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A Discrete-time Scheduling Model for Continuous Power-intensive Processes Considering Fatigue of Equipment

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Abstract

In the light of the growing renewable energy generation, matching of electricity supply and demand has become increasingly challenging. By participating in demand side management programs, industry can contribute to counter this challenge. However, the frequent adjustment of operation conditions according to volatile electricity prices leads to additional dynamic loads for the equipment. In this work, a mixed-integer linear programming based discrete-time model is proposed for scheduling of a single air separation unit, explicitly considering fatigue of equipment occurring during transient operation. Besides constraints for describing the feasible region and the process dynamics, this model includes constraints for considering mechanical fatigue of some key equipment. The resulting model is applied to investigate the impact of mechanical constraints on the potentials of demand side management.

Keywords: Scheduling, Fatigue, Mechanical limitations, Air Separation, Demand Side Management

1. Introduction

Demand side management (DSM) has been recognized as one of the key enablers for a cost-efficient energy transition. Especially, energy-intensive industries can contribute to the energy transition by offering high potentials for grid stabilization in terms of DSM and at the same time mitigate their own economic risks related to volatility in energy supply. Depending on the electricity market the industry has various measures to participate in DSM programs, whereby the programs can be distinguished into two main DSM categories (Charles River Associates, 2005): Energy efficiency (EE) and demand response (DR). In the first category attempts are made to increase the efficiency of the industrial process and thus to reduce the energy consumption. The second category is focused on the load profile adjustment, driven by market incentives. A more detailed explanation of DSM as well as a comprehensive review of existing works on planning and scheduling for industrial DR is provided in the work of Zhang and Grossmann (2016). Here, contributions are listed which address the application of DR in various energy-intensive industries such as aluminum, cement, chlor-alkali, steel, and air separation.

In particular, the operational planning (scheduling) of cryogenic air separation units (ASUs) under time-sensitive electricity prices has gained considerable attention. As one of the first, the work of Daryanian et al. (1989) addressed the topic of DSM, using a simplified model. For a more accurate representation of an ASU, Ierapetritou et al. (2002) proposed the notion of operating modes to take into account that one process may show operation regions with different configurations and states. In such a mode-based model, each operating mode is defined by a specific feasible region and the process can only operate in one of these operating modes in each time step (Zhang and Grossmann, 2016). Based on this model, Karwan and Keblis (2007) as well as Mitra et al. (2012, 2013) further developed the concept of mode-based models. Moreover, Mitra et al. introduced additional constraints to better capture the process dynamics, plus addressing the uncertainty in forecast of electricity prices. The aspect of uncertainty related to electricity prices, product demand, and dispatchable DR is also investigated in other studies (Ierapetritou et al., 2002; Mitra et al., 2014; Zhang et al., 2015, 2016a). Once again based on the concept of mode-based models Mitra et al. (2014) described a multiscale capacity planning model for finding the optimal investment strategy for purchasing new components or upgrading existing components over a time horizon of multiple years. A further development of the mode-based modeling approach was proposed by Zhang et al. (2015), whereby each mode is specified by a Convex Region Surrogate (CRS) model according to Zhang et al. (2016b). In contrast to all aforementioned works Manenti and Rovaglio (2013) have increased the number of ASUs to investigate the optimization of gas supply networks, applying multiscale approaches to implement this so-called plant-wide or enterprise-wide optimization. The same topic was addressed in Zhang et al. (2016c) whereby the combination of mode-based modeling approach and CRS models is used to model a network of continuous power-intensive processes. A similar approach was applied by Zhou et al. (2017) to examine the optimal scheduling of a real-world production network.

As can be seen here, a great deal of effort has gone into the improvement of approaches for planning and scheduling power-intensive processes under time-sensitive electricity prices, whereby the plants (respectively process networks), the electricity markets with their energy contracts as well as uncertainties of input variables are described with increasing detail. However, the participation in DSM programs may be associated with frequent adjustment of operating conditions and thus triggers the necessity for a paradigm change in plant design and operating philosophies, away from static conditions towards transient operation. Consequently, process equipment is increasingly subjected to additional dynamic loads and the resulting stress is potentially reducing its lifetime. In order to ensure mechanical integrity of all plant components over the whole life span, the lifetime consumption due to transient operation has to be considered in both plant design and operations planning (scheduling).

2. Model formulation

In this work, a method is proposed for explicitly considering fatigue of equipment occurring during transient operation. In the following section, the method and the related optimization model is described in more detail.

