Planning and Scheduling for Industrial Demand Side Management: Advances and Challenges

Qi Zhang and Ignacio E. Grossmann

Abstract In the context of the so-called smart grid, the intelligent management of electricity demand, also referred to as demand side management (DSM), has been recognized as an effective approach to increase power grid performance and consumer benefits. Being large electricity consumers, the power-intensive process industries play a key role in DSM. In particular, planning and scheduling for industrial DSM has emerged as a major area of interest for both researchers and practitioners. In this work, we provide an introduction to DSM and present a comprehensive review of existing works on planning and scheduling for industrial DSM. Four main challenges are identified: (1) accurate modeling of operational flexibility, (2) integration of production and energy management, (3) optimization across multiple time scales, (4) decision-making under uncertainty. Two real-world case studies are presented to demonstrate the capabilities of state-of-the-art models and solution approaches. Finally, we highlight research gaps and future opportunities in this area.

1 Introduction

Smart Grid and Demand Side Management The power grid is designed to reliably match electricity supply and demand. This task has become increasingly challenging due to high fluctuations in electricity demand and increasing penetration of intermittent renewable energy into the electricity supply mix. Also, the deregulation of electricity markets and the pressure to reduce greenhouse gas emissions have fur-

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ther amplified the need to improve the efficiency, reliability, and sustainability of the power grid.

In recent years, the notion of a *smart grid* has been evolving, which represents the concept of a power grid in which the major operations—electricity generation, transmission, distribution, and consumption—are executed in a coordinated and efficient manner. To establish such a smart grid, three essential components are required: (1) An information and communications infrastructure has to be in place such that data on grid conditions can be collected and exchanged in real-time. (2) Advanced decision-making tools have to be developed that can use the collected information to optimize operations in the grid. (3) With the help of the decision-making tools, the grid operator may know which actions should be taken to achieve optimal performance; however, these actions have to be actually implemented by the different participants in the grid, e.g. generators and consumers. To encourage and to a certain extent control these actions, efficient markets are required, which provide appropriate financial incentives to the participants.

The idea of a smart grid has gained considerable interest in industry, research, and public policy. Since 2009, the U.S. Department of Energy and the electricity industry have jointly invested over $7.9 billion in smart grid projects as part of the Smart Grid Investment Grant Program (DOE, 2013), and similar efforts have been undertaken in many other countries.

Traditionally, in power systems engineering, the focus has been on improving the power supply for given electricity demands (loads) in the grid. A major innovation in smart grid is to also include the management of flexible loads, which is generally referred to as demand side management (DSM) since it involves the enhancement of energy systems on the electricity demand side. DSM is expected to play a crucial role in the improvement of grid efficiency and reliability as well as the creation of additional benefits for the consumers (Levy, 2006; Strbac, 2008; Siano, 2014); this has spurred tremendous research efforts across multiple disciplines, such as electrical engineering, civil and environmental engineering, economics, data science, behavior science, and engineering public policy.

Two Perspectives on DSM The opportunities in DSM can be viewed from two distinct perspectives: the grid operator's perspective, and the electricity consumer's perspective. On the one hand, the grid operator's main objective is to increase efficiency and ensure stability in the power grid. In this context, DSM is regarded as a means to reduce the overall electricity demand, to flatten the load curve and hence reduce the required peak generation capacity, as well as to provide the flexibility to quickly react to supply-demand mismatch in the grid by adjusting loads. On the other hand, the electricity consumer's objective is simply cost reduction. For electricity consumers, DSM is required in order to adapt to price signals coming from the electricity market, and it is a way to take advantage of new financial incentives specifically created for DSM purposes. Therefore, ideally, DSM leads to a win-win situation in which both the power grid and the consumers benefit.

Fig. 1 illustrates the activities on the grid operator and electricity consumer sides, which are connected by operations in the physical power grid and the opportunities in the electricity markets. Until recently, DSM has been analyzed primarily from the grid operator's perspective. In the U.S., for example, the power grid is operated by the various independent system operators (ISOs) and regional transmission organizations (RTOs), which control the transmission networks and operate the electricity markets. In terms of DSM, the main task of the grid operator is to set up DSM programs with appropriate financial incentives such that electricity consumers are encouraged to participate (Walawalkar et al, 2010). In models that are typically used for market design problems, simplistic assumptions are made on consumers' load adjustment capabilities (Albadi and El-Saadany, 2008; Mohsenian-Rad et al, 2010); however, such simplified models are often not sufficiently accurate to capture the real DSM potential that each consumer has as well as the costs occurring on the consumer side when implementing different DSM measures.

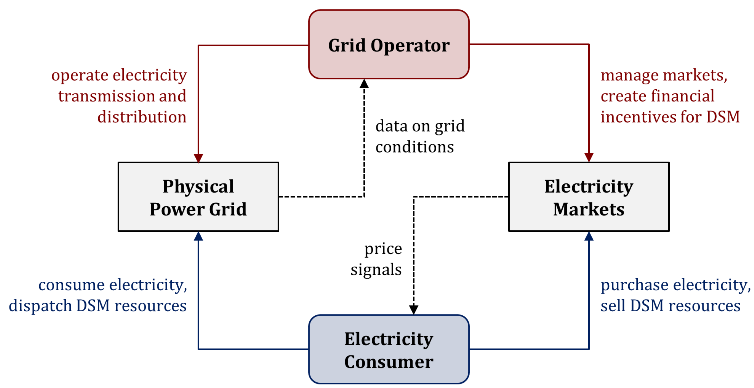


Fig. 1 Two perspectives on DSM, which requires both the grid operator and the consumer to interact through physical grid operations and the electricity markets.

The electricity consumer's perspective has to be considered in order to achieve a more accurate assessment of individual consumers' DSM potentials. This knowledge will consequently lead to more active participation of consumers and make electricity markets more efficient and competitive (Kirschen, 2003). Here, domain knowledge is required since each process has its own operational limitations, costs, safety requirements etc. Also, different preferences in terms of convenience and risk have to be taken into account.

One distinguishes between three consumer sectors: residential, commercial, and industrial. DSM in the first two sectors deals with residential and commercial buildings (Motegi et al, 2007), in which load adjustment is mainly achieved by controlling the HVAC and lighting systems, whereas industrial DSM is concerned with power-intensive industrial processes (Samad and Kiliccote, 2012).

Scope and Organization of Review In this work, we take the standpoint of power-intensive industries, which engage in DSM as large electricity consumers. The high potential impact of industrial DSM is widely acknowledged (Paulus and Borggrefe, 2011; Samad and Kiliccote, 2012) and has been the focus of increased research efforts in recent years. Because of the time-sensitive nature of electricity prices and DR events, efficient planning, scheduling, and control of plant operations are crucial for enabling effective DSM (Merkert et al, 2014). This is especially true in an industrial setting due to the high standards in terms of product quality and process safety.

The focus of this review is on models and systematic methods for industrial DSM that optimize process operations at the planning and scheduling level. This is still a relatively new research topic; therefore, with this work, we hope to provide a comprehensible introduction to industrial DSM to interested researchers, while reviewing existing works addressing the main challenges that we see in this area.

The remainder of this review is organized as follows. In Section 2, a definition of DSM and a classification of the DSM activities are provided. Section 3 describes the special characteristics of DSM in power-intensive process industries. Four main challenges in industrial DSM are identified: (1) accurate modeling of operational flexibility, (2) integration of production and energy management, (3) optimization across multiple time scales, (4) decision-making under uncertainty. A state-of-the-art review of existing works addressing these four topics is presented in Section 4. To demonstrate some of the recently developed models, two case studies are presented in Section 5. Future opportunities and challenges that we see in this research area are listed in Section 6. Finally, in Section 7, we close with some concluding remarks.

2 Definition of Demand Side Management

When it comes to defining DSM, most descriptions represent the grid operator's perspective. For example, in a report released by The World Bank (Charles River Assosicates, 2005), DSM is defined as the

> systematic utility and government activities designed to change the amount and/or timing of the customer's use of electricity for the collective benefit of the society, the utility and its customers.

