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Optimal Operational Control for Complex Industrial Processes ⋆

Tianyou Chai

State Key Laboratory of Synthetical Automation for Industrial Processes, Northeastern University, Shenyang, P R China (Tel: 86-24-83687794; email: tychai@mail.neu.eud.cn).

Abstract: Process control should aim at not only ensuring that controlled variables to best follow their set points, but also requiring the optimal control for the operation of the whole plant to make the operational indices (e.g. quality, efficiency and consumptions during the production phase) into their targeted ranges. It also requires that operational indices for quality and efficiency should be enhanced as high as possible, whilst the indices related to consumptions are kept at their lowest possible level. Based upon a survey on the existing operational optimization and control methodologies, this paper presents a data-driven hybrid intelligent optimal operational control for complex industrial processes and a hybrid simulation system. Simulations and industrial applications to a roasting process for the hematite ore mineral processing industry are used to demonstrate the effectiveness of the proposed method. Issues for future research on the optimal operational control for complex industrial processes are outlined in the final section.

1. INTRODUCTION

In general, under the assumption that the set points for controllers are known, research into conventional process control has been focused on how the controller can be designed so that the closed loop system is stable and then the controlled variables can follow these set points as closely as possible. The fact that optimal operation of systems cannot be achieved by feedback control when the actual set points deviate from their desired values is ignored.

The development of modern process industries and the increasingly fierce competition of the world market have inevitably led to new demand on process control from various industrial sectors. Not only the outputs of the controlled plant are required to best follow their set points, but also the operation of the whole industrial plant is required to be well controlled so that the operational indices (i.e. the production quality, efficiency and consumptions during production phase) are well controlled into their targeted ranges. Moreover, the quality and the efficiency indices are enhanced as much as possible whilst the consumption indices are reduced to their lowest possible level. This means that the optimal operation control for industrial processes can be realized. The fast developments of computer and communication technologies have provided an implementation platform for the optimal operational control for industrial processes.

The operational optimization and control for industrial process are of increasing importance in industries and have attracted attentions of many researchers (Engell [2007], Darby et al. [2011], Scattolini [2009], Mehmet et al. [2008], Hasikos et al. [2009], Jaschke et al. [2011], Tatjewski [2008], Adetola et al [2010], Alvarez [2010], Wu et al [2009]). In as early as late 1950s, the first use of computers to calculate an on-line economic optimal operating point for a process unit appears to have taken place. At the same time, computer control system could realize real-time control and optimization in American chemical companies such as Texaco and Union Carbide (Bischoff [2001]). For industrial processes whose mathematical models can be established such as chemical processes, model based operational optimization and control methods were established. In this context, self-optimizing control uses traditional feedback regulation to realize optimal operation. Such methods would select the set points of the controlled variables which correspond to economically optimal steady state for industrial processes. By adjusting relevant control variables to follow these set points, the whole process can be made to operate near the economically optimal steady state in the presence of disturbances (Skogestad [2000]). However, for some industrial processes, the selection of appropriate set points for controlled variables is difficult to perform. Moreover, when the system is subjected to unexpected disturbances, there is no guarantee that the process will operate near its economically steady state even if the controlled variables can follow their set points. To solve this problem, the well-known real-time optimization (RTO) combines the regulatory control with the optimization of the process operation, where a two-layered structure has been employed. The top layer optimizes relevant economical functions using a nonlinear steady state model so as to produce proper set points for the low layer control loops. The later realizes the tracking of the controlled variables to these set points so that the process can operate near its economically optimal state (Findeisen et al [1980], Marlin et al [1997]). However, since RTO uses static models, it can

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only re-optimize the process once the system reaches its new steady state after the occurrence of disturbances. This leads to a delayed optimization effect where RTO method cannot cope with the variation of operational condition. As such, effort has been made by combining steady state optimization with model predictive control (MPC), where three-level structure (i.e. RTO, MPC and regulation control) has been adopted to solve the issues of inconsistence that the period of RTO is too long and that the running period of the control loops is too fast (Adetola et al [2010], Nath et al [2000], Hartmann [1998]). In addition, since RTO uses open loop optimization under steady state, it lacks robustness in response to model uncertainties and disturbances. As such, a direct online optimal control is employed (Engell [2007], Bartusiak [2005]). By including an economical function as an extra term in the performance function of nonlinear MPC, it is optimized in a finite horizon (Qin et al [2003]). On the other hand, the work reported in Adetola et al [2010] proposed a controller design 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's state. The above approaches generally require that the industrial process can be described by mathematical models.

