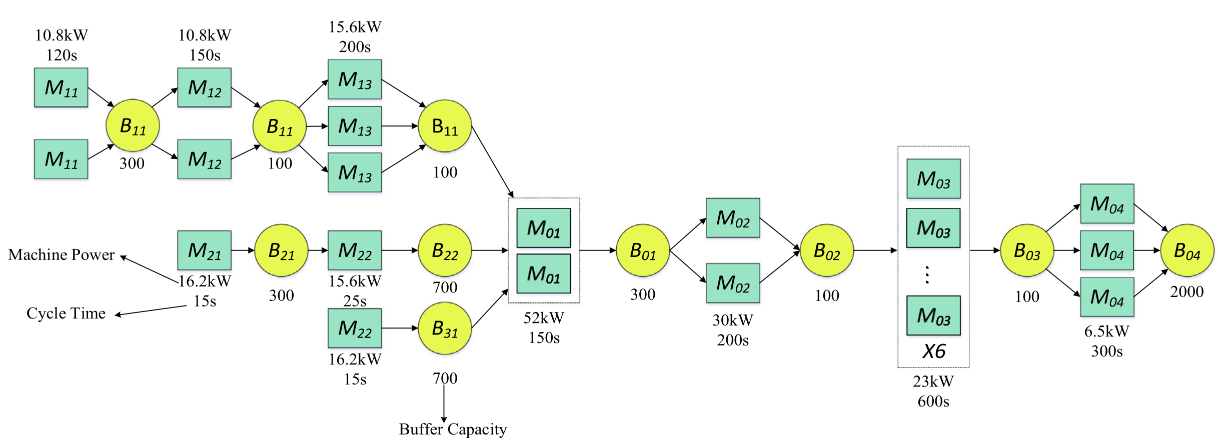

Fig. 6. Architecture of DR energy management scheme for industrial facilities.

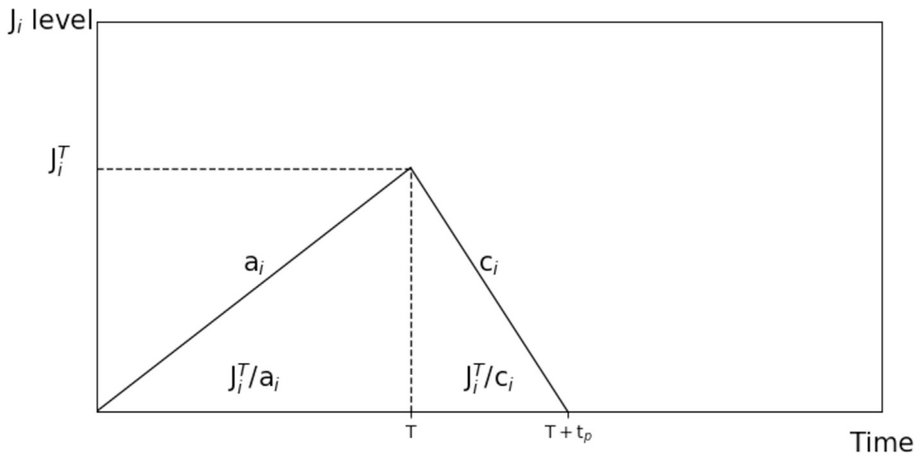

Fig. 8. "Just-for-peak" buffer inventory behavior during a production horizon.

problems from more dimensions, such as asset lifetime and environment protecting. According to the theory applied in the multi-objective models, we could get the two groups of these models, optimality theory based scheduling models and game theory based scheduling models. The optimality theory could be regarded as a process of single person decision, and game theory can be regarded as multiple decision making process. In the decision-making process of the optimization theory, all variables that affect the result are controlled by the decision makers themselves. In the decision-making process of game theory, the variable of influencing result is manipulated by many decision-makers, and the final result of decision does not only depend on the decision maker itself but also the decisions of other decision makers (Dekker and Rooy, 1999).

3.2.1. Optimality theory based scheduling models

The decision subject is the individual from the perspective of optimization theory, so in the IDR program the individual could been seen as an industrial plant. Industrial plants pay more attention to the renewable resources, reducing network losses, the loss of assets life, improving reliability of service, and reducing peak load and operational costs with the aim of sustainable development. Industrial plants could build the plant-level microgrid to participate in the IDR program more intelligently for achieving the above goals.

The combined objectives of high availability, quality and sustainability are often beyond the capabilities of the local utility, so the microgrid-enabled multi-objective optimal models have been proposed to achieve the goals. Microgrids have the potential to reduce local costs, energy losses, and greenhouse gases while enhancing energy reliability. And microgrids are the effective ways to utilize the regenerative clean energy, especially the photovoltaic (PV) and wind resources. Many studies focused on the designs of microgrid, for instance the type of distributed generators, the capacity of energy storage device. And infrastructure designs in microgrid focusing on the metering infrastructure (Huh and Seo, 2015), inverter controllers design (Wang et al., 2013) also attracted lots of attention. Some other scholars have viewed the problem as optimal allocation of available energy capacity, subject to their variabilities and operational constraints, in order to supply the existing load, especially during islanded operation of a Microgrid. Under the theme of this study, the focus should lie in the joint scheduling of microgrid and manufacturing system (Wester and Amro, 2017). Taking the study presented by Aghaei and Alizadeh (2013) as an example, implementing energy storage systems and DR programs could reduce 1.5% of the daily operating cost, which could be a meaningful reduction for industrial plants.

An architecture of the microgrid with gas turbine, PV and wind generators is shown in the Fig. 9 (Guerrero et al., 2009). The microgrid includes Combined Heat and Power (CHP), such as gas turbine and fuel cell, and Non-Combined Heat and Power, such as wind generator, PV generator and energy storage system, connecting the power grid through the Point of Common Coupling (PCC), which improve power supply reliability. Microgrid and power grid get two-way connection for energy exchange, and are the backup energy for each other. The distributed systems consolidate the reliability of the power supply (Zakariazadeh et al., 2014c). The CHP units could also meet the heat demand as well as power demand with the aim of reducing greenhouse gases and economic dispatch (Nazari-Heris et al., 2016). As reported by Khodaei et al. (2018), they achieved 0.84% and 35.8 kg reduction of operation cost and emission through heat and power hub energy management.