Notice that according to this definition, only activities on the utility and government sides are considered DSM, whereas electricity consumers take a rather passive role and only react to those DSM activities. Although such a definition is perfectly correct and underlines the origin of DSM as a concept proposed by utilities (Gellings, 1985), it understates the degree of freedom that consumers have in their decision-making. In fact, only the consumers can actually change their electricity consumption; utilities and governments can only provide incentives that encourage such activities. Hence, a more comprehensive definition of DSM considering both perspectives could be:

> DSM encompasses systematic activities at the interplay between grid operator and electricity consumer aiming at changing the amount and/or timing

of the consumer's use of electricity in order to increase grid performance and consumer benefits. DSM activities on the grid operator side involve the assessment of the need for load adjustment and the creation of financial incentives for the consumer, while the consumer reacts to these financial incentives and performs the actual physical load adjustment operations.

Note that depending on the level of regulation in the electricity market, the grid operator could be an independent organization or the electric utility itself. Depending on the size, an electricity consumer could be one individual consumer or an aggregator that manages many small consumers.

Fig. 2 shows a general classification of DSM activities, which consist of various DSM programs introduced by the grid operator (rectangular boxes) and the measures that need to be taken by the consumer (rounded rectangles) in order to participate in these DSM programs. The two main DSM categories are energy efficiency (EE) and demand response (DR) (Charles River Assosicates, 2005). The goal of EE is to reduce power consumption while accomplishing the same tasks, and DR refers to load profile adjustment, such as load shifting and load shedding, driven by market incentives.

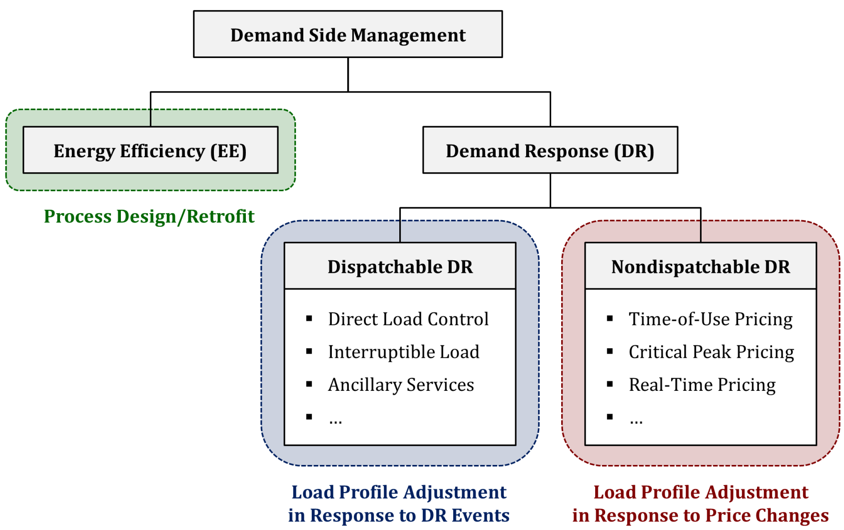


Fig. 2 Classification of DSM activities. Rectangular boxes depict DSM programs introduced by the grid operator, whereas rounded rectangles indicate measures to be taken by the consumer.

In DR, one distinguishes between dispatchable and nondispatchable DR (FERC, 2010), which are often also referred to as incentive-based and price-based DR (DOE, 2006), respectively. Dispatchable DR refers to load adjustment capacities that consumers provide to the grid operator such that these capacities can be dispatched to maintain grid stability or in times of emergency. The grid operator has control over dispatchable DR resources by either direct load control or by requesting the consumers to reduce their power consumption (interruptible load) when a DR event, e.g. a generator failure, occurs. The various types of dispatchable DR resources, many of which classified as ancillary services, mainly differ in the amount of time within which the consumer has to respond to DR requests. In general, the faster one can react, the more valuable is the DR service, i.e. the more consumers get paid for providing such DR capacities.

Nondispatchable DR resources are not controlled by the grid operator; instead, consumers choose to adjust their power consumption profile based on price signals from the electricity market. Time-of-use (TOU), critical peak, and real-time pricing are just three of many pricing schemes designed to encourage consumers to change their load profiles according to the power grid's needs.

EE can be primarily achieved by improved process design or retrofit of the existing process that results in higher efficiency. Also, efficiency can be increased by optimal scheduling and control strategies that maximize the time in which the process runs at its most energy-efficient operating point. Effective planning, scheduling, and control are even more critical in DR. Here, operational flexibility is key. In nondispatchable DR, electricity is treated as any other commodity that can be purchased, but with two distinct characteristics: it is difficult to store electricity, and electricity prices are extremely volatile. Hence, processes have to be flexible in order to react to price changes. In dispatchable DR, consumers are rewarded not so much for the actual dispatch of DR resources rather than for the capability of quickly reacting to DR events whenever they occur. Providing dispatchable DR requires a very high degree of flexibility in the consumer's process since requests by the grid operator, which typically cannot be anticipated in advance, have to be met while maintaining process feasibility and safety.

3 Characteristics of Industrial DSM

Although there are large untapped DSM potentials in all three—residential, commercial, and industrial—sectors (Gellings et al, 2006), there are some distinguishing features of industrial processes that facilitate the deployment of DSM strategies:

- In the industrial sector, individual power consumption is very high, which motivates and eases participation in DSM programs. For example, aluminum production has an energy intensity of 71 GJ per tonne (Worrell et al, 2008), and a typical aluminum plant produces hundreds of tonnes of aluminum on a daily basis.
- In most cases, advanced metering infrastructure is already in place; therefore, the capital investment required to implement DSM in industry is close to zero.
- Industrial processes operate in isolated environments such that human comfort is usually not an issue; this is in contrast to the residential and commercial sectors, where e.g. HVAC control is constrained by the maximum decrease in comfort induced by temperature changes.

However, industrial processes are often highly complex and subject to strict safety requirements. In industrial DSM, it is therefore crucial to carefully evaluate the flexibility of each process in order to avoid detrimental disruptions caused by sudden changes in the plant operation.

In the following, we list some distinct characteristics of industrial electricity consumers, which need to be considered in the DSM decision-making process:

- Many manufacturing processes are highly integrated and have critical temporal dependencies, which have to be taken into account when operating the plant; this requires deep process knowledge.
- While direct load control is common in the residential sector, it usually cannot be applied in industry because of safety considerations.
- Electricity is difficult to store; however, most commodity products are not. Product inventory naturally increases the flexibility in plant operations and therefore allows more room for DSM.
- Industrial electricity consumers often enter into power contracts which offer special rates under given conditions.
- Large industrial power-intensive plants often have substantial onsite electricity generation capacities. Some of the generated electricity may even be sold at the market price or transferred offsite.
- Industrial usage data are typically confidential since they could reveal competition-sensitive information on operations strategies and process performance. Hence, all DSM efforts have to be managed within the same company.

According to the EIA (2012), the total net electricity demand by the U.S. industry in 2010 amounted to 850 TWh, with the five most power-intensive sectors—chemicals, primary metals, paper, food, and petroleum and coal products—combined consuming 560 TWh. Highly power-intensive processes include gas compression, electrolysis, and electric heating. Samad and Kiliccote (2012) present five real-world case studies in which industrial DSM has been successfully implemented and has generated considerable cost savings. Among the examples, the most prominent case is probably the one of Alcoa (Todd et al, 2009), which uses the operational flexibility of its aluminum smelting facilities to provide ancillary services through which the company is achieving large economic benefits.

4 Optimization of Planning and Scheduling for Industrial DSM

Because of the strong dependence of electricity price, electricity availability, and DR events on time, effective planning and scheduling tools are essential in DSM, especially in an industrial setting where complex manufacturing processes are involved. Production scheduling has been an active field of research in operations research since the 1950s (Graves, 1981), and it started to attract increased attention in the process systems engineering (PSE) community in the 1970s (Reklaitis, 1982). Since then, considerable progress has been made in the modeling of production scheduling problems as well as in the development of efficient methods for solving these models. For recent reviews of works on production scheduling in PSE, we refer to Méndez et al (2006), Maravelias (2012), and Harjunkoski et al (2014). Furthermore, Maravelias and Sung (2009) discuss the integration of scheduling and planning, which involves longer time horizons; and Li and Ierapetritou (2008) and Verderame et al (2010) review approaches proposed for scheduling under uncertainty.