The dynamic model of the controlled processes for the optimal operational control consists of two types of models, namely, models for concerned control loops and models of operational processes between the operational indices and the controlled variables. In this regard, the operational indices are of a multiple nature that constitutes the quality, efficiency, energy and material consumptions during the production phase. In general, for complex industrial processes such as metallurgical industry, the dynamical characteristics between operational indices and the controlled variables in control loops exhibit hybrid complexity in terms of strong nonlinearity and multivariable coupling, uncertainties and difficulties in establishing mathematical model due to non-clear mechanism. Moreover, these dynamics have different characteristics for different industrial sectors Operational indices usually cannot be measured online. Thus, at present there is no unified optimal operational control approach that can be widely applied to complex industrial processes. Their operational control has been realized via case-by-case approaches.

Indeed, the metallurgical industry generally firstly preprocess the production boundary conditions, and then employ either production specification models or empirical models to produce set points for control loops in an open loop setting, where the controlled variables can be made to follow these set points to realize operation control. As for China, since raw material resources and production conditions vary frequently (for example the composition of raw ores are subject to large variations and their grades are low), it is difficult to use the above methods to perform open loop settings for control loops. In Li et al [2001], a supervisory control strategy for a hot-rolled strip laminar cooling process has been proposed by combining traditional control method with intelligent control techniques so as to improve the performance of the final products. In Wang et al [2004], an optimal setting control method for a six-zone walking beam re-heating furnace has been developed to improve its heating efficiency. As reported in Yang et al [2009], for the raw slurry preparing of alumina sintering production a quality prediction model is presented by combining a first principle with neural networks and then a multi-objective hierarchical expert reasoning strategy is proposed to determine the optimized set points for raw slurry proportioning. Moreover, in Wu et al [2009] an intelligent integrated optimization and control method has been developed for lead-zinc sintering process based on a model for predicting quantity and quality of products.

Indeed, although the Chinese production output of process industries such as steel making, aluminium, mineral processing, papermaking and cement productions etc is in the top position in the world, there are some problems in terms of high energy consumption, large resources usage and low product quality. These are many energy intensive plant in operation for these processes industries such as shaft furnace, rotary kiln and ball mill, etc. Since their dynamic mathematical models are difficult to be built using first principle analysis, their operational indices cannot be measured online and their production boundary conditions vary frequently in term of the raw material composition and low grades etc, it is difficult to use the above operational optimization and control method. As a result, manual operation has been widely used to select set points for control loops in an open loop way. In this context, on-site operators determine the required set points and then loop controllers would enforce controlled variables to follow these set points so as to realize operational control. However, when the operating conditions fluctuate, these set points cannot be tuned timely and accurately. As a result, the plant always operates under a non-optimized economic status, leading to high energy consumption and even fault operating conditions. For example, the hematite mineral processing industry in China widely use shaft furnace to transfer low grade and weak magnetic ore into high magnetic ore. However, 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, namely the heating zone temperature, gas flow rate and ore discharging time. The relevant dynamics would therefore exhibit integrated complexity in terms of heavy nonlinearity, strong coupling and variations along with the frequent changes of operational conditions. Such complexities cannot be expressed by mathematical models. As a result, only manual operation can be employed, where on-site operators would firstly observe the combusting status inside the combustion chamber using visual inspection and then determine the set points of control loops based on their operational experiences. When the size of ore, their grades and composition are subjected to large and frequent variations, these on-site operators cannot accurately and timely tune these set points so that the operational indices can be kept inside their targeted ranges. Such manual based operations would generally lead to various faults operating conditions such as fire-emitting, ore-melting, flame-out, under- and over-deoxidizing. When these faults occur, on-site operators would normally diagnose the fault operating condition using visual inspection and their experience, and then adjust the set points of the control loops for the combustion chamber temperature, gas flow rate and ore discharging time, so that the operation of shaft furnace can be gradually moved far away from these fault operating conditions. Since on-site operators cannot correctly and timely diagnose the operating conditions and tune these set points, the operational performance of shaft furnace will get worse and even result in the break down of the production (Chai et al [2007b]). Therefore, it can be concluded that the operational control for industrial processes not only influence the product quality, production efficiency, energy and resource consumptions, but also have significant impact on the reliable and safe operation.

Green manufacturing and automation for process industries have been emphasized in the national strategic plan for medium and long term science and technology development of China. Specifically, optimal operational control for complex industrial processes has been regarded as one of the encouraged future research areas in the state industrial automation field in China.

By reviewing the existing operational optimization and control methodologies, this paper presents data driven hybrid intelligent optimal operational control and a hybrid simulation system for operational control in order to speed up the application of proposed operational control methods to real industrial processes supported by Chinese national fundamental research program. Using the shaft furnace in hematite mineral processing as a benchmark, the simulation results and real application to 22 shaft furnace systems in the largest mineral processing in China are given by adopting the proposed operational control method. Issues for future research on the optimal operational control for complex industrial processes are outlined.