Each energy load in microgrid has its own characteristics. Wind, PV and other regenerative clean energy are of great benefit to the environment, but their output has the intermittent, randomness, uncontrollability, the unfriendly factors. The diesel generator other generators though need coal and fossil energy, they have the stable power output at the expense of emission of greenhouse gases, which contributes to the environmental degradation. How to balance the economic and environmental scheduling has attracted lots of attention (Zakariazadeh et al., 2014a). The reasonable use of these generators with stable power output could offset the disadvantages of regenerative clean energy and give plants greater flexibility to the energy scheduling (Moghaddam et al., 2011). Many studies have developed solutions for energy management (Safamehr and Rahimi-Kian, 2015) to achieve the goal of sustainability. In order to promote sustainability, majority of these approaches focused on hybrid microgrids combing the renewable and non-renewable resources.

With the support of microgrid, how to model the optimal scheduling problems with the goal of sustainable development will be discussed then. The IDR program does not only play an important role in decreasing of the operational costs, but also have great impact on emissions reducing. Emission has also been incorporated into the IDR optimal scheduling models. Energy management of industrial power load is not the only way to decrease of the operational costs. Another significant factor is to optimize the utilization of assets, and try to minimize the financial losses due to repairs and the resultant production shutdown, and possible asset replacement due to damages in the long run. The internal factors such as

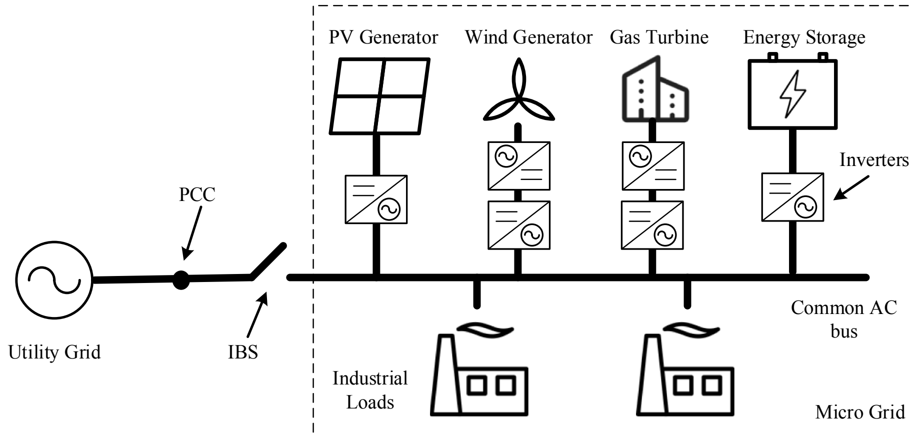

Fig. 9. An architecture of the microgrid with CHP and non-CHP.

improper operations, and the external factors such as extreme weather (Choobineh and Mohagheghi, 2016b) would affect the life of assets. The impacts on components can be modeled in the form of accelerated impacts of the asset. Many studies have developed solutions for DR program of microgrids combing the renewable and non-renewable resources, and a detailed review of energy management solutions for microgrid considering loss minimization and voltage regulation was discussed in (Choobineh and Mohagheghi, 2015). Khan et al. (2016) listed the types of objective functions and constraints that are used for modelling microgrid enabled optimal scheduling models. Moreover, in order to promote sustainable development, maximizing the energy generated by renewable resources becomes more and more important. Due to the unbalance between supply and demand side, sometimes the problem, abandoning wind and solar resources caused by the excess installed capacity, become more prominent especially in China (NEA, 2017). How to assimilate the surplus renewable resources is also the key factor which should be taken into account in DR program. For example, the objective function, denoted as Equ. (5), is to maximize the energy generated by renewable resources.

$$Elec_{clean} = \sum_t \left(P_t^{PV} + P_t^{wind} + P_t^{GT} \right) \tag{5}$$

where P_t^{PV}, P_t^{wind} and P_t^{GT} are the power output of PV generator, wind generator and gas turbine at interval t.

The multi-objective models focusing on sustainable development should pay more attention to the total revenue maximization, overall emissions minimization, assets losses minimization, such as transformer lifetime loss, which creating a multi-objective optimization problem with objectives contradicting from each other. Its goal is to find a way that it minimizes the operational costs, the emissions produced, and the loss of life of assets exposed to excess temperatures achieving the sustainability in operation and energy consumption.

3.2.2. Game theory based scheduling models

The above studies are standing at the individual's perspective, and try to solve the problems with low costs and high revenue. However, there are such models introducing game theory to solve the multi-players involved DR program for social optimization. The players are usually one utility company and multiple industrial electricity consumers or multiple utility companies and multiple industrial electricity consumers. Most of the models introduced the game theory have simplified these problems. The models do not provide the scheduling plan of industrial power load, but the overall electricity demand during the DR program. It means that plants would choose the optimal predefined scheduling plan rather than the real-time scheduling of the industrial power load (Ma et al., 2015).

Depending on the deployed consumer model, the research works which consider consumers discomfort costs (Alizadeh et al., 2012) and aim to jointly minimize the consumers billing and discomfort costs (Li et al., 2011) could be classified into two categories.

The first category is with the assumption that the consumers are price-taking meaning that the consumers do not consider how their consumption will affect the prices. The decision making of a single foresighted consumer is formulated as a stochastic control problem aiming to minimize its long term total cost. Alternatively in (Joe-Wong et al., 2012), multiple myopic consumers aim to minimize their current total costs and their decisions are formulated as static optimization problems among cooperative users.

The second category assumed that the consumers are myopic and price-anticipating who take into account how their consumption will affect the prices. In this case, each consumers power usage affects the other consumers billing costs. These research works modeled the interactions emerging among myopic consumers as one-shot games (Ibars et al., 2010) and studied the Nash equilibrium (NE) of the emerging game (Mohsenian-Rad et al., 2010).

From the perspective of consumers, this problem would be a game of electricity demand during peak periods among the players, especially the other consumers. If the price goes up due to others' growth of electricity demand, the unpleasant additional electricity expenses would also increase. From the perspective of utility company, its objective is not only to maximize its profit through selling electricity, but also to induce customers' consumption in a way that maximizes the social welfare (Song et al., 2014). Jiang et al. (2017) compared industrial and social welfare approaches from the perspective of utility company for optimal control strategy.

Single or multi-objective is just a standard to classify the models in the previous studies. Single-objective models are easier to handle compared to the multi-objective ones. The linear models could be solved by the advanced mathematical solvers, even some nonlinear programming, such as quadratic programming. Multi-objective models could find optimal or near optimal with multiple objectives at the expense of more time and memory resources. For example, Nazari-Heris et al. (2016) made effort to get the economic and environmental dispatch of microgrid units to satisfy the electricity demand.