For industrial DSM, we can leverage the tremendous advances in production planning and scheduling made over the last few decades; however, there are unique challenges that require special attention. The four main challenges that we see in planning and scheduling for industrial DSM are the following:

1. *Modeling operational flexibility*
   Electricity prices are extremely time-sensitive. In a typical day-ahead market, the price varies from hour to hour; in the real-time market, it changes every few minutes. In order to capture this time dependence and determine a process' ability to quickly respond to price changes, very detailed scheduling models are required. In these models, the representation of time and the accurate modeling of constraints on transitions between different process operating points are especially critical.
2. *Integration of Production and Energy Management*
   Traditionally, production and energy management are handled separately. For planning and scheduling, this means that first, a production scheduling problem is solved, and once the production schedule is determined, the objective of energy management is to minimize the cost for purchasing the electricity required for this particular production schedule. This sequential approach can easily lead to suboptimal solutions since possible synergies between production and energy management are not taken into account. Hence, an integrated approach that considers both parts simultaneously can be very beneficial, especially when power contracts with complex constraints are applied. Moreover, energy management can be further complicated by the presence of onsite generation and participation in dispatchable DR programs.
3. *Decision-making across multiple time scales*
   To perform DSM scheduling, a detailed model with a fine time representation is required; the typical time horizon for such a scheduling problem is one day or one week. In contrast, in long-term planning, the time horizon may span multiple months or years. In that case, however, we cannot simply apply the same detailed model with an extended time horizon because the resulting model would be computationally intractable, nor can we use an aggregate model with a coarse time representation since then we would not be able to model DSM activities. Hence, computationally efficient planning models have to be developed that can capture both long-term as well as short-term effects.
4. *Optimization under uncertainty*
   The level of uncertainty in the power grid is extremely high due to various factors such as fluctuating electricity demand, deregulation of electricity markets, and increasing penetration of intermittent renewable energy. The most apparent result

of this uncertainty is the high volatility in electricity price. Also, all dispatchable DR activities are intrinsically uncertain because the consumer does not know in advance when the grid operator will request the dispatch of those DR services. Furthermore, uncertainties on the production side, e.g. regarding product demand and processing time, also exist. The major challenge lies in the accurate characterization of the relevant sources of uncertainty and optimal decision-making while considering these uncertainties.

Associated with all the above is the challenge of computational efficiency. With the incorporation of new features, the models become more complex and computational tractability becomes an issue. Many large-scale real-world problems cannot be solved by using off-the-shelf tools. Therefore, along with novel modeling approaches, efficient solution methods have to be developed in order to improve the computational performance.

In the following, we present a comprehensive review of existing works addressing the aforementioned four main challenges. All reviewed works are listed in Table 1, presented in chronological order with respect to the publication date. Table 1 shows various features of the different models, and we will refer back to this overview in the next subsections.

4.1 Modeling Operational Flexibility

The key to industrial DSM is operational flexibility, which allows load profile adjustment in response to electricity market signals. In this context, a production facility's operational flexibility is mainly defined by its ability to ramp up and down production and its product inventory capacity. In order to assess the potential benefits from DSM for an industrial plant, a detailed scheduling model capturing all relevant process constraints and interactions with electricity markets is required. The development of such scheduling models has been identified as a promising research topic only very recently. From Table 1, one can see that almost all works addressing this subject have been conducted after year 2000, with the vast majority published within the past five years.

Relevant Industrial Processes Industrial processes considered in the literature can be grouped into two general categories: continuous production and batch production. For example, air separation and aluminum manufacturing are typical continuous processes, whereas steel production is mainly operated in batch mode. Table 1 shows for each reference whether the proposed model is primarily designed for continuous or batch production processes. Note that some of the models can also be applied to model hybrid (continuous and batch) production environments.

Also, Table 1 lists particular industrial processes to which each model has been applied. Cryogenic air separation and steel manufacturing, which are arguably the most complex production processes among the ones listed, have been considered more extensively. Cryogenic air separation is power-intensive because of the large

Table 1 Overview of reviewed works. The table lists the papers in chronological order and shows various features of the applied models. The different features are shown in thematic groups.

	Continuous Production	Batch Production	Air Separation	Aluminum	Cement	Chlor-Alkali	Flour/Pulp	Machining	Steel	Power Contracts	Onsite Generation	Dispatchable DR	Stochastic Programming	Robust Optimization	Discrete-Time	Continuous-Time	LP	NLP	MILP	MINLP	CP
Daryanian et al (1989)	✓		✓												✓		✓				
Ashok and Banerjee (2001)	✓						✓								✓				✓		
Ierapetritou et al (2002)	✓		✓										✓		✓					✓	
Everett and Philpott (2002)	✓						✓						✓		✓				✓		
Ashok (2006)		✓							✓						✓				✓		
Karwan and Keblis (2007)	✓		✓												✓				✓		
Babu and Ashok (2008)	✓					✓									✓					✓	
Castro et al (2009)	✓				✓										✓	✓			✓		
Yusta et al (2010)	✓							✓							✓			✓			
Nolde and Morari (2010)		✓							✓							✓			✓		
Haït and Artigues (2011)		✓							✓							✓			✓		
Castro et al (2011)	✓				✓										✓	✓			✓		
Fang et al (2011)		✓														✓			✓		
Mitra et al (2012a)	✓		✓		✓										✓				✓		
Mitra et al (2012b)	✓		✓											✓	✓				✓		
Wang et al (2012)		✓							✓		✓				✓				✓		
Vujanic et al (2012)		✓			✓							✓		✓	✓				✓		
Castro et al (2013)		✓							✓						✓				✓		
Artigues et al (2013)		✓														✓			✓		✓
Tan et al (2013)		✓							✓							✓			✓		
Ding et al (2014)	✓		✓												✓				✓		
Wang et al (2014)	✓					✓									✓		✓				
Mitra et al (2014)	✓		✓										✓		✓				✓		
Labrik (2014)		✓							✓	✓	✓					✓			✓		
Zhang and Hug (2014)	✓			✓								✓	✓		✓				✓		
Shrouf et al (2014)		✓							✓						✓				✓		
Zhang et al (2015c)	✓		✓								✓	✓		✓	✓				✓		
Zhang and Hug (2015)	✓			✓								✓	✓		✓				✓		
Zhang et al (2015e)	✓		✓							✓					✓				✓		
Zhang et al (2015b)	✓		✓							✓			✓		✓				✓		
Hadera et al (2015)		✓							✓	✓	✓					✓			✓		
Tan et al (2015)		✓							✓						✓				✓		
Zhang et al (2015d)	✓		✓									✓		✓	✓				✓		
Zhang et al (2015a)	✓		✓							✓			✓		✓				✓		

amount of compression that is required in the separation and liquefaction processes. In steel manufacturing, the most power-intensive production stages are the melting process in the electric arc furnace and the hot rolling process.

Other power-intensive industrial processes considered in case studies are aluminum, cement, chlor-alkali, flour, and pulp production, and machining. Aluminum and chlor-alkali manufacturing involve electrolysis, while the high power intensities in cement, flour, pulp, and machining processes stem from mechanical operations such as grinding, milling, and turning.

Prevalent Modeling Concepts In one of the first works on DSM scheduling, Daryanian et al (1989) propose a multiperiod model that merely consists of inventory constraints and bounds on the production rate. However, industrial processes are seldom that simple, and more accurate representations require detailed models involving more complex constraints.

In cases where the scheduling problem is primarily concerned with the sequencing and timing of power-intensive production tasks, typical machine scheduling formulations have been applied in several proposed models (Nolde and Morari, 2010; Fang et al, 2011; Wang et al, 2012). Tan et al (2013) and Hadera et al (2015) further include constraints on waiting times between consecutive production stages, which are especially important in steel manufacturing.

Many chemical production environments exhibit a network structure (Maravelias, 2012) in which material handling constraints play an essential role. The scheduling of such processes is the focus of the works by Ashok and coworkers (Ashok and Banerjee, 2001; Ashok, 2006; Babu and Ashok, 2008), who emphasize the impact of storage in industrial DSM. For the same purpose, Ding et al (2014) apply the well-known concept of the state-task network (STN) (Kondili et al, 1993), in which state nodes represent feeds, intermediates, and final products, and task nodes represent processing operations. A similar concept is the one of the resource-task network (RTN) (Pantelides, 1994), which forms the basis for several DSM scheduling models proposed by Catro and coworkers (Castro et al, 2009, 2011, 2013).

