Annual Reviews in Control 38 (2014) 81–92

Contents lists available at ScienceDirect

Annual Reviews in Control

journal homepage: www.elsevier.com/locate/arcontrol

Optimal operational control for complex industrial processes ☆

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ARTICLE INFO

Article history:
Received 1 November 2013
Accepted 15 February 2014
Available online 26 April 2014

ABSTRACT

Process control should ensure not only controlled variables to follow their setpoint values, but also the whole process plant to meet operational requirements optimally (e.g., quality, efficiency and consumptions). Process control should also enable that operational indices for quality and efficiency be improved continuously, while keeping the indices related to consumptions at the lowest possible level. This paper starts with a survey on the existing operational optimization and control methodologies and then presents a data-driven hybrid intelligent optimal operational control for complex industrial processes where process operational models are difficult to obtain. Applications via a hybrid simulation system and an industrial roasting process for hematite ore mineral processing are presented to demonstrate the effectiveness of the proposed operational control method. Issues for future research on the optimal operational control for complex industrial processes are outlined before concluding the paper.

1. Introduction

Conventional process control research has focused on how to design feedback controllers so that the closed loop system is stable and the controlled variables follow the setpoints as closely as possible, under the assumption that the setpoint values for the controllers are given. However, optimal process operation cannot be guaranteed by conventional feedback control when the setpoints differ from their optimal values. This fact has been largely ignored in control design research.

The increasingly fierce global competition has inevitably led to new scrutiny on process control in all sectors of the modern process industries. Not only are the controlled plant outputs required to best follow their setpoints, but also the operation of the whole plant is required to be well controlled so that the operational indices (i.e., the product quality, efficiency and consumptions during the production phase) are controlled in their target ranges. Moreover, the quality and the efficiency indices should be improved continuously while the consumptions are reduced to their lowest possible level. The optimal control of the operational indices along with other process variables is referred to as *optimal operational control* (OOC) for industrial processes in this paper. The fast development of computer and communication technologies has enabled the implementation for the optimal operational control for industrial processes.

Operational optimization and control for industrial processes are of increasing importance and have attracted the attention of many researchers (Adetola & Guay, 2010; Alvarez & Odloak, 2010; Darby, Nikolaou, Jones, & Nicholson, 2011; Engell, 2007; Hasikos, Sarimveis, Zervas, & Markatos, 2009; Jaschke & Skogestad, 2011; Mehmet & Doyle, 2008; Riccardo, 2009; Tatjewski, 2008; Wu, Cao, He, & She, 2009). In late 1950s, the first use of computers to calculate on-line economic optimal operating points for a process unit appears to have taken place. At the same time, computer control systems can realize real-time control and optimization in American companies such as Texaco and Union Carbide (Bischoff & Denn, 2001). For industrial processes with established mathematical models such as refinery and petrochemical processes, model based operational optimization and control methods are established. In this context, self-optimizing control uses traditional feedback regulation to realize optimal operation. Such methods would select the setpoints of the controlled variables which correspond to economically optimal steady state operations of industrial processes. By adjusting relevant controlled variables to follow these setpoints, the whole process can be operated at or near the economically optimal steady state in the presence of disturbances (Skogestad, 2000). However, for some industrial processes, it is difficult to select appropriate setpoints

☆ Part of the paper was presented as a keynote at the IFAC ADCHEM Symposium, July 10–13, 2012, Singapore and the 13th IFAC Symposium on Large Scale Complex Systems: Theory and Applications (IFAC LSS, 2013), Shanghai, China.

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http://dx.doi.org/10.1016/j.arcontrol.2014.03.005
1367-5788/

for the controlled variables. When the system is subject to unexpected disturbances, there is no guarantee that the process will operate near its economically optimal state even if the controlled variables can follow these setpoints. To resolve this problem, real-time optimization (RTO) is developed by combining the regulatory control with the optimization of the process operation, where a two-layered structure has been employed. The upper layer optimizes relevant economic objectives using a nonlinear steady state model to generate proper setpoints for the lower layer control loops. The lower layer realizes the tracking of the controlled variables to these setpoints (Findeisen et al., 1980; Marlin & Hrymak, 1997). However, since RTO uses steady state models, it can optimize the process only when the system reaches a new steady state after the occurrence of disturbances. This can lead to a long period of time without optimization. As a consequence, RTO cannot cope with the dynamic variation of operational conditions. Effort has been made to combine steady state optimization with model predictive control (MPC), where a three-level structure (i.e. RTO, MPC and regulatory control) is adopted to deal with the issue that the period of RTO is too long comparing to the fast execution period of the control loops (Adetola & Guay, 2010; Hartmann, 1998; Nath & Alzein, 2000). Reference (Qin, Cherry, Good, Wang, & Harrison, 2006) uses fab wide control and optimization along with lower level control to optimize electrical properties of microelectronic products. Since RTO uses open loop optimization under steady state, it lacks robustness in the presence of model uncertainties and disturbances. As such, direct online optimal control is employed (Bartusiak, 2005; Engell, 2007). By including an economic objective function as an extra term in the performance objective of nonlinear MPC, it is optimized in a finite horizon (Qin & Badgwell, 2003). On the other hand, the work reported in Adetola and Guay (2010) proposes a controller design method for uncertain nonlinear systems by integrating real-time optimization with MPC under the assumption that the economic function is a known function of the constrained system state. When the economic objective and the process dynamics share the same time scale, such as real time electricity pricing in the optimization of building energy operation, Reference (Ma, Qin, Salsbury, & Xu, 2012) proposes to use the economic objective subject to the building thermal dynamic model and real time pricing information to generate room temperature setpoints in real time.