Normally, a process is modeled by using detailed equations describing the heat and mass balance of each apparatus. However, the non-linear characteristic of these equations leads to a non-linear optimization model that is hard to solve in particular if the time horizon increases. For this reason, another approach is chosen. Similar to Mitra et al. (2012) the plant is described applying a data based surrogate model; more specifically, results from steady-state process simulations are used to represent the feasible region of the plant. In terms of the steady-state simulations, a highly detailed simulation model was applied to generate the data base for the surrogate model. For example, the simulation model does not only include equations for capturing the basic heat and mass balance but also detailed equations for describing the realistic behavior of the installed equipment in off-design, i.e., partial load and over load. More precisely, it covers inter alia: load-dependent efficiency and boundaries of the turbo compressors and turbines, load-dependent heat transfer, and hydraulic behavior of process equipment and piping. Consequently, by means of this detailed simulation model the steady-state behavior within the feasible region and its boundaries can be well described, but also a representative data base can be generated for the surrogate model. For approximating the non-linear characteristic of this data base, a piecewise linear surrogate model is applied.

In a scheduling model, the time can generally be represented applying a discrete- or continuous-time formulation. Here, the optimization model is structured as discrete-time scheduling model, since in contrast to continuous-time models discrete-time model generally show better computational performance in terms of the application to large-scale problems. Castro et al. (2009) showed that only small-sized problems can be solved efficiently by continuous-time models, whereas comparable discrete-time models can handle large-scale problems.

2.1. Feasible region

Along the lines of aforementioned studies, this study also applies the approach of mode-based models, whereby a mode is defined as a set of operating points that show the same set of active discrete operating decisions (i.e., selection of running machines). By using this approach, discrete operating decisions of a plant can be distinguished by selecting various operating modes. But, within each mode the operating points vary only in terms of the continuous variables (i.e., flow rate of material). For capturing theses variations each mode is separately described using the surrogate models as described above.

The focus of this study lies on investigating the impact of mechanical fatigue on optimal plant operation. For this reason, the feasible region of the plant is only considered in a reduced manner to keep the optimization model simple. More precisely, the feasible region of each mode $m \in M$ is spanned by several steady state operation points ($i \in I_m$) and the consecutive interpolation between two adjacent points results in a piecewise linear surrogate model. Note, that this surrogate model may be thought of as path of lines through the feasible region. In order to capture non-linear characteristics of various attributes within the region, the path can be easily adapted by adding further operation points within this subregion. Figure 1 illustrates such path/surrogate model in a two-dimensional product space with the products A and B.

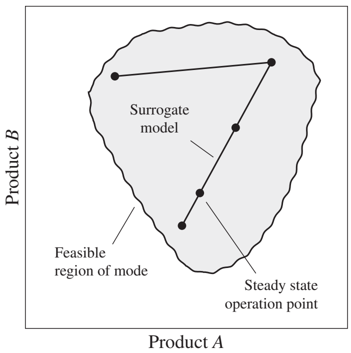

Figure 1: Visualisation of surrogate model within the feasible region of an arbitrary mode.

The plant is captured by the combination of several of these modes, whereby the feasible regions of the modes can overlap, but for each discrete time step $t \in T$ only one mode $m \in M$ can be selected.

2.2. Mass balance

A mass balance is implemented to capture the relationship between production, export and content in the storage facilities. The export EXP_c^t is defined by the demand of the respective product c.

Over the whole observation period, the production PRO_c^t must be equal to or higher than the total export to guarantee the demands of the customer. This relationship can be expressed for each product in the set C by

$$\sum_{t\in T} PRO_c^t \geq \sum_{t\in T} EXP_c^t \quad \forall c \in C. \tag{1}$$

The content CON_c^t of such storage facilities can be described by applying the mass balance:

$$CON_c^t = CON_c^{t-1} - EXP_c^t + PRO_c^t \quad \forall t \in T, \forall c \in C^{liq}, \tag{2}$$

$$CON_c^{min} \leq CON_c^t \leq CON_c^{max} \quad \forall t \in T, \forall c \in C^{liq}. \tag{3}$$

Additionally, the content must satisfy the technical requirements of the installed storage facility (CON_c^{min} and CON_c^{max}), whereby the Equation (2) is only valid for the reduced set of liquid products C^{liq}.