2. DESCRIPTION OF OPTIMAL OPERATIONAL CONTROL FOR COMPLEX INDUSTRIAL PROCESSES

2.1 Operational Control Process for Complex Industrial Processes

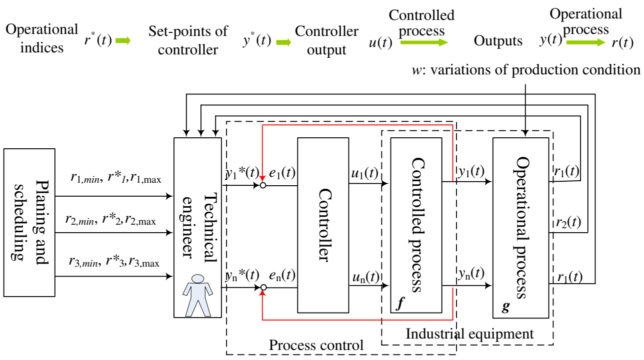


Fig. 1. The operational control for industrial processes

Fig. 1 shows the operational control process for complex plant, where the targeted values of the operational indices r_i^* $(i = 1, 2, 3)$ are obtained from planning and scheduling. r_1^* $(i = 1)$ represents the quality index, r_2^* $(i = 2)$ stands for the efficiency index and r_3^* $(i = 3)$ denotes consumption index. Operational indices $r_i(t)$ satisfy $r_{imin} < r_i(t) < r_{imax}$, where r_{imin} and r_{imax} are the lower and upper limits. The technical engineers use the above targeted values and their ranges of indices to determine set point y_j^* $(j = 1, 2, \ldots, n)$ based on their experience. The controllers would produce the required inputs $u_j(t)$ $(j = 1, 2, \ldots, n)$ to the plant to make their outputs $y_j(t)$ $(j = 1, 2, \ldots, n)$ follow these set points y_j^* so that the operational indices $r_i(t)$ are controlled into their targeted ranges, namely $r_{imin} < r(t) < r_{imax}$.

2.2 Problem Statement of Optimal Operational Control

Under the assurance of safe operation, the optimal operational control for industrial processes aims at controlling the actual operational indices into their targeted ranges, i.e.

$$r_{imin} < r_i(t) < r_{imax}, \ i = 1, 2, 3. \tag{1}$$

At the same time the operational indices that reflect the quality and efficiency are enhanced as high as possible by performing the following optimization

$$\max\, r_1(t), \ \max\, r_2(t).$$

In addition, the index that reflects the consumption is reduced as low as possible, i.e.

$$\max\, r_3(t).$$

In this regards, the dynamic model of the optimal operational control consists of the dynamical models in the operational layer and in the loop control layer. The dynamic model in the operational layer can be expressed as

$$\dot{r}(t) = g(r(t), y(t), d_r(t)) \tag{2}$$

where $g(\cdot)$ is a unknown nonlinear function represents the disturbances of the variations of the raw materials and wear and tear of the equipment, etc.

As for the dynamic model in the loop control layer, it can be expressed as follows

$$\dot{y}(t) = f(y(t), u(t), d_y(t)) \tag{3}$$

where d_y is the unknown yet bounded disturbance caused by measurement noises etc.

For actual control of industrial processes, the input and output and their rates of changes are subjected to the following constraints,

$$y^*_{min} \le y(t) \le y^*_{max}, \Delta y^*_{min} \le y(t) - y(t-1) \le \Delta y^*_{max}, \tag{4}$$

$$u_{min} \le u(t) \le u_{max}, \Delta u_{min} \le u(t) - u(t-1) \le \Delta u_{max}. \tag{5}$$

Also, the decision variables of the optimal operational control are the desired set points $y^*(t)$ for the control loops and control law $u(t) = p(y^*(t) - y(t))$, where p represent the control law. As a result, the problem of optimal operational control can be mathematically described as follows:

Control objective:

$$r_{imin} < r_i(t) < r_{imax}, \; i = 1, 2, 3. \tag{6}$$
$$\max\, r_1(t), \; \max\, r_2(t), \; \max\, r_3(t). \tag{7}$$

Constraints:

$$\dot{r}(t) = g(r(t), y(t), d_r(t)) \tag{8}$$
$$\dot{y}(t) = f(y(t), u(t), d_y(t)) \tag{9}$$
$$y^*_{min} \leq y(t) \leq y^*_{max}, \Delta y^*_{min} \leq y(t) - y(t-1) \leq \Delta y^*_{max}, \tag{10}$$
$$u_{min} \leq u(t) \leq u_{max}, \Delta u_{min} \leq u(t) - u(t-1) \leq \Delta u_{max}. \tag{11}$$

Disturbances: d_r, d_y.