4. Solving methods of industrial power load scheduling models

Model solving is an important step after completing the modelling of industrial power load scheduling problem, the precondition of testing the effect of the models. And the application value of the models could be found by comparing the results before and after applying the models. By classifying the models from the perspective of mathematical formulas, the existing mathematical theories can be used to quickly find the corresponding model solving methods. For example, MILP is the most common model among industrial power load scheduling models, and the branch and bound method and cutting-plane method are the appropriate methods. Exact algorithms are the basis of model solving and mathematical solvers, such as the branch and bound method, and the heuristic algorithms could present the near optimal solutions or optimal solution, the satisfactory solution with limited cost.

4.1. Categories of the methods

From the above mathematical models, we could get the categories on the basis of the theory proposed in (Hillier and Lieberman, 1986), which is shown in Table 1. In the DR models of the industrial power load scheduling, the static programming problem can be understood as the one-time decision-making problem for the plants conducting the DR program. According to whether the constraints or the objective function are linear, the linear programming problem and the nonlinear programming problem are divided. In many studies, decision variables include both continuous and integer variables, which makes the MILP and Nonlinear Mixed Integer Programming (NMIP) common. The industrial power load would be shut down or turned on during the DR event, so the binary variables (Li and Hong, 2016) have frequent appearance, which could denote the machine is on or off. Sometimes the load would be switched to different operating states, and it the time for integer variables to come in handy. For example, 0, 1, 2 could present the off, half load running, full load running states of gas turbine respectively (Aghaei and Alizadeh, 2013). The continuous variables often denote the electricity price, electricity purchase and materials consumption for electricity generation.

DP is a mathematical method to solve the optimization of decision-making process, and many static programming problems can be converted into dynamic programming problems. The multistage decision problems would be split into a series of single-stage problems, then the problems would be solved one by one by utilizing the relationship between stages. Under the theme of this study, the dynamic programming problems were usually modeled by Markov's decision-making process (Sun and Li, 2014), which is a standard model for systems that exhibit both stochastic and deterministic behaviors. In the IDR models, the stochastic behavior can be the time of equipment maintenance, the time of normal operation of the equipment, etc. The state of each period is related to the state in the preceding period. Stochastic programming is a generalization of linear programming problems. The coefficients of the constraints and the parameters of the objective function are all random variables. And the optimal solution is not a definite value, but an optimal expected value provided by the model (Zakariazadeh et al., 2014b). As the wind and solar have a probabilistic nature, the intermittent, randomness, uncontrollability must be taken into account and their outputs would be considered as random variables (Aghajani et al., 2017). Meanwhile, amounts of optimization problems in engineering involve objective functions with uncertain models in which stochastic programming is applied to assess the expected objective among a set of possible scenarios.

When considering the optimal scheduling model of industrial power load involving multi-player, game theory needs to be introduced to build the game model to find the social optimization, which usually divided into one-shot game and repeated game (Kreps, 2011). Generally, the Nash Equilibrium (NE) is not a pareto-optimal solution, and thus it is possible to improve the payoffs of all the consumers simultaneously. Often the repeated game is introduced to improve the pareto efficiency of NE. The social optimization would be find by analyzing the consequences of betrayal or cooperation. So the punishment mechanism must be established for reaching the social optimization (Ma et al., 2015).

According to that the solution obtained from the methods is optimal solution or near optimal solution, the algorithms can be divided into exact algorithm and heuristic algorithm. As the scientific computing gains better development, many effective and state-of-the-art mathematical solvers, have been developed, including Gurobi, CPLEX, Lingo and GAMS. They have the advantage to solve the linear programming with less time and more efficiency. Taking Gurobi as an example, it allows users to state their toughest business problems as mathematical models, and then automatically considers billions or even trillions of possible solutions to find the best one. A common MILP proposed by Li and Hong (2016) was solved by the Lingo software. The energy consumption of the production during each hour indicate that the load during the RT-DB event was slightly reduced.

4.2. Exact algorithms

Exact algorithms are the methods which could provide the exact optimal solution rather than the near optimal solution. Common methods are branch and bound method, cutting-plane method, dynamic programming and so on. Many previous studies have already researched the first two methods, there is no more tautology about them. As for the dynamic programming, its solution methods could be divided into backward method and forward method (Li et al., 2012). Backward method starts at the final decision stage and steps backward by looping over all the possible states and available actions until the optimal decision for the first stage is found. Though the concept of the backward recursion is easy and understood, the method would be feeble in face of the "curse of dimensionality", which requires the algorithm to loop over all the states and actions. The limited applicability due to the

Table 1
The Categories of the DR models' methods.

Category		Typical Methods
Static Programming	Linear Programming	MILP
	Nonlinear Programming	NMIP, NIP
Dynamic Programming (DP)		Backward method, forward method
Stochastic programming (SP)		Two stage SP
Game Theory		One-shot Game, Repeated Game (RG)

NMIP: Nonlinear Mixed Integer Programming.

leading to computational intractability would be more and more obvious. The means to solving the problem is to use a forward method which proceeds by estimating the approximation of value functions iteratively to obtain a proper solution.

Due to the complexity of these problems, it is not very ideal to use the exact algorithms by programming directly. The current mainstream optimization software is very convenient for solving the optimization problem, which integrate the exact algorithms commendably.

4.3. Heuristic algorithms

Heuristic algorithms are relative to exact algorithms and they are mainly bionic algorithms, such as Particle Swarm Optimization (PSO), Artificial Bee Colony Algorithm (ABC), Simulated Annealing Algorithm (SAA), Artificial Neural Network Algorithm (ANN) and so on and so forth. Heuristic algorithms (Beheshti and Shamsuddin, 2013) have greater similarity in the optimization process, which are mainly neighborhood search structure. The algorithms are based on a or a group of initial solution, the key parameters of the algorithm under the control of the neighborhood function to generate a number of neighborhood solutions, according to the acceptance criteria, deterministic, probabilistic or chaotic mode, to update the current state and then the key parameters would be modified to adjust the criteria. So the search steps are repeated until the convergence criterion of the algorithm is satisfied, and finally the optimization results would be obtained. The algorithms, such as PSO, ABC, are very common when solving the optimal scheduling problems in the field of DR. PSO is suitable for solving nonlinear problems in high dimension space. In the study presented by Sun et al. (2016), each particle has sub matrix indicating the production scheduling and let 3000 and 1000 be the swarm size and iteration. However we could find that the results provided by the heuristic algorithms are not always the optimal solutions, but the near optimal solutions. Heuristic algorithms have good performance in the optimization problems in many fields, such as the field of railway (Chevrier et al., 2011), the field of building energy saving (Bre and Fachinotti, 2017), the field of scheduling problems with energy considered such as studies presented by Luo et al. (2013), Liu et al. (2014) and Che et al. (2017), which establish the referential examples to guide the implantation of heuristic algorithms. As for the solution methods solving the IDR optimal models, the summary of them is shown in Table 2.

