SCHEDULING, OPTIMIZATION AND CONTROL OF POWER FOR INDUSTRIAL COGENERATION PLANTS

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Abstract

Scheduling, optimization and control of power for three industrial cogeneration plants at one of Dow's Louisiana site is presented in this paper. A first principle mathematical model that includes mass and energy balances for gas turbines, heat recovery units, steam turbines, pressure relief valves and steam headers is used to formulate multiple optimization problems to recommend the best strategy to trade power. The model has detailed operational information that includes equipment status and control curves for different operating scenarios. The scheduled power offer curve is obtained by solving multiple optimization problems using the validated process model along with operational and equipment limitations. Adjustment of power schedule offer is done in the real-time market thirty minutes prior to the hour and implementation of the dispatched power schedule is done using a model predictive controller.

Keywords

industrial cogeneration process, day-ahead scheduling, real-time optimization, model predictive control

Introduction

Scheduling power in day-ahead market for a combined heat and power (CHP) cogeneration plant requires accurate predictions of steam and electricity production, and fuel consumption for various operating scenarios. A good survey on short term cogeneration planning that includes day-ahead market has been published by Salgado and Pedrero (2008). Day-ahead short term planning typically consists of hourly planning intervals that require good predictions of fuel consumption and power generation by the cogeneration plant. The literature on cogeneration planning focuses on solution of the economic scheduling problem using mixed-integer linear programming (MILP) models (Marshman et al. (2010), Mitra et al. (2013)). The nonlinear process behavior is approximated using linearized models for turbines and boilers with constant efficiency (Marshman et al. (2010), Mitra et al. (2013)). MILP models are used to avoid numerical difficulties associated with fundamental models that are non-linear. A two-tier formulation for real-time economic optimization based on steady-state nonlinear models and model predictive control using linear dynamic models has also been developed for industrial cogeneration processes (Emoto et al. (1998)). The power scheduling calculations in this paper use a detailed steady-state, non-linear model that is also used for real-time optimization of the industrial process. A steady-state model is appropriate for scheduling power in cogeneration plants because the process dynamics for exported power are fast with a settling time of 3 minutes as compared to the scheduling interval of each hour. Implementation of the optimized power schedule is done using a linear model predictive controller that uses empirical dynamic models. The modeling details of the scheduling application for cogeneration plants and its real-time implementation have been published (Bindlish (2016)). The process model for scheduler consists of approximately 18,000 equations and is deployed online for both scheduling and real-time optimization (Figure 1). Model validation is done by calculating appropriate model

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parameters to match real-time plant data before using it for scheduling and real-time optimization.

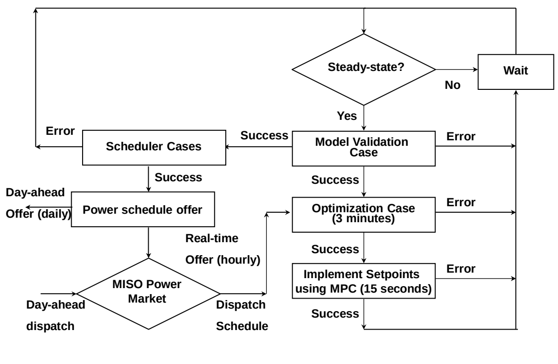

Figure 1. Scheduler and real-time optimization

Power Scheduling

Power scheduling calculations are done for the scheduling interval of each hour by solving multiple optimization cases using the validated process model (Figure 1). The power offer curve for day-ahead and real-time MISO power market takes into account

- Operating conditions and process limitations
- Site power and steam demand
- Plant produced fuel flow and composition
- Fuel price
- Ambient temperature
- Equipment Contingency

The offer curve for the power schedule includes exported power and incremental heat rate (*IHR).* Heat rate *(HR*) is the common measure of system performance in a cogeneration power plant. It is defined as the fuel input energy divided by the output power energy. The fuel energy input takes into account the heating value of different types of fuels used by the power plant

$$HR = \frac{Fuel\,Input}{Output\,power} \tag{1}$$

Lower heat rate implies higher efficiency and better conversion of energy. Plant heat rate is a measure of the combined performance of the gas turbines, steam turbines, and other associated equipment. Incremental heat rate (*IHR)* is defined as

$$IHR = \frac{\Delta Fuel\,Input}{\Delta Output\,power} \tag{2}$$

Incremental heat rate is compared to market heat rate to vary the power output. Market heat rate (*MHR)* is defined as the ratio of power price to fuel price

$$MHR = \frac{Power\,price}{Fuel\,price} \tag{3}$$

Power Offer Curve

After meeting the site steam and power requirements, power is scheduled both in the day-ahead and real-time markets (Figure 1) by submitting an offer curve that includes exported power and incremental heat rate. The power offer curve is obtained after solving multiple optimization problems over the entire range of exported power (Bindlish (2016)). The exported power that is scheduled takes into account power produced from gas turbines and steam turbines along with the site power demand.