Output of optimal operational control:

$$y^*(t) \; and \; u(t) = p(y^*(t) - y(t)). \tag{12}$$

From the above problem description, it can be seen that optimal operational control involves multi-objective optimization. The dynamic model of plant to be controlled consists of two layers, described by (9) and (10) together with relevant constraints in (11). The former (i.e. (9)) are related to knowledge of the relevant industries and exhibit hybrid complexity in terms of nonlinearity, multivariable nature, so that it is difficult to be described mathematically. Moreover, the disturbances of operational process are also difficult to be modelled mathematically. In addition, optimal operational control not only needs to produce the required control laws for the loop control layer, but also needs to produce appropriate set points for control loops. Therefore it is difficult to directly use the existing control and optimization technologies to solve the above problem. The following part of this paper will indicate that an operational control strategy combining optimization, prediction, feedforward and feedback would solve the above mentioned problem of multi-objective dynamic optimization.

3. DATA DRIVEN HYBRID INTELLIGENT OPTIMAL OPERATIONAL CONTROL STRATEGY

For engineering implementation, optimal operational control has employed two layered structure, namely the loop control layer and the setting control layer. Indeed, existing controller design methods can be used for loop controller. Mathematical model based controller design method select the controller structure based on the model of the plant to be controlled, and then obtains the parameters of the controller. However, since operational process is difficult to be modelled mathematically, operational controller design can only be carried out using process data. The idea of data driven controller design is to pre-specify the structure of the operational controller and then use process data to formulate each part of the controller. Since the operational dynamics of the above mentioned industrial plant are generally unknown and are subjected to uncertain disturbances, and they often operate under a dynamic environment, the optimal operational control should be robust. Therefore, the closed-loop dynamic optimization strategy should be realized by combining feedback with optimization. Since the optimal decision making for the set points of the control loops can only be achieved using either approximated models or intelligent methods such as case-based reasoning or rule -based reasoning. The obtained set points from the operational experience of experts often drift away from the optimized set points. This indicates that prediction and tuning of the operational indices should be utilized. In order to avoid the fault operating conditions caused by the inappropriate set points, the fault diagnoses and self-recovery control strategy should be used to tune the control loop set points so that the concerned industrial plant operates far away from the faulty operation conditions.

A hybrid data driven intelligent optimal operational control structure has been proposed as shown in Fig. 2. This control strategy integrates modeling with control and optimization with feedback. It also combines prediction with feedforward and links case-based reasoning and rule-based reasoning with intelligent computing. This proposed operational control structure therefore consists of pre-setting module for control loops, module for operational indices prediction, feed-forward and feedback compensation together with diagnosis of fault operating conditions and self-recovery control modules. In the following these modules will be described respectively.

Control loop pre-setting module: This module generates a set of pre-setting points $\tilde{y}(t)$ for the control loops using the targeted values of the operational indices r^*_i $(i = 1, 2, 3)$ and their targeted ranges $[r_{imin}, r_{imax}]$. The outputs of the loop controls $y(t)$ and the boundary conditions B, such as the variations of type and composition of raw material, are also taken into account.

Prediction module of operational indices: This module produces the predicted value $\bar{r}(t)$ for the operational indices using the pre-setting value $\tilde{y}(t)$ for the control loops at time instant t.

Feed-forward compensator: Using the difference between the targeted operational indices r^*_i and their predicted values $\bar{r}_i(t)$, namely $\Delta r_{iF}(t) = r^*_i - \bar{r}_i(t)$, this module produces the compensated value of the set points $\Delta\tilde{y}_F(t)$, which is then used to obtain the control loop set points $y^*(t) = \bar{y}_F(t) = \tilde{y}(t) - \Delta\tilde{y}_F(t)$ at the time instant t.

Feedback compensator: This module produces the set points $y^*(t) = \bar{y}_B(T) = \bar{y}_F(t) + \Delta\tilde{y}_B(T)$ at sample time T using the tuning value for set points $\Delta\tilde{y}_B(T)$ based on the errors $\Delta r_{iB}(T) = r^*_i - r_i(T)$, where $r_i(T)$ is the actual value with $T = nt$, where t is the sampling interval and n is an integer.

The principle of the feed-forward and feedback compensations can be described as follows: When the operational indices $r_i(t)$ $(i = 1, 2)$ (which reflect the quality and efficiency) is less than r^*_i and exceeds its threshold a (i.e. either $\Delta r_{iF}(t) \geq a$ or $\Delta r_{iB}(t) \geq a$), the required compensation will be performed. On the other hand, when the operational index $r_i(t)$ $(i = 3)$ (which reflects the consumption) is larger than its targeted value and exceeds its threshold a (i.e. either $\Delta r_{iF}(t) < 0$ with $|\Delta r_{iF}(t)| > a$ or $\Delta r_{iB}(t) < 0$ with $|\Delta r_{iB}(t)| > a$), the proposed compensation will also take place.