With the progress of scientific computing, most mathematical solvers aim to be both robust and scalable, and are capable of solving problems involving millions of decision variables, which could be of more effectiveness for solving the DR optimal scheduling models with large amounts of operational decision variables in the industrial plants.

5. Conclusions

In the smart grid environment, the optimal scheduling models of industrial power load are an important aspect to achieve the goal to gain the friendly interaction between utility companies and industrial electricity consumers. There is still a long way to reduce the electricity consumption during peak periods for improvements. The goal of this study is to present gaps and opportunities for the advancement of this research field, outlining the challenges before intelligent DR program regarding potential research areas for optimal DR scheduling models of industrial power load. The novel method, “just-for-peak” buffer inventory, gives us the inspiration that optimization issues in industrial process involve many items which are needed great attention. Some heuristic algorithms, such as PSO, ABC and ANN algorithm, are promising methods to solve the problems, both single-objective problems and multi-objective problems. The final scheduling plans illustrate that significant reduction of energy consumption and decreased cost can be achieved.

From the above studies, we can conclude that there are still lots of challenges before industrial power load scheduling considering the DR. The first one is the hardware, the basic supporter of the DR program. It is important to standardize the communication interfaces for DR energy management in order to implement the DR algorithm in practical industrial plants. Taking smart meter as an example, the wireless communications from it to network require real-time sensors and power quality monitoring for conduction of DR. Secondly, the uncertainties in the real world are unavoidable, which brings great challenges to the optimal modelling of the industrial power load during the DR event. The uncertainties of wind

Table 2
Models and methods information of the existing studies.

Single/Multi-objective	Method type	Solving technique	Solving tool or algorithm	Ref.
single-objective	MILP	Heuristic algorithm	PSO	(Sun et al., 2016)
	MILP	Mathematical solvers	–	(Li and Hong, 2016)
	DP	Forward method	–	(Sun and Li, 2014)
	DP	Forward method	–	(Li and Sun, 2013)
	MILP	Mathematical solvers	Gurobi	(Ding et al., 2014)
	MINLP	Mathematical solvers	–	(Babu and Ashok, 2008)
	SP	Ordinal optimization	–	(Liu et al., 2012)
	NIP	Mathematical solvers	GAMS	(Sun et al., 2014)
	NIP	Mathematical solvers	GAMS	(Fernandez et al., 2013)
	SP	Latin hypercube sampling (LHS)	–	(Mazidi et al., 2014)
	DP	Moving Window Markov Chain	–	(Wang et al., 2015)
	NMIP	Mathematical solvers	GAMS	(Choobineh and Mohagheghi, 2016b)
	DP	Forward method	time-dependent pricing	(Joe-Wong et al., 2012)
	MILP	Mathematical solvers	CPLEX	(Zhang et al., 2016)
	MILP	Heuristic algorithm	ANN	(Huang et al., 2017)
multi-objective	One-shot Game	Stackelberg Game approach	–	(Chen et al., 2012)
	RG	Best response method	–	(Nguyen et al., 2012)
	RG	Best response method	–	(Yang et al., 2013)
	SP	Heuristic algorithm	ABC algorithm	(Safamehr and Rahimi-Kian, 2015)
	NMIP	Mathematical solvers	GAMS	(Choobineh and Mohagheghi, 2016a)
	MIP	Mathematical solvers	CPLEX	(Aghaei and Alizadeh, 2013)
	RG	Cooperative game	–	(Song et al., 2014)
	RG	Cooperative game	–	(Ma et al., 2015)

or PV and the lifetime or repair-time of machine threaten the throughput, even would cause irreversible damage in some specific process industries due to the machines' breakdown. The stochastic factors, such as the real-time electricity price and the duration of the peak periods, can be taken into account. From another perspective, the predictive models and methods could also contribute to the optimal scheduling, such as auto regressive moving-average for short-time prediction of energy storage. The third one is about the game between accuracy and efficiency of the solving methods. Large amounts of decision variables, complex manufacturing process, the cutting edge of smart grid technology and so forth would improve accuracy at the expense of more computational time consumed. Also, with the environment problems attracting more and more attention, the goal of environment protecting becomes an important objective which should be taken into account in the modelling process. How to balance the accuracy and efficiency of solving methods will become more prominent.

Meanwhile, the future research must go around the three aforementioned aspects, taking DR as an important resource which can be utilized to promote the friendly interaction between the utility companies and industrial consumers. Furthermore, with the presence of Energy Internet, industrial energy management system should include water, electricity, gas, heat and other energy for the future research. And the Energy Internet will be the integration of the data collection, data analysis, abnormity diagnosis, implement of DR program and energy efficiency evaluation. which would make energy in the Energy Internet flows from suppliers to consumers like data packets do in the Internet.

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References

Agency, I.E, 2017. Key World Energy Statistics 2017.

Aghaei, J., Alizadeh, M.-I., 2013. Multi-objective self-scheduling of CHP (combined heat and power)-based microgrids considering demand response programs and ESSs (energy storage systems). Energy 55, 1044–1054. https://doi.org/10.1016/j.energy.2013.04.048.

Aghajani, G.R., Shayanfar, H.A., Shayeghi, H., 2017. Demand side management in a smart micro-grid in the presence of renewable generation and demand response. Energy 126, 622–637. https://doi.org/10.1016/j.energy.2017.03.051.

Alcázar-Ortega, M., Álvarez-Bel, C., Escrivá-Escrivá, G., Domijan, A., 2012. Evaluation and assessment of demand response potential applied to the meat industry. Appl. Energy 92 (4), 84–91. https://doi.org/10.1016/j.apenergy.2011.10.040.

Alizadeh, M., Scaglione, A., Thomas, R.J., 2012. From packet to power switching: digital direct load scheduling. IEEE J. Sel. Area. Commun. 30 (6), 1027–1036. https://doi.org/10.1109/JSAC.2012.120702.