Another popular modeling concept is based on the notion of operating modes. First proposed by Ierapetritou et al (2002) and further developed by Karwan and Keblis (2007), it takes into account that production and power consumption characteristics can vary within the same process depending on the configuration or state in which the process is operating. In a mode-based model, the process can only operate in one of the given operating modes, and each mode is defined by a specific feasible region in the product space and a power consumption function with respect to the production rates. Mitra et al (2012a, 2013) reformulate the model by Karwan and Keblis (2007) to improve the tightness of the formulation, and develop additional constraints to impose restrictions on the transitions between different modes. The proposed mode transition constraints are as follows:

$$\sum_{m} y_{mt} = 1 \qquad \forall t \tag{1a}$$

$$\sum_{m' \in TR_m^{\mathrm{f}}} z_{m'm,t-1} - \sum_{m' \in TR_m^{\mathrm{t}}} z_{mm',t-1} = y_{mt} - y_{m,t-1} \qquad \forall m, t \tag{1b}$$

$$y_{m't} \geq \sum_{k=1}^{\theta_{mm'}} z_{mm',t-k} \qquad \forall\,(m,m') \in TR,\, t \tag{1c}$$

$$z_{mm',t-\bar{\theta}_{mm'm''}} = z_{m'm''t} \qquad \forall\,(m,m',m'') \in SQ,\, t \tag{1d}$$

where the binary variable y_{mt} takes the value 1 if mode m is selected in time period t. Eq. (1a) states that one and only one mode has to be selected in each time period. Eq. (1b) ensures that the binary variable $z_{mm't}$ takes the value 1 if and only if the plant switches from mode m to mode m' at time point t. Here, TR_m^{f} denotes the set of modes from which mode m can be directly reached; similarly, TR_m^{t} denotes the set of modes which can be directly reached from mode m. Eq. (1c) states that after switching from mode m to mode m', the plant has to remain in mode m' for at least $\theta_{mm'}$ time periods. Moreover, for an allowed mode transition sequence from m to m' to m'', Eq. (1d) can be used to fix the number of time periods that the plant has to remain in mode m' to $\bar{\theta}_{mm'm''}$.

Mode-based models have been applied in some of the most recent works on DSM planning and scheduling (Shrouf et al, 2014; Zhang et al, 2015c,e,b,d,a). In the most recent development, Zhang et al (2015e) have further generalized the model such that it can also be used to represent continuous process networks.

Time Representation One important attribute of scheduling models is the representation of time, which is especially critical in DSM applications because of the highly time-sensitive nature of electricity prices. In general, one distinguishes between discrete- and continuous-time models, and there is a large body of work in the literature discussing different formulations and their strengths and limitations (Floudas and Lin, 2004; Méndez et al, 2006; Sundaramoorthy and Maravelias, 2011).

As shown in Table 1, predominantly discrete-time models have been used in DSM scheduling. In a discrete time representation, in which the scheduling horizon is divided into discrete time periods, it is straightforward to model the time-varying electricity price by simply assigning different price values to different time periods. In most cases, hourly electricity prices are considered, with a scheduling horizon of one day or one week resulting in 24 or 168 time periods, respectively.

Unlike discrete-time models, a continuous time representation allows processing tasks to start at any point in the continuous time domain. In scheduling problems in which tasks can change within small time intervals, continuous-time models can be beneficial since an appropriate discrete-time model may require a very fine time discretization, which could dramatically increase the size of the model. However, with time-varying electricity prices, modeling the electricity cost becomes a challenge in continuous-time formulations. Castro et al (2009) propose a continuous-time formulation in which different electricity prices e are defined over price periods $p \in P_e$ with starting times L_{ep} and ending times U_{ep}. Also, tasks are disaggregated into tasks executed at different electricity prices, forming the price-dependent sets of tasks $\bar{I}_e$. This time representation is illustrated in Fig. 3, where τ_t denotes the absolute time at event point t, and $\hat{\tau}_t$ denotes the starting time of tasks executed during time interval t. The corresponding timing constraints are:

$$\sum_{e}\sum_{p\in P_e} y_{tpe} = 1 \qquad \forall t \neq |T| \qquad (2a)$$

$$\hat{\tau}_t \geq \sum_{e}\sum_{p\in P_e} L_{ep}\, y_{tpe} \qquad \forall t \neq |T| \qquad (2b)$$

$$\hat{\tau}_t + \sum_{i\in \bar{I}_e} \frac{\bar{\mu}_{ri}\,\xi_{it}}{\rho_i^{\max}} \leq \sum_{p\in P_e} U_{ep}\, y_{tpe} + M\left(1 - \sum_{i\in \bar{I}_e} \bar{\mu}_{ri}\, z_{it}\right) \qquad \forall t \neq |T|, e, r \in R^{\mathrm{TC}} \qquad (2c)$$

where the binary variable y_{tpe} takes the value 1 if during time interval t, tasks are processed within price period $p \in P_e$. Eq. (2a) states that there is one active price period during each time interval. Eqs. (2b) and (2c) ensure that a task starts and finishes within the corresponding price period. Here, $\bar{\mu}_{ri}$ is the discrete interaction of resource r with task i at its end, ξ_{it} is the amount handled by task i during interval t, $\rho_i^{\max}$ is the maximum processing rate of task i, M is a big-M parameter, z_{it} is a binary variable that takes the value 1 if task i is executed in interval t, and R^{TC} denotes the set of equipment resources involved in timing constraints.

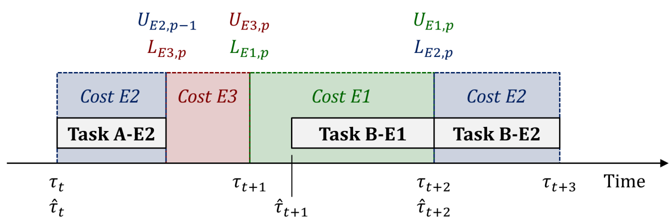


Fig. 3 Illustration of continuous time representation with timing constraints (Castro et al, 2009).

Nolde and Morari (2010) propose a continuous-time model for load tracking in which the electricity consumption in prespecified load intervals is determined by computing the overlap of tasks with the load intervals. The same concept can be applied to determine electricity cost when electricity prices vary with time (Tan et al, 2013). The idea is illustrated in Fig. 4, which shows six different task-interval overlap cases that need to be considered for each task-interval pair. Nolde and Morari (2010) present a formulation using binary variables and corresponding big-M constraints for each of the six cases. This formulation has been further improved by Haït and Artigues (2011) who compute the overlaps by introducing binaries indicating whether a task begins before or during a price interval. This reformulation greatly reduces the number of constraints and binary variables. A continuous-time model applying a similar approach has been proposed by Hadera et al (2015).

Computational performance is often the key criterion when choosing between discrete- and continuous-time scheduling models. An analysis of the reviewed works shows that at this point, discrete-time models generally show better computational performance when applied to large-scale problems. Castro et al (2009) show that only problems of small size can be handled effectively by the continuous-time model, while problems of industrial significance can be solved efficiently with

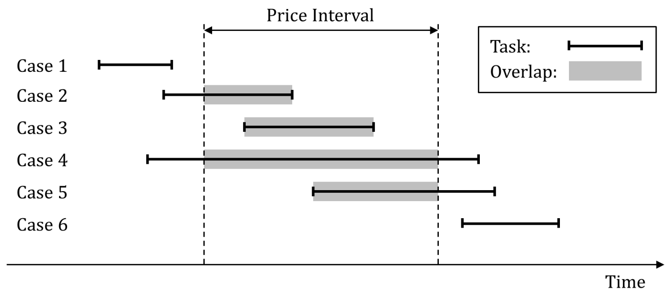


Fig. 4 Six possible task-interval overlap cases (Nolde and Morari, 2010).

a comparable discrete-time model. In order to mitigate this limitation, Castro et al (2011) propose an aggregate discrete-time model that is used in conjunction with a continuous-time model in a rolling horizon framework. The computational results show that the proposed solution approach is considerably more efficient than both full-space traditional discrete- and continuous-time models. However, under restricted power availability, the rolling horizon approach may lead to suboptimal solutions, in which case the full-space discrete-time model becomes the better choice. Hadera et al (2015) apply a heuristic bilevel decomposition approach to solve the proposed continuous-time model. The decomposition approach significantly reduces the solution time; however, the problem is still only tractable for a one-day scheduling horizon.