Diagnosis of fault operating condition: When fault either occurs or will imminently occur for the production operating conditions, this diagnostic module produces the

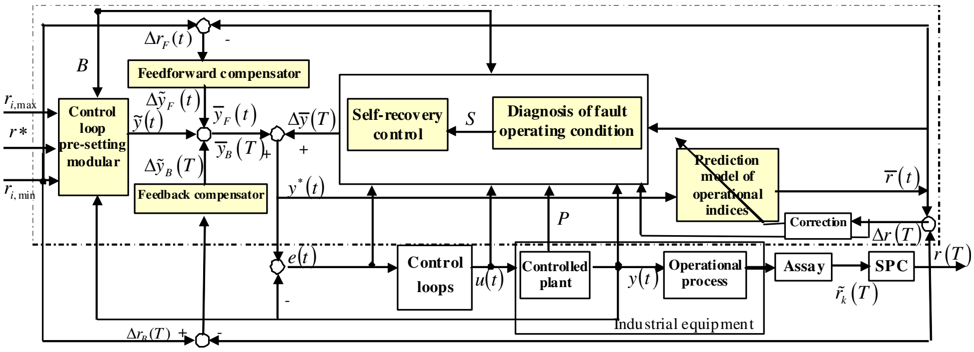


Fig. 2. The structure of the optimal operational control for industrial processes

fault diagnosis results of fault operating condition S using the targeted value of operational indices r_i^*, the predicted value $\bar{r}_i(T)$ and the actual value $r_i(T)$. The control loop output $y(T)$ and its rate of changes $\Delta y(T)$ together with the control input $u(T)$ are also used in the diagnosis together with process variable $P(T)$, its rate of changes $\Delta P(T)$ and boundary conditions B.

Self-recovery control module: This module generates the adjusted incremental value $\Delta\bar{y}(T)$ of the set points using the diagnosed fault operating condition S, the control loop output $y(T)$ and the control input $u(T)$ together with the tracking error of the control loop $e(T) = y^*(T) - y(T)$, where process variable P and the production boundary conditions B will also be used for this purpose.

Therefore the newly obtained control loop set points $y^*(T) = \bar{y}_B(T) + \Delta\bar{y}(T)$ can be finally formulated which will be tracked by the relevant controlled variables so that the system can be gradually moved away from the fault operating condition caused by inappropriate set point selection. In this phase there is no need to replace and change hardware of equipment. This self-recovery control scheme would realize the required control objectives given in (7)-(9) (for details please refer to Chai et al [2008]).

Indeed, the actual design of each module of the above optimal operational control strategy varies along with different dynamic characteristics of different industrial processes. Control loop pre-setting module adopts case-based reasoning (Chai et al [2007a],Chai et al [2011a]) or data-based approximate model and quadratic programming (Zhou et al [2012]). Prediction model of operational indices uses a method that combines fuzzy logic based reasoning and neural network (Wu et al [2010],Chai et al [2011a]). Feedforward and feedback compensators employ fuzzy logic based reasoning (Zhou et al [2009]) or case reasoning driven self-tuning PI control (Chai et al [2011a]). Diagnosis of fault operating condition and self-recovering control module adopts case-based reasoning and rule-based reasoning (Chai et al [2007b],Chai et al [2011a]).

4. HYBRID SIMULATION SYSTEM FOR OPERATIONAL CONTROL

Since the dynamics of complex plant differs from each other to a large extend, the operational control can only be designed using various process data. The operational control exhibits mismatch with respect to the actual model for the operational processes. This means that experimental based research should be adopted so as to validate and improve the design methodologies for operational controller. To ensure the safe operation of the industrial plant and avoid costly operational control testing on real industrial plant, simulated experiment should be carried out first. As a result, in order to apply the proposed operational control method to real industrial plants, a hybrid simulation system has been developed.

The hardware structure of the proposed hybrid simulation system is composed of the implementation platform of control systems operated under real industrial environment, the virtual equipments for actuators and sensors and the simulation computers for industrial plant.

In this context, the software system consists of the operational control software, DCS based configuration software, simulation software of actuators and sensors as well as the simulation software for actual industrial plant. This software system has the platform function and configuration ability which can be defined and extended based upon user's needs without re-programming and re-compiling. This flexibility allows the implementation of various optimal operational control algorithms and can easily be used to simulate different kinds of actuators and sensors. For complex industrial plant, we only need to establish models for each component and then use the flexible configuration ability of the simulation software to simulate the characteristics of dynamical models in the operational layer and the loop control layer.

5. CASE STUDY ON THE OPERATIONAL CONTROL OF SHAFT FURNACE SYSTEM

5.1 Problem Statement of Optimal Operational Control

Although China has rich hematite ore resources, the grade of useful ore is relatively low, making their separation difficult. Consequently the roasting process of shaft furnace is adopted to carry out the high-temperature-reduction roasting in order to enhance the magnetism to obtain the concentrated iron ore that can be used for the follow-up magnetic separation procedures. As shown in Fig. 3, the basic roasting process of a shaft furnace consists of ore feeding, ore preheating, heating, reduction, cooling and discharging phases. Detailed operation of each of these production phases (as shown in Fig. 3) is described as follows.