Baboli, P.T., Eghbal, M., Moghaddam, M.P., Aalami, H., 2012. Customer behavior based demand response model. In: Power and Energy Society General Meeting, pp. 1–7. https://doi.org/10.1109/PESGM.2012.634510.

Babu, C.A., Ashok, S., 2008. Peak load management in electrolytic process industries. IEEE Trans. Power Syst. 23 (2), 399–405. https://doi.org/10.1109/TPWRS.2008.920732.

Barbosa-Póvoa, A.P., Macchietto, S., 1994. Detailed design of multipurpose batch plants. Comput. Chem. Eng. 18 (11–12), 1013–1042. https://doi.org/10.1016/0098-1354(94)E0015-F.

Barbosa-Póvoa, A.P.F.D., Pantelides, C.C., 1997. Design of multipurpose plants using the resource-task network unified framework. Comput. Chem. Eng. 21 (10), S703–S708. https://doi.org/10.1016/S0098-1354(97)87585-0.

Beheshti, Z., Shamsuddin, S.M., 2013. A review of population-based meta-heuristic algorithm. Int. J. Adv. Soft Comput. Its Appl. 5 (1), 1–35.

Beil, I., Hiskens, I., Backhaus, S., 2016. Frequency regulation from commercial building HVAC demand response. Proc. IEEE 104 (4), 745–757. https://doi.org/10.1109/JPROC.2016.2520640.

Blarke, M.B., Jenkins, B.M., 2013. SuperGrid or SmartGrid: competing strategies for large-scale integration of intermittent renewables? Energy Pol. 58 (9), 381–390. https://doi.org/10.1016/j.enpol.2013.03.039.

Bre, F., Fachinotti, V.D., 2017. A computational multi-objective optimization method to improve energy efficiency and thermal comfort in dwellings. Energy Build. 154. https://doi.org/10.1016/j.enbuild.2017.08.002.

Brundage, M.P., Chang, Q., Li, Y., Xiao, G., Arinez, J., 2013. Energy efficiency management of an integrated serial production line and HVAC system. In: IEEE International Conference on Automation Science and Engineering. IEEE, vol. 11, pp. 789–797. https://doi.org/10.1109/CoASE.2013.6653896.

Casola, G., Eberle, L.G., Siegmund, C., Mattern, M., Sugiyama, H., 2016. Mid-term scheduling model based on state-task-network for considering plant specific constraints in pharmaceutical manufacturing. Computer Aided Chemical Engineering 38, 1141–1146. https://doi.org/10.1016/B978-0-444-63428-3.50195-8.

Castro, P.M., Harjunkoski, I., Grossmann, I.E., 2009. Optimal scheduling of continuous plants with energy constraints. Comput. Chem. Eng. 35 (2), 372–387. https://doi.org/10.1016/j.compchemeng.2010.05.008.

Chang, H.H., Yang, H.T., Lin, C.L., 2007. Load identification in neural networks for a non-intrusive monitoring of industrial electrical loads. In: 11th International Conference on Computer Supported Cooperative Work in Design, vol. 5236, pp. 664–674.

Chao, X., Chen, F.Y., 2005. An optimal production and shutdown strategy when a supplier offers an incentive program. Manuf. Serv. Oper. Manag. 7 (2), 130–143. https://doi.org/10.1287/msom.1040.0066.

Che, A., Zhang, S., Wu, X., 2017. Energy-conscious unrelated parallel machine scheduling under time-of-use electricity tariffs. J. Clean. Prod. 156. https://doi.org/10.1016/j.jclepro.2017.04.018.

Chen, J., Yang, B., Guan, X., 2012. Optimal demand response scheduling with Stackelberg game approach under load uncertainty for smart grid. In: IEEE Third International Conference on Smart Grid Communications, pp. 546–551. https://doi.org/10.1109/SmartGridComm.2012.6486042.

Chevrier, R., Marlière, G., Vulturescu, B., Rodriguez, J., 2011. Multi-objective Evolutionary Algorithm for Speed Tuning Optimization with Energy Saving in Railway: Application and Case Study. Railrome.

Choobineh, M., Mohagheghi, S., 2015. Emergency electric service restoration in the aftermath of a natural disaster. In: Global Humanitarian Technology Conference, pp. 183–190. https://doi.org/10.1109/GHTC.2015.7343971.

Choobineh, M., Mohagheghi, S., 2016a. A multi-objective optimization framework for energy and asset management in an industrial Microgrid. J. Clean. Prod. 139, 1326–1338. https://doi.org/10.1016/j.jclepro.2016.08.138.

Choobineh, M., Mohagheghi, S., 2016b. Optimal energy management in an industrial plant using on-site generation and demand scheduling. IEEE Trans. Ind. Appl. 52 (3), 1945–1952. https://doi.org/10.1109/TIA.2015.2511094.

Coe, S., Ott, A., Pratt, D., 2010. Demanding standards. Power Energy Magazine IEEE 8 (3), 55–59.

Colak, I., Bayindir, R., Fulli, G., Tekin, I., Demirtas, K., Covrig, C.F., 2014. Smart grid opportunities and applications in Turkey. Renew. Sustain. Energy Rev. 33 (2), 344–352. https://doi.org/10.1016/j.rser.2014.02.009.

Conejo, A.J., Morales, J.M., Baringo, L., 2010. Real-time demand response model. IEEE Trans. Smart Grid 1 (3), 236–242. https://doi.org/10.1109/TSG.2010.2078843.

Cortés-Arcos, T., Bernal-Agustín, J.L., Dufo-López, R., Lujano-Rojas, J.M., Contreras, J., 2017. Multi-objective demand response to real-time prices (RTP) using a task scheduling methodology. Energy 138. https://doi.org/10.1016/j.energy.2017.07.056.

Cui, Y., Geng, Z., Zhu, Q., Han, Y., 2017. Review: multi-objective optimization methods and application in energy saving. Energy 125, 681–704. https://doi.org/10.1016/j.energy.2017.02.174.

Dekker, P.J.E., Rooy, v.R.A.M., 1999. Optimality Theory and Game Theory. Papers on Optimality Theoretic Semantics, pp. 22–45.

Ding, Y., Hong, S.H., 2013. A model of demand response energy management system in industrial facilities. In: IEEE International Conference on Smart Grid Communications, pp. 241–246.

Ding, Y.M., Hong, S.H., Li, X.H., 2014. A demand response energy management scheme for industrial facilities in smart grid. Indus. Info. IEEE Trans. 10 (4), 2257–2269. https://doi.org/10.1109/TII.2014.2330995.