$$Power_{\exp} = Power_{gas} + Power_{steam} - Power_{demand} \tag{4}$$

The thirty-four optimized setpoints for the multiple optimization problems can be listed as

- Gas turbine power (8)
- Steam turbine power (4)
- High pressure steam flows from duct burner firing (6)
- Steam turbine extraction flows (12)
- Gas turbine steam injection ratios (4)

The power offer curve is calculated by evaluating the minimum operating cost to produce the specified exported power ($Power_{exp}$) over the entire operating range using the following objective function with the same thirty-four optimized setpoints. Operating cost takes into account purchased fuel, condensate make-up cost and the credit due to power sales

$$\begin{aligned} \min Cost = & \sum_j Fuel_j \times C_j + Cond \times C_w - \\ & Power_{\exp} \times C_p \end{aligned} \tag{5}$$

in which C_j is cost of fuel j, C_w is cost of condensate water and C_p is cost of power. The governing constraints for the optimization problems are set by process model and constraints of site steam and power demand along with limitations for plant equipment. The process model can be expressed as

$$f(x,u,d,b) = 0, \quad y = h(x,u,d,b) \tag{6}$$

where *y* are outputs, *x* are states, *u* are inputs, *d* are measured disturbances, and *b* are model parameters. Most of the power produced is used by internal chemical plant consumers at the Dow site and the surplus is exported into the power market for the scheduling interval of each hour. The day-ahead power offer curve is calculated for each hour of the following day by taking into account equipment contingency and ambient temperature predictions. A real-time market offer curve that takes into account the current operating conditions including ambient temperature and equipment availability is used to make appropriate adjustments 30 minutes prior to each hour to the power schedule offer (Figure 1).

Power Schedule Implementation

Implementation of the power schedule is done using a real-time optimizer along with a model predictive controller (MPC) (Figure 1). Real-time optimization is performed using fundamental steady-state models in Aspen Plus Optimizer (Emoto et al. (1998)), whereas model predictive control is done using empirical linear dynamic models in Aspen DMCplus (Cutler and Ramaker (1979)).

Real-time Optimization

The validated fundamental model used for optimization is the same that is used for power scheduling. The objective of real-time optimization is to minimize total operating cost (Equation 5) along with the equation oriented process model (Equation 6) and process information using the same thirty-four optimized setpoints that are used to determine the power offer curve for scheduling. Exported power ($Power_{exp}$) is constrained within a band from the scheduled power for real-time optimization

$$Power_{\exp}^{sched} - \delta \leq Power_{\exp} \leq Power_{\exp}^{sched} + \delta \qquad (7)$$

The governing constraints for the above optimization problem are set by process model (Equation 6) and constraints of site steam and power demand along with limitations for plant equipment. The on-line optimization problem is solved every three minutes and the setpoints are implemented using a linear model predictive controller. Real-time optimization cycle consists of a model validation case followed by an optimization case as depicted in Figure 1. After the model is parameterized to match current plant operating conditions, an optimization run is executed. The optimization case takes into account the current control status of each optimized setpoint. If a particular setpoint is placed out-of-control in the linear model predictive controller, then its behavior in the plant is replicated by mimicking the underlying control system scheme instead of optimizing it. The particular variable is typically maintained within limits by the underlying control system scheme even though it is not controlled at a particular target value. The global optimality and stability of the implemented solution is ensured by capturing the behavior of the underlying control system for variables that are not controlled to a target by the linear model predictive controller. At the end of the optimization case, optimized plant setpoints are implemented by controlling them to their target values using a linear model predictive controller. The optimization cycle, from collecting plant data to sending optimized setpoints, is done continuously and takes approximately 3 minutes. The closed-loop optimizer uses a validated process model to keep the plant at optimum conditions based on process data and economics.