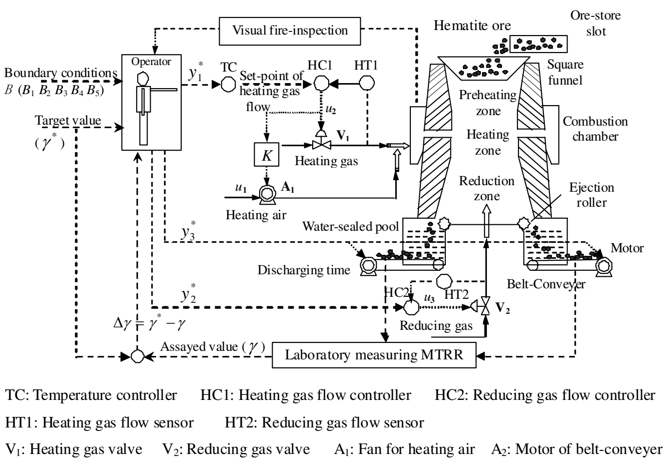


Fig. 3. Technical process and current control of the shaft furnace

Ore feeding: The raw hematite ores are fed into the furnace from an ore-store slot and a square funnel at its top.

Preheating: In the preheating zone those ores interact with the ascending hot gas so that their temperature rises to 100∼150°C.

Heating: In the heating zone, the ores temperature is increased to 700∼850°C when they are attained the heat produced by the inflammation of air-mixed heat gas in the combustion chamber.

Deoxidizing: In this phase, the hot low magnetic ores flow down into the deoxidizing zone and are deoxidized to high magnetic ones.

Cooling and ore discharging: This is the final processing where the ores are laid down into the water-sealed pool by two ore ejection rollers. The ores are cooled down and are moved out of the furnace by two carrier machines which operate synchronously with their corresponding rollers.

The operational indices that reflect the quality and the efficiency of the shaft furnace, namely the magnetic tube recovery rate $r(t)$, are related to the combustion temperature $y_1(t)$, the ore discharging time $y_2(t)$ and the coal gas flow rate $y_3(t)$. Since $r(t)$ cannot be measured online and its dynamical relationship with $\{y_1(t), y_2(t), y_3(t)\}$ is subjected to heavy nonlinearity and strong coupling, and such a relationship is difficult to be modelled and varies along with the operating conditions, only on-site operators can be employed to obtain the set points $\{y_1^*, y_2^*, y_3^*\}$ for these three control loops using their operational experience together with the targeted magnetic tube recovery rate r^* and its assayed value $r(T)$ in the on-site laboratory. Once these set pints are obtained, they are tracked by these three control loops of combustion temperature, the ore discharging time and the gas flow rate so as to realize the control of $r(t)$, ensuing that it is within its targeted range.

When the sizes, grades and composition of the raw ore vary frequently, on-site operators cannot adjust the required set points in time and it is therefore generally difficult to control the index well inside its targeted range, leading to the following fault operating conditions (FOCs) denoted by S which stands for Fire-emitting (FE), Flame-out (FO), Ore-melting (OM), Under-reduction (UD) and Over-reduction (OD), respectively. The definitions of these fault operating conditions as given as follows:

Fire-emitting (S1): This stands for the fire emit out of the combustion chamber.

Flame-out (S2): This means that the flames reach out of the top of the furnace.

Ore-melting (S3): This represents the fault that the iron ores stick inside the furnace so that further entry of ores is difficult.

Under-reduction (S4): This denotes the fault of under deoxidization.

Over-reduction (S5): This stands for the fault of over deoxidization.

Over a long period of time, these fault operating conditions could only be diagnosed by the visual inspection of the surface status of the shaft furnace, where assessment was made by experienced operators who would adjust the set-points of the control loops on trial and error basis to avoid some fault operating conditions, which have occurred frequently for the improperness and delay of some manual operations. Therefore, the quality and efficiency of the production are severely affected and even personnel safety is also in danger.

5.2 Hybrid Simulation Tests

The purpose of optimal operational control of shaft furnace is to ensure that the magnetic tube recovery rate is controlled inside its targeted range $[r_{min}, 1]$ for r^* so that $r(t)$ is made as larger as possible than r^*. In this case we have selected r^*=0.82 and r_{min}=0.79.