The aforementioned approaches generally require that the industrial processes can be adequately described by mathematical models, either from experimental or first principles. The dynamic models for OOC generally include models for the control loops and models for process operations relating operational indices to the controlled variables. In this regard, the operational indices consist of quality, efficiency, energy and material consumptions during the production phase. For complex industrial processes such as those in the metallurgical industry, the dynamic characteristics between the operational indices and the controlled variables in the lower-level control loops exhibit compounded complexity in terms of strong nonlinearity and multivariable coupling. Uncertainties and unknown mechanism in solid or slurry material processing make it difficult to establish mathematical models with any reasonable accuracy. These dynamics usually have time-varying characteristics for different operation conditions. In addition, the operational indices usually cannot be measured online and timely. Thus, currently there is no unified optimal operational control approach that can be widely applied to these hard-to-model complex industrial processes.

Indeed, the metallurgical practices generally first pre-process the production boundary conditions, and then employ either production specification models or empirical models to produce setpoints for the control loops in an open loop setting, where the controlled variables can be made to follow these setpoints to realize operational control. As for China, raw material resources and production conditions tend to vary frequently (for example, the composition of raw ores suffers from large variations and low grades). It is difficult to use the model based methods to perform open loop settings for control loops. In Li and Guan (2001), a supervisory control strategy for a hot-rolled strip laminar cooling process is proposed by combining traditional control with intelligent control techniques to improve the quality of the final products. In Wang, Wu, and Chai (2004), an optimal setting control method for a six-zone walking beam reheating furnace is developed to improve the heating efficiency. As reported in Yang, Gui, and Kong (2009), a quality prediction model is proposed for the raw slurry preparation of alumina sintering production by combining a first principles model with neural networks. A multi-objective hierarchical expert reasoning strategy is then proposed to optimize the setpoints for raw slurry proportioning. Further, in Wu, Xu, She, and Yokoyama (2009) an intelligent integrated optimization and control method is developed for a lead–zinc sintering process based on a model for product quantity and quality.

Although the Chinese manufacturing output from process industries is the largest in the world, including steel making, aluminum, mineral processing, papermaking and cement productions, challenges exist in terms of high energy consumption, intensive resources usage and low product quality. These plants are energy intensive, for example, shaft furnaces, rotary kilns and ball mills. Due to the lack of adequate mathematical models and the online measurement of the operational indices, manual operation is often the only option to select setpoints for low level control loops. In this context, on-site operators determine the required setpoints and then the feedback controllers try to make the controlled variables follow these setpoints. However, when the operating conditions fluctuate, these setpoints cannot be tuned timely and appropriately. As a result, the plant usually operates under a non-optimized economic status, leading to high energy consumption and even fault operating conditions.

One example is the hematite mineral processing industry in China that uses shaft furnaces to transfer low grade and weak magnetic ore into high magnetic ore. The operational indices (i.e., the magnetic tube recovery rate) that reflect the metal recovery rate cannot be measured online. Moreover, this operational index is affected by a number of controlled variables, such as the heating zone temperature, gas flow rate and ore discharging time. The relevant dynamics, therefore, exhibit compounded complexity in terms of heavy nonlinearity, strong coupling and variations along with frequent changes of operation conditions. The complexities cannot be expressed adequately by mathematical models. As a result, manual operation is employed by operators who would firstly visually observe the combustion status inside the combustion chamber and then determine the setpoints of the control loops based on experience. When the ore size, grades, and composition vary frequently, the operators cannot timely tune these setpoints to keep the operational indices inside their target ranges. Such manual operations frequently lead to various faulty operating conditions such as fire-emitting, ore-melting, flame-out, under- and over-deoxidizing. When these faults occur, operators normally use visual inspection and experience to diagnose the faulty operating condition, and then adjust the setpoints of the control loops, so that the operation of shaft furnace can be gradually returned to normal operating conditions. Since operators cannot correctly diagnose the operating conditions and tune these setpoints in a timely manner, operational performance loss of shaft furnace and even shutdown of the production will result. Therefore, process operational control is not only critical for the product quality, production efficiency, energy and resource consumptions, but also has significant impact on the reliable and safe operation.