Dyer, C.H., Hammond, G.P., Jones, C.I., Mckenna, R.C., 2008. Enabling technologies for industrial energy demand management. Energy Pol. 36 (12), 4434–4443. https://doi.org/10.1016/j.enpol.2008.09.028.

El-Metwally, M.M., El-Sobki, M.S., Attia, H.A., Wahdan, S.A., 2009. Priority ranking of industrial loads and application of Demand Side Management technique. In: Power Systems Conference, 2006. MEPCON 2006. Eleventh International Middle East, pp. 341–346.

Erickson, V.L., Cerpa, A.E., 2010. Occupancy based demand response HVAC control strategy. In: ACM Workshop on Embedded Sensing Systems for Energy-efficiency in Building, pp. 7–12. https://doi.org/10.1145/1878431.1878434.

Fang, X., Misra, S., Xue, G., Yang, D., 2012. Smart grid — the new and improved power grid: a survey. IEEE Commun. Surveys. Tutorials 14 (4), 944–980. https://doi.org/10.1109/SURV.2011.101911.00087.

Fernandez, M., Li, L., Sun, Z., 2013. "Just-for-Peak" buffer inventory for peak electricity demand reduction of manufacturing systems. Int. J. Prod. Econ. 146 (1), 178–184. https://doi.org/10.1016/j.ijpe.2013.06.020.

Gholian, A., Mohsenian-Rad, H., Hua, Y., Qin, J., 2013. Optimal industrial load control in smart grid: a case study for oil refineries. In: Power and Energy Society General Meeting, pp. 1–5. https://doi.org/10.1109/PESMG.2013.6672710.

Greening, L.A., 2010. Demand response resources: who is responsible for implementation in a deregulated market? Energy 35 (4), 1518–1525. https://doi.org/