Types of Models From Table 1, we can see that the vast majority of the reviewed models are formulated as mixed-integer linear programs (MILPs). Two very simplistic models (Daryanian et al, 1989; Wang et al, 2014) are formulated as linear programs (LPs). A nonlinear programming (NLP) formulation is proposed by Yusta et al (2010) for machining process scheduling, where the nonlinearity stems from the equation expressing the lifetime of the cutting tool as a nonlinear function of the cutting speed and the power consumption function.

Ierapetritou et al (2002) apply a quadratic power consumption function, which gives rise to a mixed-integer nonlinear programming (MINLP) formulation. Generalized Benders decomposition (Geoffrion, 1972) and outer approximation (Duran and Grossmann, 1986) have been applied to solve the problem. Since the MINLP is convex in the continuous variables, both solution algorithms are guaranteed to obtain the global optimal solution; however, they require considerable computational expense for solving industrial-scale problems. Hence, Ierapetritou et al (2002) create an approximate MILP by linearizing the power consumption function and solve the MILP instead of the original MINLP. The results show that the MILP model can be solved in significantly less computational time and obtains solutions that are very close to the true optimal solutions of the MINLP. Babu and Ashok (2008) propose an MINLP model with quadratic functions expressing the power factors and efficiencies of each subprocess. The model has been solved with the global optimization algorithm implemented in the LINDO solver.

Clearly, the preference of linear over nonlinear models is a result of the fact that in general, linear models are considerably easier to solve than nonlinear ones. However, many processes exhibit nonlinear behavior that needs to be approximated in linear models. A recent attempt to improve the accuracy of the process representation in MILP models has been proposed by Zhang et al (2015c,e). Here, the idea is to approximate the generally nonconvex feasible region of a process or a certain configuration of a process by a set of polytopes with a linear power consumption function associated with each polytope. Such models are referred to as Convex Region Surrogate (CRS) models (Zhang et al, 2014). The advantage of a CRS model is that it captures nonlinearities and nonconvexities, yet it can be formulated as a set of mixed-integer linear constraints, which do not increase the computational complexity of the scheduling model if it is already formulated as an MILP.

Moreover, Artigues et al (2013) show an interesting application of constraint programming (CP) in industrial DSM. Here, the scheduling problem is solved in two steps. In the first step, a job assignment and sequencing problem with fixed job durations is solved with a CP model; then in the second step, an MILP scheduling model is solved with the job assignment and sequencing obtained in the first step. Obviously, this is another attempt to reduce the computational effort by decomposing the problem.

Main Insights from Case Studies A number of case studies have been presented in the reviewed references, some using real-world data from industry. Here, we summarize some of the main insights drawn from these case studies in which scheduling under time-sensitive electricity prices has been considered.

All case study results show the high potential benefit of industrial DSM, accomplished primarily by shifting load toward low-price periods. Cost savings up to 20 % can be achieved compared to scheduling assuming constant electricity prices (Castro et al, 2009). The optimization even shows that in certain cases, it can be beneficial to shut down the plant for a long period of time (Ierapetritou et al, 2002; Mitra et al, 2012a). However, the impact of DSM strongly depends on the level of operational flexibility. In particular, if a plant is highly utilized, i.e. it has to operate at close to full capacity in order to meet the product demand, there will be hardly any room for load shifting (Ashok, 2006; Mitra et al, 2012a). Therefore, DR should be mainly considered for plants with a relatively low level of utilization.

4.2 Integration of Production and Energy Management

Industrial DSM relies on the integrated optimization of production and energy management. In most existing works on DSM planning and scheduling, the energy management part only consists of purchasing electricity at time-varying prices with possibly an upper bound constraint on the amount of electricity that can be purchased in each time period. As indicated by the overview shown in Table 1, only very recently, more complex energy management activities involving power contracts with various price structures, onsite generation, and dispatchable DR have been considered.

Nolde and Morari (2010) consider a load tracking problem in which the actual electricity consumption of a steel plant is supposed to match a committed load curve; penalties incur for over- and underconsumption. Besides load tracking, the models proposed by Labrik (2014) and Hadera et al (2015) account for multiple electricity sources as well as onsite generation, which generates electricity that can be either used to power the steel plant or sold to the electricity market. A network flow formulation is applied to incorporate the electricity purchase and sales options into the scheduling model. Results from case studies show that often a substantial amount of electricity is generated onsite, some of which is sold to the market in order to reduce the net electricity cost. Also, the penalties for deviating from the committed load curve can be quite significant and are often in the same order of magnitude as the net electricity cost. Onsite generation is also considered in the model proposed by Wang et al (2012), which further includes fuel storage constraints and gas emissions in the objective function.

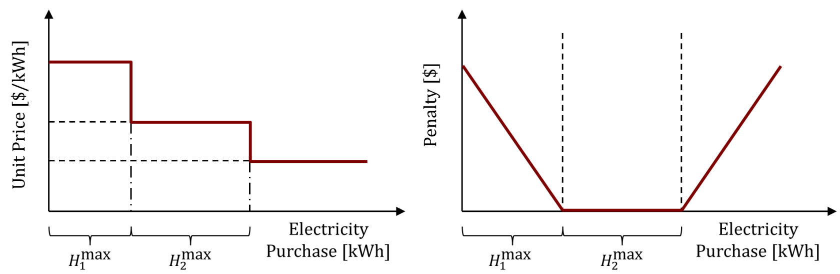
Zhang et al (2015b) consider the integrated optimization of short-term production scheduling and electricity procurement. In the proposed model, power contracts are assumed to have two price components: a time-dependent, and an amount-dependent component. A block contract formulation is applied to model the amount-dependent price component, which allows discount prices depending on the purchase amount. To also accommodate penalty contracts, Zhang et al (2015e) propose a more general block contract formulation which can be expressed as the following disjunction:

$$\bigvee_{b \in B_c} \begin{bmatrix} X_{cbt} \\ H_{cb't} = H_{cb'}^{\max} \quad \forall b' \in B_c, b' < b \\ H_{cb} \leq H_{cb}^{\max} \\ H_{cb't} = 0 \quad \forall b' \in B_c, b' > b \end{bmatrix} \qquad \forall c, t \tag{3a}$$

$$\underline{\bigvee}_{b \in B_c} X_{cbt} \qquad \forall c, t \tag{3b}$$

$$X_{cbt} \in \{true, false\} \qquad \forall c, b \in B_c, t \tag{3c}$$

where B_c is the set of blocks for contract c, H_{cbt} denotes the amount of electricity purchased in block $b \in B_c$ in time period t, and $H_{cb}^{\max}$ is the amount of electricity that one has to purchase in block $b \in B_c$ before reaching the next block. X_{cbt} is a boolean variable that is true if block b is the highest block reached for contract c in time period t. Disjunction (3a) states that if X_{cbt} is true, the maximum amount is purchased in all lower blocks $b' < b$, the electricity purchase in block b is bounded by $H_{cb}^{\max}$, and no electricity is purchased in higher blocks $b' > b$. According to logic constraint (3b), one and only one X_{cbt} has to be true. By applying the hull reformulation (Balas, 1985), Eqs. (3) can be transformed into a set of mixed-integer linear constraints and incorporated into the MILP scheduling model. Fig. 5 illustrates how discount and penalty contracts can be represented as block contracts with appropriate prices assigned to the corresponding blocks. Note that in the example shown in Fig. 5b, penalties incur for both over- and underconsumption.



(a) Discount contract (b) Penalty contract

Fig. 5 Discount and penalty contracts can be modeled as block contracts (Zhang et al, 2015e).