2.3. Transitions

The surrogate models only capture the plant itself – the steady-state behavior within the feasible region and its boundaries – but not process dynamics. However, a transient plant operation implies frequent transitions between several operating points and thus the introduction of representative transitional states and associated differential constraints is necessary to include the process dynamics in the scheduling model.

In a mode-based model all transitions can be distinguished in two major types: transitions between operating points which are assigned to one operation mode or transitions which are assigned to different operation modes. Transitions of the former type are basically dominated by a differential constraint that limits the change in power consumption within a defined time slot, whereas various logical constraints are used with respect to the second type of transitions to define permitted transitions as well as specific operation sequences.

2.4. Mechanical fatigue

As mentioned above, fatigue design is considered for some key equipment in order to ensure mechanical integrity over the whole plant lifetime. More specifically, the estimated life expectancy of machinery, e.g. compressors and of heat exchangers is integrated in the mixed-integer linear programming (MILP) problem by using equipment specific parameters. The concept may however easily be extended to other process components (e.g., piping).

The lifetime of compressors can be considered in a simplified way by limiting the number of starts according to the fatigue design of the compressor casings and the electrical drives. More precisely, the maximum number of starts per day is usually kept under a machine-specific limit following the recommendations of the machine manufactures. For integrating these recommendations binary variables and logical constraints are added to the MILP to count and limit the start per day and thus prevent excessive loads for the machines.

In terms of heat exchangers there are two aspects affecting its lifetime: Purely mechanical stress from pressure cycling and thermo-mechanical stress originating from transient temperature profiles. Similar to the previously outlined compressors, design numbers of pressure cycles at specified stress levels are specified during the fatigue design. By using this number as a reference, the lifetime consumption due to the first aspect can be described in a simplified way as a linear function of the number of pressure cycles. Lifetime consumption due to the second aspect is considered by implementing equipment-specific results of a thermo-mechanical stress analysis – generated by dynamic FEM simulations (finite element method) – in a piece-wise linear function. As worst-case scenario, both aspects can be captured by applying the approach of linear damage accumulation.

2.5. Electricity market

Specifics about energy markets are primarily dependent upon their geographical location and originate from differences in power generation technology portfolios, degrees of integration of local electric energy grids as well as regulatory background. The location of the plant and its associated energy market thus imply large impact upon the optimal operation strategy. Consequently, the energy market requires modeling in an adequate manner.

2.6. Objective function

As mentioned in section 1 the objective of DR is the load profile adjustment according to market incentives and thus the minimization of operational expenditure (OPEX). With regard to ASUs the OPEX is primarily characterized by energy costs, caused by the electric-driven machines of the compressors. Hence, the objective can be formulated as the sum of the product of the electrical power consumption and the corresponding electricity price for each time step.

3. Illustrative Examples

The above outlined model is used to generate illustrative examples investigating the impact of mechanical fatigue on the potentials of DSM, more precisely on the objective during the operation of a specific ASU.

The examples are performed using an air separation plant, which mainly produces two products, liquid oxygen (LOX) and liquid nitrogen (LIN). Each liquid product can be stored in a separate storage tank. Gaseous products like nitrogen are not considered as such to keep the example simple. Consequently, a merchant liquid plant is considered that supplies a local gas market without having on-site customers.

The demand of each liquid product and state of the storage facilities are described by applying the constraint (1) and (2), respectively. Since, the impact of technical limitations on the plant operation can be investigated independently of the fluctuating product delivery rate, a constant average demand is specified for each product.

The plant is described using this work's approach along with realistic constraints in order to capture its performance, dynamics and the fatigue design of its key equipment. More precisely, the maximum number of starts per day is specified for each machine as well as the design number of allowed pressure cycles and the equipment-specific results of thermo-mechanical stress analyses for heat exchangers. Note, that these results are specific to the installed type of heat exchanger and strongly depend on the assumed operation schemes for shutting down the plant, leaving it in cold standby, and restarting it.

For this study, the European Electricity Exchange (EEX) electricity market is considered, more precisely the hourly-based day-ahead prices of 2016 are applied for an integral period of 31 days (January 1, 2016 to January 31, 2016). The period is represented by using a moving horizon approach with 7 days forecast updated on a daily basis.

In order to investigate the impact of mechanical fatigue on the potentials of DSM, various cases with different fatigue specifications, regulatory constraints and tank volumes are defined. As a detailed discussion on all parameters is beyond the scope and will be supplied in future publications, only exemplary findings of a simplified reference scenario will be given at this point.