Using the proposed structure of operational process control and considering the features of the shaft furnace system, a hybrid intelligent optimal operational control algorithm has been developed as described in Chai et al [2011a], where cascaded control and PI control are used for the control loops of the combustion temperature, the gas flow rate and the ore discharging time (Yan et al [2006]). For this proposed optimal operational control, the case based reasoning has been used for the control loop setting module whilst the cased based reasoning of a PI structure has been used for the feed-forward and feedback compensation (Chai et al [2011a]). Moreover, a hybrid intelligent modelling method that integrates fuzzy system and RBF neural networks is established for the predictive model of the magnetic tube recovery rate (Wu et al [2010]). As for the diagnosis of fault operating conditions and self-recovery control, case based reasoning and rule based reasoning have been used respectively (Chai et al [2007b]).

Using the above algorithm, the operational control software for the shaft furnace is developed via the use of configuration function of the operational control software. Adopting the above loop control algorithm, the monitoring and control software of the shaft furnace is developed using the DCS configuration software. Moreover, using the real process data, the models of the pre-heating, the heating, the combustion, the deoxidizing, ore discharging time and the magnetic tube recovery rate have been obtained through the proposed hybrid intelligent modelling techniques (Wu et al [2010]). The simulation experiments are then carried out adopting the hybrid simulation system. The simulation results show that the magnetic tube recovery rate can be controlled well inside its targeted range.

5.3 Industrial Application

Fig. 4. The shaft furnaces

For the 22 shaft furnaces of a hematite ore mineral processing production plant in China (as shown in Fig.4), an operational control system has been developed adopting the proposed operational control method for the shaft furnace. The responses of the combustion chamber temperature, the gas flow rate and the ore discharging time are shown in Fig.5 for the operation period from 7:00am to 12:00pm, where from these responses it can be seen that when the particle size of ore (B3) changes from "large" to "medium" and when the variations take place for negative pressure (P2) inside the furnace, the coal gas heating value (P3), the heating air pressure (P4) and the rate of changes of the hot coal gas flow (P6), the proposed operational control system can adaptively tune the set points of combustion chamber temperature, the coal gas flow rate and the ore discharging time so that these controlled variables are be made to best follow these set points ensuing that the magnetic tube recovery rate can be controlled well inside its targeted range [0.79,1].

The operational control system has been in operation for three years, its operation has clearly shown that the proposed system can effectively provide appropriate set-points for the control loops in time under the variation of operating points or fault of conditions (FOCs). The application results of the proposed system can be obtained from Tables 1 that the total frequency of FOCs is reduced by over 50%, the production rate per furnace is increased by 0.7 T/h from previous 24.9 T/h to the current 25.62 T/h. Moreover, the magnetic tube recovery rate has been increased by 2% and the equipment usage rate is enhanced by 2.98%. As such, the metal recovery ratio is improved by 2.01% and the concentrate grade raised by 0.57% (see Chai et al [2011a]).

To illustrate the steady operation of the roasting process, the monthly averages of magnetic tube recovery rate of three years are shown in Fig. 6, which demonstrates that the system runs steadily and reliable.

6. OPEN ISSUES

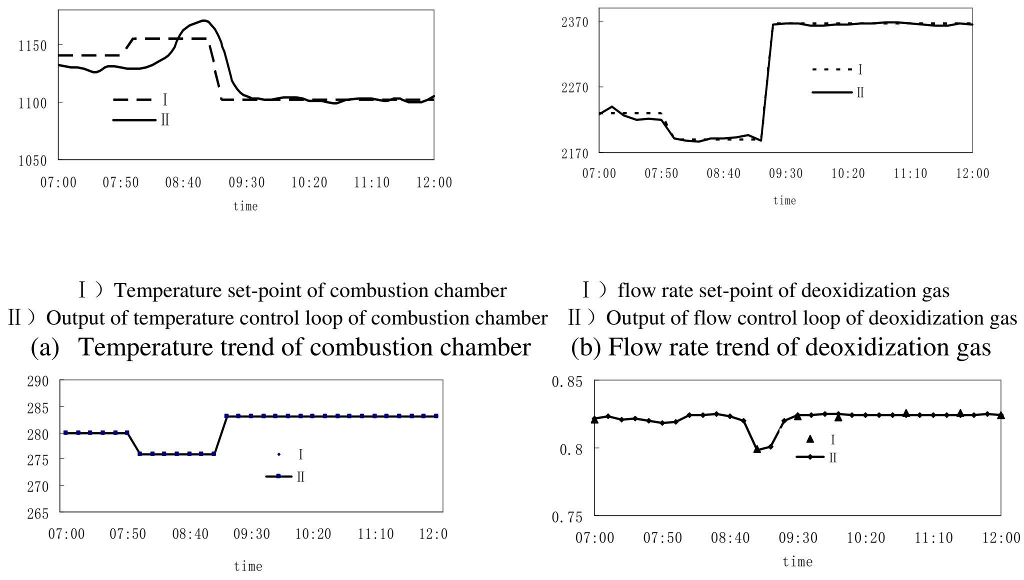
For complex industrial processes which are difficult to establish mathematical models, data driven operational control is an effective approach. Further investigations are also needed so as to obtain industrially applicable design method of the data driven operational controller. In terms of methodologies to be used for such research, analytical methods should be effectively combined with experimental approach. The operational controller design method should be studied and then the simulation models should be established that reflect the dynamic characteristics of the plant to be controlled. The simulation experiments for proposed method applied to the simulated models of the industrial plant and the industrially experiments should be carried out so as to validate and improve the design methods for operational controller. The following open issues should be addressed in the future research.