Vujanic et al (2012), Zhang and Hug (2014, 2015), and Zhang et al (2015c,d) develop systematic approaches for the optimization of dispatchable DR activities, e.g. the provision of regulation and operating reserve services. Participation in dispatchable DR programs creates new unconventional revenue streams that can significantly reduce net operating costs; however, the process is associated with high degree of uncertainty due to the unpredictability of DR events. Handling these cases requires advanced stochastic optimization methods; hence, we postpone further detailed discussion of this topic to Section 4.4.

4.3 Decision-making Across Multiple Time Scales

In long-term DSM planning, tactical and strategic decisions may be considered, such as investment decisions for capacity expansion and retrofit, and the selection of long-term power contracts. Since planning problems involve much longer time horizons, they are typically solved using models that are considerably less detailed than short-term scheduling models. However, such aggregate models cannot be applied to industrial DSM problems because they do not capture time-sensitive electricity prices and DR events with sufficient accuracy.

Integrated decision-making across multiple time scales—short-term operational and long-term tactical and strategic DSM decisions—has barely been considered in the literature. Mitra et al (2014) propose a multiscale capacity planning model for power-intensive continuous processes considering hourly changes in electricity price. The objective is to find the optimal investment strategy for purchasing new equipment, performing equipment upgrades, and installing additional storage facilities over a planning horizon of multiple years. Instead of applying a detailed representation across the entire time horizon, which would be computationally intractable, the model is simplified by leveraging the seasonality of electricity prices.

Here, each year is divided into four seasons, and each season is represented by one week, which is repeated cyclically and characterized by a typical electricity price profile that reflects the price's seasonal behavior. An hourly time discretization is applied, which results in 672 time periods representing each year (4 seasons, each with a week divided into 168 time periods). While the number of time periods is rather large, it is considerably smaller compared to the 8,760 time periods that would be required to represent hourly discretization over one year.

Zhang et al (2015a) apply a similar approach, but represent each season of the year by two weeks. While the first week is repeated cyclically, the second is used to impose mass balance constraints between adjacent seasons. In this way, unlike in the model proposed by Mitra et al (2014), a consistent inventory profile throughout the year is achieved since inventory can be carried over from one season to the next. Using this modeling idea, which is illustrated in Fig. 6, Zhang et al (2015a) solve a long-term electricity procurement problem under uncertainty over a one-year planning horizon.

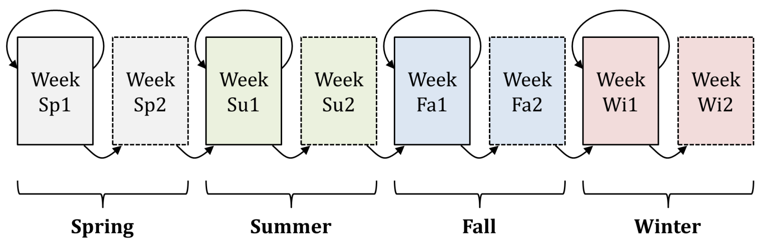


Fig. 6 In the multiscale model proposed by (Zhang et al, 2015a), each of the four seasons of the year is represented by two weeks, where the first has a cyclic schedule and the second is noncyclic.

4.4 Optimization Under Uncertainty

Most existing planning and scheduling tools for DSM are deterministic, i.e. they assume that all given input parameters are certain, including future electricity prices. However, this assumption is rarely valid, especially in the case of spot electricity prices, which are extremely difficult to forecast (Zareipour et al, 2010). In the light of the high level of uncertainty in DSM problems, optimization models have been developed that consider the characteristics of the uncertain parameters instead of simply assigning to them their expected values. In this way, a more realistic representation of the problem can be achieved, which forms the basis for improved decision-making.

Two major uncertainty modeling approaches have been applied to DSM planning and scheduling problems: stochastic programming (Birge and Louveaux, 2011), and robust optimization (Ben-Tal et al, 2009). In stochastic programming, the uncertainty is represented by discrete scenarios with given probabilities, and decisions are made at different stages, which are defined such that realization of uncertainty is observed between two stages. At each stage, actions depending on previous observations are taken; such reactive actions are also referred to as recourse decisions. In robust optimization, the uncertainty is specified in terms of an uncertainty set from which any point is a possible realization of the uncertainty. A robust optimization model is formulated such that it is feasible for the entire uncertainty set and optimizes the worst case.

Modeling Electricity Price Uncertainty Ierapetritou et al (2002) present a two-stage stochastic programming framework in which the electricity prices for the first three days of the scheduling horizon are assumed to be known while the prices for the remaining days are assumed to be stochastic. The uncertain prices are characterized by a set of scenarios with each scenario corresponding to a particular price profile for the time beyond the first three days. While the first-stage decisions are related to the first three days, the second-stage decisions are related to the remaining days of the scheduling horizon and can be different for each scenario. Given probabilities for each scenario, the objective is to minimize the total expected operating cost. A similar approach is taken by Everett and Philpott (2002) who assume that all future electricity prices are uncertain; hence, each scenario represents a price profile over the entire scheduling horizon.

Monte Carlo simulation with a stochastic price forecasting model can be used to generate electricity price profiles that are needed in a scenario-based approach. However, in order to accurately characterize the price uncertainty over a longer period of time, many price profiles are required, which leads to a large-scale stochastic programming model that may be computationally intractable. This limitation has motivated Mitra et al (2012b) to apply a robust optimization approach to model uncertain electricity prices, which features different possible price ranges and can account for correlated data. Here, the problem is formulated as follows:

$$\min_{x} \; \max_{c,z} \; \sum_t \alpha_t \, E_t \tag{4a}$$

$$\text{s.t. } \alpha_t = \sum_{t'} \zeta_{tt'} \, c_{t'} \qquad \forall t \tag{4b}$$

$$c_{tk}^{\min} z_{tk} \leq \bar{c}_{tk} \leq c_{tk}^{\max} z_{tk}, \; z_{tk} \in \{0,1\} \qquad \forall t, k \tag{4c}$$

$$c_t = \sum_k \bar{c}_{tk}, \; \sum_k z_{tk} = 1 \qquad \forall t \tag{4d}$$

$$\sum_t z_{tk} \leq \Gamma_k \qquad \forall k \tag{4e}$$

$$\text{s.t. } x \in X \tag{4f}$$

where x denotes the operational decision variables including E_t, the amount of electricity purchased in time period t. Given the scheduling constraints that are generally represented by Eq. (4f), this bilevel formulation minimizes the cost of purchasing electricity for the worst case within the uncertainty set defined by Eqs. (4b)–(4e). As shown in Eq. (4b), the electricity price in time period t, α_t, is stated as a weighted sum of random variables $c_{t'}$, which allows the modeling of correlations between electricity prices across different time periods. To have a more realistic characterization of the uncertainty as well as to allow adjustment of the level of conservatism, the uncertainty space for the electricity price is split into multiple price ranges (Düzgün and Thiele, 2015). Eqs. (4c)–(4d) ensure that only one price range k is chosen in each time period t, and the parameter Γ_t in Eq. (4e) represents an upper bound on the number of time periods in which the electricity price is within price range k. Finally, by applying duality theory, the inner maximization problem is reformulated into a minimization problem, which transforms the overall bilevel formulation into a tractable single-level minimization problem.

Electricity Price and Product Demand Uncertainty, and Risk Since DSM comprises both production and energy management, only accounting for uncertainty related to electricity is often insufficient. Uncertainty on the production side may have a different and possibly larger impact on the plant operations, and decision-making in the presence of multiple sources of uncertainty is certainly nontrivial. In their proposed stochastic programming model, Mitra et al (2014) consider product demand uncertainty, which is a parameter that can have a profound impact on the solution and is often associated with high degree of uncertainty. For different cases, Mitra et al (2014) compute the value of stochastic solution (VSS), which measures the improvement in the objective function value achieved by solving the stochastic model compared to the solution obtained from the deterministic model. The results show that the VSS can be quite significant, especially for skewed demand distributions with large standard deviations.