In this scenario, the consideration of mechanical fatigue during the operational scheduling leads to a modified operation profile. As a result, the plant is operated in a manner where the specified equipment lifetimes of 25 years can be met, whereas non-consideration would lead to the reduction of individual equipment lifetimes as much as one order of magnitude. However, the operation is restricted by additional constraints and thereby is less optimal in terms of adjusting plant operation to the variations of the electricity market. In doing so, the objective function is increased only by about 2 % maintaining the mechanical integrity of the plant on a long-term basis.

4. Conclusions & Outlook

This contribution demonstrates that the consideration of mechanical fatigue during operation scheduling is essential to avoid excessive stress on equipment as well as associated production losses due to damage driven down-times. Note, that equipment specific fatigue design may impact the potentials of scheduling of DSM strongly. Therefore, it is concluded that the proposed method allows the assessment of different equipment designs regarding their suitability for transient operation and thus allows for the optimization of plant designs for different energy market requirements.

In future work, the method shall be extended to include a more detailed description of the plant performance to exclude effects due to the reduced description of the feasible region.

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References

P. M. Castro, I. Harjunkoski, I. E. Grossmann, 2009. New continuous-time scheduling formulation for continuous plants under variable electricity cost. Industrial & Engineering Chemistry Research 48 (14), 6701–6714.

Charles River Associates, 2005. Primer on demand-side management with an emphasis on price-responsive programs. Tech. rep., World Bank.

B. Daryanian, R. E. Bohn, R. D. Tabors, Aug 1989. Optimal demand-side response to electricity spot prices for storage-type customers. IEEE Transactions on Power Systems 4 (3), 897–903.

M. G. Ierapetritou, D. Wu, J. Vin, P. Sweeney, M. Chigirinskiy, 2002. Cost minimization in an energy-intensive plant using mathematical programming approaches. Industrial & Engineering Chemistry Research 41 (21), 5262–5277.

M. H. Karwan, M. F. Keblis, 2007. Operations planning with real time pricing of a primary input. Computers & Operations Research 34 (3), 848 – 867, logistics of Health Care ManagementPart Special Issue: Logistics of Health Care Management.

F. Manenti, M. Rovaglio, 2013. Market-driven operational optimization of industrial gas supply chains. Computers & Chemical Engineering 56, 128 – 141.

S. Mitra, I. E. Grossmann, J. M. Pinto, N. Arora, 2012. Optimal production planning under time-sensitive electricity prices for continuous power-intensive processes. Computers & Chemical Engineering 38, 171–184.

S. Mitra, J. M. Pinto, I. E. Grossmann, 2014. Optimal multi-scale capacity planning for power-intensive continuous processes under time-sensitive electricity prices and demand uncertainty. part i: Modeling. Computers & Chemical Engineering 65, 89 – 101.

S. Mitra, L. Sun, I. E. Grossmann, 2013. Optimal scheduling of industrial combined heat and power plants under time-sensitive electricity prices. Energy 54, 194 – 211.

Q. Zhang, J. L. Cremer, I. E. Grossmann, A. Sundaramoorthy, J. M. Pinto, 2016a. Risk-based integrated production scheduling and electricity procurement for continuous power-intensive processes. Computers & chemical engineering 86, 90–105, druck-Ausgabe: 2016. - Online-Ausgabe: 2015.

Q. Zhang, I. E. Grossmann, 2016. Planning and Scheduling for Industrial Demand Side Management: Advances and Challenges. Springer International Publishing, Cham, pp. 383–414.

Q. Zhang, I. E. Grossmann, C. F. Heuberger, A. Sundaramoorthy, J. M. Pinto, 2015. Air separation with cryogenic energy storage: Optimal scheduling considering electric energy and reserve markets. AIChE Journal 61 (5), 1547–1558.

Q. Zhang, I. E. Grossmann, A. Sundaramoorthy, J. M. Pinto, Jun 2016b. Data-driven construction of convex region surrogate models. Optimization and Engineering 17 (2), 289–332.

Q. Zhang, A. Sundaramoorthy, I. E. Grossmann, J. M. Pinto, 2016c. A discrete-time scheduling model for continuous power-intensive process networks with various power contracts. Computers & Chemical Engineering 84, 382 – 393.

D. Zhou, K. Zhou, L. Zhu, J. Zhao, Z. Xu, Z. Shao, X. Chen, 2017. Optimal scheduling of multiple sets of air separation units with frequent load-change operation. Separation and Purification Technology 172, 178 – 191.