10.1016/j.energy.2009.12.013.
Guerrero, J.M., Vasquez, J.C., Matas, J., Castilla, M., Vicuna, L.G.D., 2009. Control strategy for flexible microgrid based on parallel line-interactive UPS systems. IEEE Trans. Ind. Electron. 56 (3), 726–736. https://doi.org/10.1109/TIE.2008.2009274.
Hillier, F.S., Lieberman, G.J., 1986. Introduction to Operations Research, fourth ed. Holden-Day, Inc.
Huang, X., Hong, S.H., Li, Y., 2017. Hour-ahead price based energy management scheme for industrial facilities. IEEE Trans. Indus. Info. 13 (6), 2886–2898. https://doi.org/10.1109/TII.2017.2711648.
Huh, J.H., Seo, K., 2015. Hybrid advanced metering infrastructure design for micro grid using the game theory model. Int. J. Soft. Eng. Appl. 9 (9), 257–268. https://doi.org/10.14257/ijseia.2015.9.9.22.
Ibars, C., Navarro, M., Giupponi, L., 2010. Distributed demand management in smart grid with a congestion game. In: IEEE International Conference on Smart Grid Communications, pp. 495–500. https://doi.org/10.1109/SMARTGRID.2010.5622091.
Jia, Z., Zhang, L., Arinez, J., Xiao, G., 2016. Performance analysis of assembly systems with Bernoulli machines and finite buffers during transients. IEEE Trans. Autom. Sci. Eng. 13 (2), 1018–1032. https://doi.org/10.1109/TASE.2015.2442521.
Jiang, B., Muzhikyan, A., Farid, A.M., Youcef-Toumi, K., 2017. Demand side management in power grid enterprise control: a comparison of industrial & social welfare approaches. Appl. Energy 187, 833–846. https://doi.org/10.1016/j.apenergy.2016.10.096.
Joe-Wong, C., Sen, S., Ha, S., Chiang, M., 2012. Optimized day-ahead pricing for smart grids with device-specific scheduling flexibility. IEEE J. Sel. Area. Commun. 30 (6), 1075–1085. https://doi.org/10.1109/JSAC.2012.120706.
Katipamula, S., Lu, N., 2006. Evaluation of Residential HVAC Control Strategies for Demand Response Programs, Winter Meeting of the American-society-of-heating-refrigerating-and-air-conditioning-engineers (ASHRAE) Chicago, IL, vol. 112, pp. 535–546.
Khan, A.A., Naeem, M., Iqbal, M., Qaisar, S., Anpalagan, A., 2016. A compendium of optimization objectives, constraints, tools and algorithms for energy management in microgrids. Renew. Sustain. Energy Rev. 58, 1664–1683. https://doi.org/10.1016/j.rser.2015.12.259.
Khodaei, H., Hajiali, M., Darvishan, A., Sepehr, M., Ghadimi, N., 2018. Fuzzy-based heat and power hub models for cost-emission operation of an industrial consumer using compromise programming. Appl. Therm. Eng. 137, 395–405. https://doi.org/10.1016/j.applthermaleng.2018.04.008.
Kondili, E., Pantelides, C.C., Sargent, R.W.H., 1993. A general algorithm for short-term scheduling of batch operations—I. MILP formulation. Comput. Chem. Eng. 17 (2), 211–227. https://doi.org/10.1016/0098-1354(93)80015-F.
Kreps, D.M., 2011. Game theory and economic modelling. J. Polit. Econ. https://doi.org/10.1093/0198283814.001.0001.
Labrik, R., 2014. Integration of Energy Management and Production Planning : Application to Steelmaking Industry. Matematik.
Li, J., Meerkov, S.M., 2009. Production Systems Engineering. Springer, US.
Li, L., Sun, Z., 2013. Dynamic energy control for energy efficiency improvement of sustainable manufacturing systems using Markov decision process. IEEE Trans. Syst. Man & Cybernetics Syst. 43 (5), 1195–1205. https://doi.org/10.1109/TSMC.2013.2256856.
Li, L., Sun, Z., Tang, Z., 2012. Real time electricity demand response for sustainable manufacturing systems: challenges and a case study. In: IEEE International Conference on Automation Science and Engineering, pp. 353–357. https://doi.org/10.1109/CoASE.2012.6386437.
Li, N., Chen, L., Low, S.H., 2011. Optimal demand response based on utility maximization in power networks. In: Power and Energy Society General Meeting, pp. 1–8. https://doi.org/10.1109/PES.2011.6039082.
Li, W., Kara, S., 2011. An empirical model for predicting energy consumption of manufacturing processes: a case of turning process. In: Proceedings of the Institution of Mechanical Engineers Part B Journal of Engineering Manufacture, vol. 225, pp. 1636–1646. https://doi.org/10.1177/2041297511398541. Sep/Oct.
Li, Y.C., Hong, S.H., 2016. Real-time demand bidding for energy management in discrete manufacturing facilities. IEEE Trans. Ind. Electron. 64 (1), 739–749. https://doi.org/10.1109/TIE.2016.2599479.
Liao, R., Li, G., Miao, S., Lu, Y., Zhu, J., Shen, L., 2012. Weather-Clustering Based strategy design for dynamic demand response Building HVAC control, ACM Workshop on Embedded Sensing Systems for Energy-Efficiency in Buildings, pp. 33–35. https://doi.org/10.1145/2422531.2422537.
Lin, X., Floudas, C.A., 2001. Design, synthesis and scheduling of multipurpose batch plants via an effective continuous-time formulation. Comput. Chem. Eng. 25 (4–6), 665–674. https://doi.org/10.1016/S1570-7946(00)80195-9.
Liu, H., Zhao, Q., Huang, N., Zhao, X., 2012. A simulation-based tool for energy efficient building design for a class of manufacturing plants. IEEE Trans. Autom. Sci. Eng. 10 (1), 117–123. https://doi.org/10.1109/TASE.2012.2203595.
Liu, Y., Dong, H., Lohse, N., Petrovic, S., Gindy, N., 2014. An investigation into minimising total energy consumption and total weighted tardiness in job shops. J. Clean. Prod. 65 (4), 87–96. https://doi.org/10.1016/j.jclepro.2013.07.060.
Luo, H., Du, B., Huang, G.Q., Chen, H., Li, X., 2013. Hybrid flow shop scheduling considering machine electricity consumption cost. Int. J. Prod. Econ. 146 (2), 423–439. https://doi.org/10.1016/j.ijpe.2013.01.028.
Ma, K., Hu, G., Spanos, C.J., 2015. A cooperative demand response scheme using punishment mechanism and application to industrial refrigerated warehouses. IEEE Trans. Indus. Inf. 11 (6), 1520–1531. https://doi.org/10.1109/TII.2015.2431219.
Maravelias, C.T., 2005. Mixed-time representation for state-task network models. Ind. Eng. Chem. Res. 44 (24), 9129–9145. https://doi.org/10.1021/ie0500117.
Maravelias, C.T., Grossmann, I.E., 2003. A new continuous-time state task network formulation for short term scheduling of multipurpose batch plants. In: 13th European Symposium on Computer Aided Process Engineering (ESCAPE-13), vol. 14, pp. 215–220. LAPPEENRANTA, FINLAND.
Mazidi, M., Zakariazadeh, A., Jadid, S., Siano, P., 2014. Integrated scheduling of renewable generation and demand response programs in a microgrid. Energy Convers. Manag. 86, 1118–1127. https://doi.org/10.1016/j.enconman.2014.06.078.
Mckane, A.T., Piette, M.A., Faulkner, D., Ghatikar, G., Radspieler, A., Adesola, B., Murtishaw, S., Kiliccote, S., 2008. Opportunities, Barriers and Actions for Industrial Demand Response in California. https://doi.org/10.2172/945364.
Moghaddam, A.A., Seifi, A., Niknam, T., Alizadeh Pahlavani, M.R., 2011. Multi-objective operation management of a renewable MG (micro-grid) with back-up micro-turbine/fuel cell/battery hybrid power source. Energy 36 (11), 6490–6507. https://doi.org/10.1016/j.energy.2011.09.017.
Mohagheghi, S., Raji, N., 2014. Managing industrial energy intelligently: demand response scheme. Indus. Appl. Magazine IEEE 20 (2), 53–62. https://doi.org/10.1109/MIAS.2013.2288387.
Mohsenian-Rad, A.H., Wong, V.W.S., Jatskevich, J., Schober, R., Leon-Garcia, A., 2010. Autonomous demand-side management based on game-theoretic energy consumption scheduling for the future smart grid. IEEE Trans. Smart Grid 1 (3), 320–331. https://doi.org/10.1109/TSG.2010.2089069.
Nazari-Heris, M., Abapour, S., Mohammadi-Ivatloo, B., 2016. Optimal economic dispatch of FC- CHP based heat and power micro-grids. Appl. Therm. Eng. 114, 756–769. https://doi.org/10.1016/j.applthermaleng.2016.12.016.
NEA, 2017. Circular of the National Energy Administration of the State Development and Reform Commission on the Implementation Plan for Solving the Problem of Abandonment of the Water Wind and Light. http://zfxxgk.nea.gov.cn/auto87/201711/t20171113_3056.htm.
Nguyen, H.K., Ju, B.S., Zhu, H., 2012. Demand side management to reduce Peak-to-Average Ratio using game theory in smart grid. Comput. Commun. Workshops 91–96. https://doi.org/10.1109/INFCOMW.2012.6193526.
Nguyen, T.A., Aiello, M., 2013. Energy intelligent buildings based on user activity: a survey. Energy Build. 56 (1), 244–257. https://doi.org/10.1016/j.enbuild.2012.09.005.
Nyberg, M., 2016. A novel approach to include limited equipment connectivity in state-task network models. Comput. Aided Chem. Eng. 38, 1305–1310. https://doi.org/10.1016/B978-0-444-63428-3.50222-8.
Olsen, D., Goli, S., Faulkner, D., Mckane, A., 2010. Opportunities for energy efficiency and demand response in the California cement industry. Office Sci. Technical Inf. Tech. Rep. https://doi.org/10.2172/1050705.
Rahimi, F., Ipakchi, A., 2010. Demand response as a market resource under the smart grid paradigm. IEEE Trans. Smart Grid 1 (1), 82–88. https://doi.org/10.1109/TSG.2010.2045906.
Roh, H.T., Lee, J.W., 2016. Residential demand response scheduling with multiclass appliances in the smart grid. IEEE Trans. Smart Grid 7 (1), 94–104. https://doi.org/10.1109/TSG.2015.2445491.
Safamehr, H., Rahimi-Kian, A., 2015. A cost-efficient and reliable energy management of a micro-grid using intelligent demand-response program. Energy 91, 283–293. https://doi.org/10.1016/j.energy.2015.08.051.
Schulze, M., Nehler, H., Ottosson, M., Thollander, P., 2016. Energy management in industry – a systematic review of previous findings and an integrative conceptual framework. J. Clean. Prod. 112, 3692–3708. https://doi.org/10.1016/j.jclepro.2015.06.060.
Shah, N., Liberis, L., Izumoto, E., Henson, R., 1996. Integrated batch plant design: a polymer plant case study. Comput. Chem. Eng. 20 (12), S1233–S1238. https://doi.org/10.1016/0098-1354(96)00213-X.
Siano, P., 2014. Demand response and smart grids—a survey. Renew. Sustain. Energy Rev. 30 (2), 461–478. https://doi.org/10.1016/j.rser.2013.10.022.
Song, L., Xiao, Y., van der Schaar, M., 2014. Demand side management in smart grids using a repeated game framework. IEEE J. Sel. Area. Commun. 32 (7), 1412–1424. https://doi.org/10.1109/jsac.2014.2332119.
Strasser, T., Andrén, F., Kathan, J., Cecati, C., Buccella, C., Siano, P., Leitão, P., Zhabelova, G., Vyatkin, V., Vrba, P., 2015. A review of architectures and concepts for intelligence in future electric energy systems. IEEE Trans. Ind. Electron. 62 (4), 2424–2438. https://doi.org/10.1109/TIE.2014.2361486.
Su, S., Zhan, D., Xu, X., 2008. An extended state task network formulation for integrated production-distribution planning in supply chain. Int. J. Adv. Manuf. Technol. 37 (11–12), 1232–1249. https://doi.org/10.1007/s00170-007-1063-3.
Sun, Z., Li, L., 2014. Potential capability estimation for real time electricity demand response of sustainable manufacturing systems using Markov Decision Process. J. Clean. Prod. 65 (4), 184–193. https://doi.org/10.1016/j.jclepro.2013.08.033.
Sun, Z., Li, L., Dababneh, F., 2016. Plant-level electricity demand response for combined manufacturing system and heating, venting, and air-conditioning (HVAC) system. J. Clean. Prod. 135, 1650–1657. https://doi.org/10.1016/j.jclepro.2015.12.098.
Sun, Z., Li, L., Fernandez, M., Wang, J., 2014. Inventory control for peak electricity demand reduction of manufacturing systems considering the tradeoff between production loss and energy savings. J. Clean. Prod. 82 (7), 84–93. https://doi.org/10.1016/j.jclepro.2014.06.071.
Tang, Y., Xu, F., Chen, L., 2011. Research into possibility of smart industrial load participating into demand response to supply the power system. In: China International Conference on Electricity Distribution, pp. 1–5.