Zhang et al (2015b) consider both electricity price and product demand uncertainty while solving an integrated production scheduling and electricity procurement problem. In the proposed two-stage stochastic programming framework, operating modes are selected and the amount of electricity purchased from power contracts with known prices is determined in the first stage, while recourse decisions in the second stage are the actual production rates and the amount of electricity purchased from the spot market where the prices are uncertain. Multiple modeling and solution strategies have been applied to address real-world problems of relevant size: (1) incorporation of conditional value-at-risk (Rockafellar and Uryasev, 2000) as risk measure; (2) generation of electricity price scenarios using ARIMAX models; (3) scenario reduction (Dupacova et al, 2003) to obtain a small subset of scenarios that still represent the uncertainty relatively well; (4) multicut Benders decomposition (Birge and Louveaux, 1988) to reduce the solution time. The case studies show that there can be substantial differences between the solutions obtained from deterministic, risk-neutral, and risk-averse optimization. Also, an extensive analysis of the VSS shows that in risk-neutral optimization, accounting for electricity price uncertainty does not result in significant additional benefit, whereas in risk-averse optimization, modeling price uncertainty is crucial for obtaining good solutions.

Uncertainty in Dispatchable DR The development of systematic decision-making tools for dispatchable DR has not been attempted until recently. The main challenge lies in the inherent uncertain nature of the problem since the consumer does not know in advance when the dispatch of the provided DR resources will be requested.

Zhang and Hug (2014) apply a stochastic programming approach to optimize the provision of regulation capacity by aluminum smelters. Likewise, by applying a scenario-based approach similar to the one proposed by Conejo et al (2002) for electricity producers, Zhang and Hug (2015) derive a bidding strategy for aluminum smelters. In the bidding process, participants state how much energy or operating reserve capacity they are willing to sell at which price. In the proposed stochastic programming framework, the price is the uncertain parameter, and a scheduling problem is solved for each price scenario. The solution provides price-amount pairs for each scenario, which can be used to construct the bidding curve.

In the above-mentioned stochastic programming approaches, the same probabilities are assumed for all scenarios. This assumption is usually not realistic; in fact, it is very difficult to obtain reasonable probability distributions for dispatchable DR events. Furthermore, when providing operating reserve, dispatch upon request has to be guaranteed since otherwise, one has to pay very high penalties or may not even be allowed to participate in the market. Hence, robust solutions are required. Vujanic et al (2012) consider uncertainty in the start times of scheduled tasks, which may be caused by load shifting required to meet operating reserve demand. Robust optimization has been applied to ensure feasibility for any changes in task start times within prespecified ranges. Note that the proposed model only identifies the provision of operating reserve as the source of the uncertainty, but does not actually optimize it.

Zhang et al (2015c) assess the operational benefit of adding cryogenic energy storage capabilities to air separation plants. Among other things, the energy storage can be used to provide operating reserve since it can be quickly ramped up to generate electricity in case of grid contingencies, which is when operating reserves are needed. Here, a robust optimization approach is applied, for which the following uncertainty set U is proposed:

$$U(R) = \left\{ w : \left(D_t = R_t\, w_t,\ 0 \leq w_k \leq 1\ \forall\, 1 \leq k \leq t,\ \sum_{k=1}^{t} w_k \leq \Gamma_t \right) \forall t \right\} \tag{5}$$

where D_t denotes the operating reserve demand in time period t, which is uncertain, and R_t is the reserve capacity provided by the plant in time period t. The normalized reserve demand in time period t, w_t, takes a value between 0 and 1. The parameter Γ_t, which defines the maximum number of time periods in which maximum reserve dispatch can occur up to time t, can be used to adjust the level of conservatism. Note that the uncertainty set depends on the amount of provided reserve capacity.

A major drawback of traditional robust optimization approaches is their inability to account for recourse, which makes the formulation overly conservative. A recent advance in the robust optimization area is the development of so-called adjustable robust formulations (Ben-Tal et al, 2004), in which recourse actions are defined in terms of affine decision rules. Zhang et al (2015d) apply this approach to optimize the provision of interruptible load, which is operating reserve that large electricity consumers can provide by reducing (interrupting) their load. Here, the production rates, which directly affect the electricity consumption, are the decision variables that need to depend on the uncertainty. Considering the uncertainty set given by Eq. (5), the affine decision rule is stated as follows:

$$Q_{it} = \overline{Q}_{it} + \sum_{k=1}^{t} q_{itk} w_k \tag{6}$$

where Q_{it} is the amount of product i produced in time period t. The coefficients q_{itk} are now also part of the decision variables. As one can see, Q_{it} is allowed to depend on uncertain parameters realized in all previous time periods, which makes this a multistage formulation. Besides forcing the production rates to decrease when interruptible load is requested, the decision rule also allows the production rates to increase after interruptible load events to make up for lost production. The case study results show that much improved solutions can be achieved by solving the proposed model compared to applying the traditional robust optimization approach.

5 Case Studies

In the following, we present two case studies in which models proposed to address some of the aforementioned challenges are applied to real-world industrial problems. In both cases, the industrial process under consideration is air separation, for which real plant data have been provided by Praxair. Note, however, that the proposed model formulations are general and can be applied to other similar continuous power-intensive processes. The models are implemented in GAMS 24.4.1 (GAMS Development Corporation, 2015) and solved by using the commercial solver CPLEX 12.6.1 on an Intel® Core™ i7-2600 machine at 3.40 GHz with 8 processors and 8 GB RAM running Windows 7 Professional.

5.1 Scheduling of Process Networks with Various Power Contracts

The first case study is taken from Zhang et al (2015e) and deals with the optimal scheduling of continuous power-intensive process networks while considering various power contracts. Fig. 7 shows the process network of the given air separation plant. The gaseous oxygen (GO2), liquid oxygen (LO2), liquid nitrogen (LN2), and liquid argon (LAr) flowing out of the air separation (AS) process can be directly sold whereas gaseous nitrogen (GN2) has to be further compressed before it can be supplied to the customers. Two kinds of GN2 are sold: medium-pressure GN2 (MPGN2) and high-pressure GN2 (HPGN2). GN2 is compressed to MPGN2 through Process LMCompGN2 and can be further compressed to HPGN2 through Process MHCompGN2; it can also be directly converted to HPGN2 by running Process LHCompGN2. Furthermore, GN2 can be liquefied to LN2 by running Process LiqGN2. Overproduced gaseous products can be vented through a venting process, and all liquid products can be converted into the corresponding gaseous products through a so-called driox process.

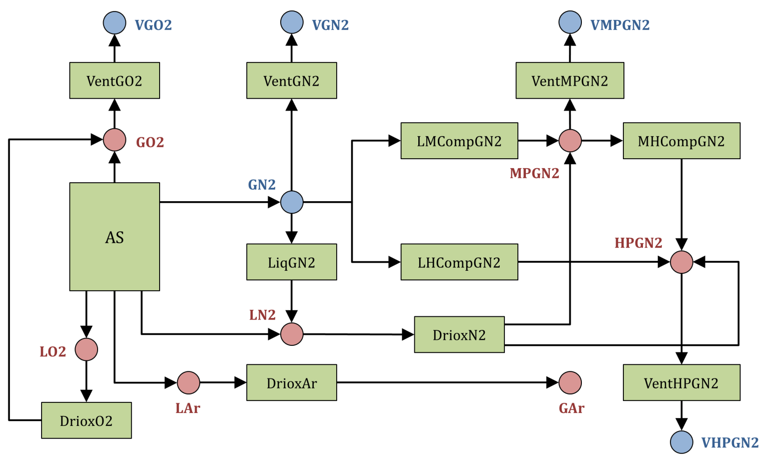


Fig. 7 Process network representing the given air separation plant (Zhang et al, 2015e).

Fig. 8 shows the electricity consumption profiles for each of the processes. The vast majority of the electricity consumption is attributed to the air separation unit (ASU). The GN2 liquefier also consumes a large amount of electricity but is only used five times, each time for a few hours. Compared to the ASU and the GN2 liquefier, the pipeline compressors contribute relatively little to the total electricity consumption. Significant load shifting can be observed in the schedule; this is mainly realized by operating the liquefier during low-price hours, which allows a fairly constant operation of the other processes.