Model Predictive Control

Aspentech's Aspen DMCplus is the commercial linear model predictive controller used for implementation of optimization setpoints and maintaining process within limits. The commercial controller uses an ARX input-output model instead of using a state-space representation to explicitly capture the dynamics of the process. Plant-model mismatch is attributed to disturbances in output measurements instead of inputs or process in the controller formulation (Cutler and Ramaker (1979)). The MPC controller runs every 15 seconds and is used to maintain the optimized exported power target while keeping plant operations within required process constraints (Figure 1). The control objectives for MPC are ranked such that the more important limits are satisfied first. The physical limits of valves and environmental safety limits are most important. The steam header pressure limits, fuel gas pressure limits and fuel gas ratio limits are next in importance because they are set by the internal chemical plant producers at the site. The economic objective of maintaining scheduled exported power is more important than the target power for each individual gas turbine or steam turbine specified by the real-time optimizer. The power produced from the individual generators varies in response to disturbances from the chemical plant producers to maintain scheduled export power.

Results

The results shown for the industrial process have been scaled to protect proprietary information. The power schedule offer consists of a curve for incremental heat rate with exported power (Figure 2) that allows the power schedule to vary with the market heat rate as per the curve. After the power is scheduled, there is a deviation band of 20 MW that can be used for real-time optimization. Incremental heat rate varies with exported power when gas turbines are getting loaded and has a completely different slope for supplemental firing from duct burners (Figure 2). The incremental heat rate curve is able to match within 2 percent error from actual plant data for different ambient temperatures and operating scenarios. The accuracy of the model predictions enables better decision making for scheduling power. Linear models would result in a constant incremental heat rate when gas turbines are getting loaded. The less accurate predictions from linear models would lead to inefficient decision making for scheduling power. The close match of the power offer curve with plant data can be attributed to the following

- Fundamental nonlinear model with process control strategy and equipment design curve details
- Continuous model validation with real-time plant data

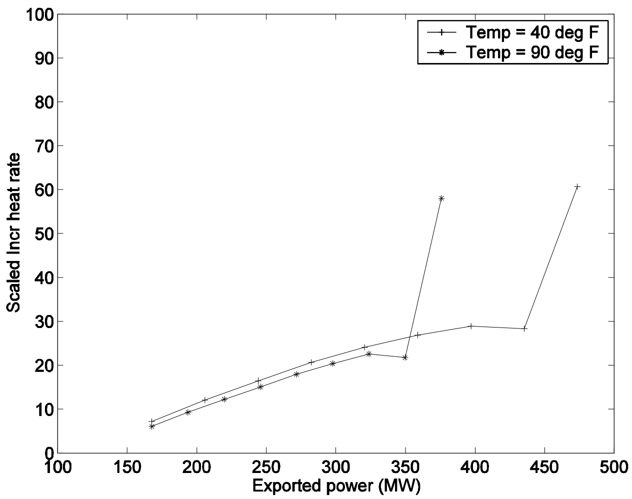

Figure 2. Scaled Incremental Heat Rate Variation

Implementation of the optimized power target is done effectively using a linear model predictive controller. The effective optimized target takes advantage of the allowed 20 MW deviation band from the power schedule and the actual exported power is able to follow the optimized target closely without requiring nonlinear models for MPC as shown (Figure 3). The exported power target is greater than the power schedule because it is profitable to generate excess power and the MPC controller is able to follow the optimized target closely.

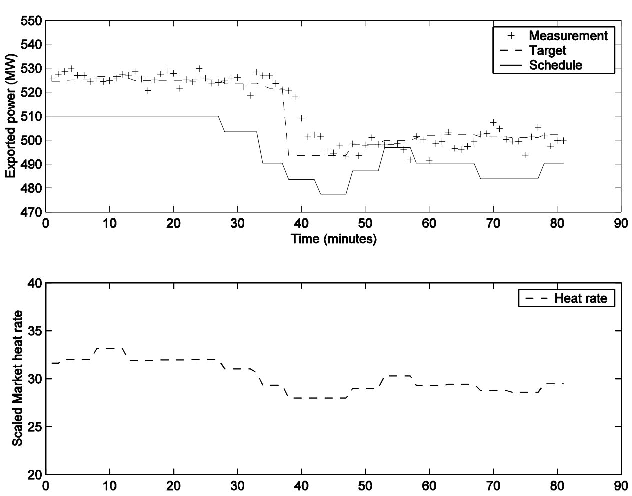

Figure 3. Schedule Implementation for Power

Conclusions

The power scheduling application has been in continuous use since January 2014 to enable efficient participation in day-ahead and real-time power markets due to its robustness and accuracy for solving multiple optimization cases. The scheduler that uses a validated fundamental nonlinear model to match plant data closely has enabled realization of significant benefits that are equal to 12.8 percent improvement in power sales margin (*$/MWhr*) as compared to selling power in the real-time market without any scheduling.

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