Tsoukalas, L.H., Gao, R., 2008. From smart grids to an energy internet: assumptions, architectures and requirements. In: International Conference on Electric Utility Deregulation and Restructuring and Power Technologies, pp. 94–98. https://doi.org/10.1109/DRPT.2008.4523385.

Vardakas, J.S., Zorba, N., Verikoukis, C.V., 2014. A survey on demand response programs in smart grids: pricing methods and optimization algorithms. IEEE Commun. Surveys. Tutorials 17 (1), 152–178. https://doi.org/10.1109/COMST.2014.2341586.

Wang, C., Li, Y., Peng, K., Hong, B., Wu, Z., Sun, C., 2013. Coordinated optimal design of inverter controllers in a micro-grid with multiple distributed generation units. IEEE Trans. Power Syst. 28 (3), 2679–2687. https://doi.org/10.1109/TPWRS.2013.2245922.

Wang, R., Wang, P., Xiao, G., 2015. A robust optimization approach for energy generation scheduling in microgrids. Energy Convers. Manag. 106, 597–607. https://doi.org/10.1016/j.enconman.2015.09.066.

Wang, Y., Li, L., 2013. Time-of-use based electricity demand response for sustainable manufacturing systems. Energy 63 (1), 233–244. https://doi.org/10.1016/j.energy.2013.10.011.

Wester, C.H., Amro, M., 2017. A dynamic model for the energy management of microgrid-enabled production systems. J. Clean. Prod. 164. https://doi.org/10.1016/j.jclepro.2017.06.119.

Wu, Y.N., Chen, J., Liu, L.R., 2011. Construction of China's smart grid information system analysis. Renew. Sustain. Energy Rev. 15 (9), 4236–4241. https://doi.org/10.1016/j.rser.2011.07.129.

Yang, P., Tang, G., Nehorai, A., 2013. A game-theoretic approach for optimal time-of-use electricity pricing. IEEE Trans. Power Syst. 28 (2), 884–892. https://doi.org/10.1109/TPWRS.2012.2207134.

Yao, J., Costanzo, G.T., Zhu, G., Wen, B., 2015. Power admission control with predictive thermal management in smart buildings. IEEE Trans. Ind. Electron. 62 (4), 2642–2650. https://doi.org/10.1109/TIE.2014.2387091.

Zakariazadeh, A., Jadid, S., Siano, P., 2014a. Economic-environmental energy and reserve scheduling of smart distribution systems: a multiobjective mathematical programming approach. Energy Convers. Manag. 78 (1), 151–164. https://doi.org/10.1016/j.enconman.2013.10.051.

Zakariazadeh, A., Jadid, S., Siano, P., 2014b. Smart microgrid energy and reserve scheduling with demand response using stochastic optimization. Int. J. Electr. Power Energy Syst. 63 (12), 523–533. https://doi.org/10.1016/j.ijepes.2014.06.037.

Zakariazadeh, A., Jadid, S., Siano, P., 2014c. Stochastic multi-objective operational planning of smart distribution systems considering demand response programs. Elec. Power Syst. Res. 111 (2), 156–168. https://doi.org/10.1016/j.epsr.2014.02.021.

Zhang, G., Jiang, C., Wang, X., Li, B., Zhu, H., 2017a. Bidding strategy analysis of virtual power plant considering demand response and uncertainty of renewable energy. IET Gener., Transm. Distrib. 11 (13), 3268–3277. https://doi.org/10.1049/iet-gtd.2016.1663.

Zhang, X., Hug, G., Kolter, J.Z., Harjunkoski, I., 2016. Model predictive control of industrial loads and energy storage for demand response. In: Power and Energy Society General Meeting, pp. 1–5. https://doi.org/10.1109/PESGM.2016.7741228.

Zhang, X., Hug, G., Kolter, Z., Harjunkoski, I., 2017b. Demand response of ancillary service from industrial loads coordinated with energy storage. In: IEEE Transactions on Power Systems, p. 99. https://doi.org/10.1109/TPWRS.2017.2704524, 1–1.

Zhou, K., Yang, S., Chen, Z., Ding, S., 2014. Optimal load distribution model of microgrid in the smart grid environment. Renew. Sustain. Energy Rev. 35, 304–310. https://doi.org/10.1016/j.rser.2014.04.028.