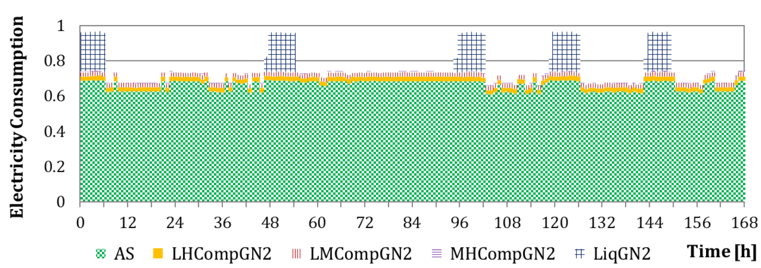


Fig. 8 Amount of electricity consumed by each process of the air separation plant.

The breakdown of the total electricity purchase into the purchases from the three different sources (TOU contract, penalty contract with penalty for underconsumption, and the spot market) as well as the corresponding electricity prices are shown in Fig. 9. One can observe that in each time period, we choose to purchase from the source with the lowest price. Two sources are chosen in the same time period only when the maximum purchase amount is reached for one of the two sources. Also, sufficient amount of electricity is purchased from the penalty contract such that no penalty has to be paid.

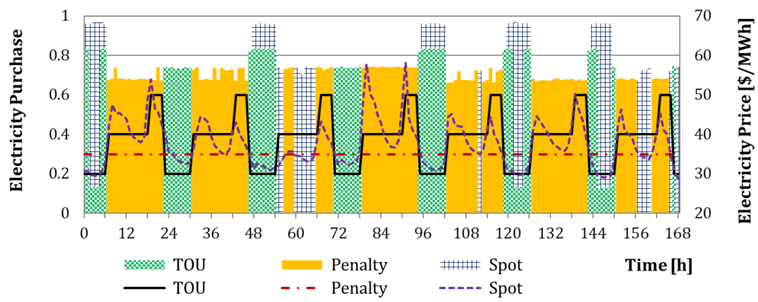


Fig. 9 Breakdown of total electricity purchase into purchases from the three difference sources.

This case study demonstrates the ability of state-of-the-art optimization models to accurately represent complex process systems and incorporate various power contract structures. One major strength of the proposed discrete-time scheduling model is the computationally efficient formulation. Zhang et al (2015b) show that large-scale problems with tens of thousands of variables and hundreds of thousands of constraints can be solved within a few minutes, which allows the use of such a scheduling tool in a real industrial setting.

5.2 Risk-based Integrated Production Scheduling and Electricity Procurement

The second case study is taken from Zhang et al (2015b) and considers the integrated production scheduling and electricity procurement under spot electricity price and product demand uncertainty. The proposed two-stage stochastic programming model incorporates CVaR as a measure of risk. Here, the main first-stage decisions are the selection of operating modes and the committed amount of electricity purchase from power contracts; second-stage decisions are the actual production rates, the amount of purchased product, and the amount of electricity purchased from the spot market. For a particular air separation case, Fig. 10 shows the electricity purchase and corresponding price profiles from the deterministic, the risk-neutral stochastic, and the risk-averse stochastic solutions. We highlight the significant differences between these three solutions.

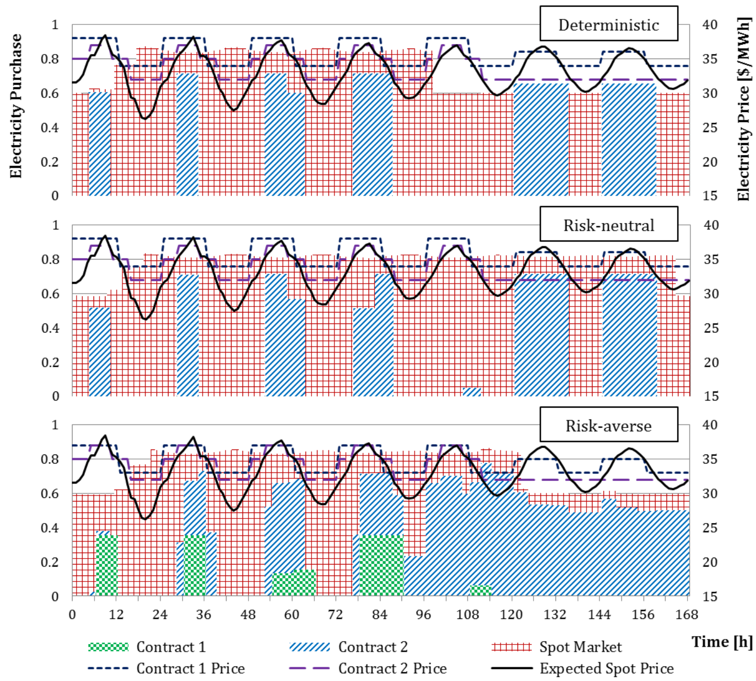


Fig. 10 Electricity purchase profiles obtained from solving the deterministic, the risk-neutral, and the risk-averse optimization models (Zhang et al, 2015b).

In deterministic optimization, uncertainty is ignored such that decisions are primarily driven by the differences between the power contract prices and the expected spot price. A significant amount of electricity is procured from Contract 2 because the price discount at this purchasing amount makes it less expensive than purchasing from the spot market during on-peak hours. However, there is a very high expected cost of purchasing additional products because the selected operating modes do not have sufficient production capacities in the high-demand scenarios.

In risk-neutral stochastic optimization, first-stage decisions are to a great extent driven by the need for flexibility that has to be maintained in the second stage in order to react to different scenarios. Deterministic and risk-neutral optimization lead to similar schedules for the electricity procurement from power contracts. However, the risk-neutral solution suggests selecting operating modes with higher production capacities in order to be able to accommodate high-demand scenarios. This strategy leads to considerably lower costs for purchasing additional products, especially during the last three days of the week. In this case, the relative reduction in total expected cost amounts to 7.2 %.

Unlike the deterministic and risk-neutral solutions, the risk-averse solution suggests to purchase more than half of the required electricity from power contracts. Here, contracts are effectively used to hedge against the risk of low-profit scenarios. In particular, considerable amount of electricity is purchased from contracts toward the end of the week when the level of uncertainty in the spot electricity price is highest. The relative VSS in this case is 8.3 %.

It is worth noting that the stochastic models were solved by applying a multicut Benders decomposition algorithm (Birge and Louveaux, 1988). When solving the full-space risk-averse model, for example, CPLEX was not able to find a feasible solution within two hours, while the proposed decomposition approach solved the problem to 0.7 % optimality gap within the same time.

6 Future Developments and Challenges

As indicated by the review presented in Section 4, planning and scheduling for industrial DSM is a relatively new research area, and there is significant need for further development. In the following, we highlight some remaining challenges and opportunities in this area:

- Power contracts can involve very complex price structures, which cannot be considered in the current models. Also, existing DSM programs are constantly revised and new ones are created. Hence, a stronger focus on the modeling of market mechanisms and the energy management side in general is needed.
- Many DSM problems, including the design of new processes, require long-term planning, which in turn results in multiscale problems as described in Section 4.3. There is much potential in the development of models for such problems.
- Synergies are expected from collaboration between multiple DSM participants, which could be a network of multiple plants that share customers but operate in different electricity markets. It could also be a joint effort of two different companies that operate interrelated power-intensive processes; a typical example is the case of a steel plant and an air separation plant that supplies oxygen to the steel plant.
- Following the same line of thought, it is also clear that collaboration between utility and consumer or, to take it a step further, the grid-wide optimization involving all participants can result in significant benefits for everyone. Here, however, besides the size and complexity of the problem, one also has to consider conflicting objectives among all decision makers.
- Decision-making under uncertainty still remains an open area of research in DSM. The accurate and computationally efficient modeling of different kinds of uncertainties is a major challenge. Here, the use of data will help in creating the models as well as in convincingly demonstrating the value of stochastic optimization.
- In general, it is crucial to develop more efficient solution methods, especially for solving multiscale and stochastic optimization models.

7 Concluding Remarks

This work provides an introduction to DSM with an emphasis on the perspective of large industrial electricity consumers, and a state-of-the-art review of existing works on planning and scheduling for industrial DSM. We have identified four major challenges in this emerging research area, and have demonstrated the capabilities of current models with two real-world case studies. We hope that this review will stimulate further research as we still face major challenges, two of which are multiscale (temporal and spatial) optimization and decision-making under uncertainty.

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