6.1 Predictive Model for Operational Indices

For model based operational optimization and control methods, their performance indices can be represented by the mathematical model of controlled variables. However, in practical industrial processes the operational indices (i.e. quality, efficiency and consumption indices) of many industrial plants cannot be represented by mathematical models of controlled variables. Moreover, they are difficult to be measured online. To achieve the operational optimization for these plants, it is necessary to establish predictive models for operational indices. Since it is generally difficult to use first principles techniques to establish the dynamical models between the operational indices and the controlled variables and these dynamical models are of different forms for different industrial sectors, we need to investigate novel hybrid intelligent modelling approaches using first principles analysis, data and knowledge, statistics analysis and intelligent computing. For example, Ding et al [2011] used least square vector support machine LS-SVM and the probability density function of the modelling error to obtain the predictive model for the concentrated grade of the hematite ore mineral processing. This method adopts the data of the shaft furnace, grinding and magnetic mineral processing such as the magnetic tube recovery rate, particle size, strong and weak concentrated grades etc.

6.2 Data Driven Controller Design

For those industrial processes where their mathematic model are difficult to obtain, the selection of control loop set points can only be achieved using either approximated mathematical model or the intelligent methods such as case based, rule based and fuzzy logical reasoning etc. based on the operational experience. However, such a selection of the control loop set points may be deviated from their optimal values. Therefore, it is necessary to determine the compensated values for the set points using the error of the targeted and actual values of the operational indices. This is in fact a controller design problem



Ⅰ）Temperature set-point of combustion chamber
Ⅱ）Output of temperature control loop of combustion chamber
(a) Temperature trend of combustion chamber

Ⅰ）flow rate set-point of deoxidization gas
Ⅱ）Output of flow control loop of deoxidization gas
(b) Flow rate trend of deoxidization gas

Ⅰ）Moving time set-point
Ⅱ）Practical value of moving time
(c) Trend of moving time

Ⅰ）Prediction of MTRR
Ⅱ）Practical value of MTRR
(d) Trend of MTRR

Fig. 5. Operational control effects of the shaft furnace's roasting process

Table 1. Comparison of the performance of the shaft furnace

	Before the system installed	After the system installed
Average MTRR (%)	80	82
Average production rate per furnace (t/h)	24.9	25.62
Average equipment usage rate (%)	92.5	95.48
Average frequency of fault (times/month)	6.5	3.2
Average metal recovery ratio (%)	74	76.01
Average concentrate grade (%)	52.1	52.67

where the operational process is taken as the process to be controlled, the operational indices and their targeted values are regarded as the output and the reference input, and finally the compensated values for set points are taken as the control inputs. Since such a dynamics is often structurally unknown and nonlinear, the existing model based controller design would be difficult to use. Therefore, it is necessary to investigate data driven design method of controller to perform the operational controller and compensator design, where process data is used in combination with knowledge retrieving techniques and intelligent methods. For example, the work reported in Ding et al [2012] used the operational data of the whole mineral processing line to establish a feedback compensation method for the set points selection of control loops using the cause-and-effect rule mining via rough set theory. Also, for nonlinear multivariable systems that cannot be modelled mathematically virtual un-modelled dynamics and data driven method can be used to design controller (Chai et al [2011b]).

6.3 Fault Prediction, Diagnosis and Self-Recovery Control for Fault Operating Conditions

In the operation of industrial plants, although the controllers, actuators and sensors are healthy, fault operating conditions would still occur if inappropriate setting control takes place. The fault operating conditions affect directly the operational indices and can lead to severe deterioration of product quality, efficiency and increase consumptions. They can also lead to the break down of production and even cause severe personnel injuries. Therefore, research into the prediction and diagnosis of fault operating conditions and self- recovery control to remove the faults so as to ensure the safe operation of industrial plant is of paramount importance. Fault operating conditions are different from the faults of the actuators and sensors in the sense that they relate to a number of factors such as plant parameters, the input and output of control loops and production boundary conditions, etc. Moreover, the dynamics of fault operating conditions vary along with different industrial plant. In this context, existing methods on fault diagnosis and tolerant control are difficult to be used. In this regard, it is a challenging to study the prediction and diagnosis of fault operating condition as well as self-recovery control. For this purpose, the first

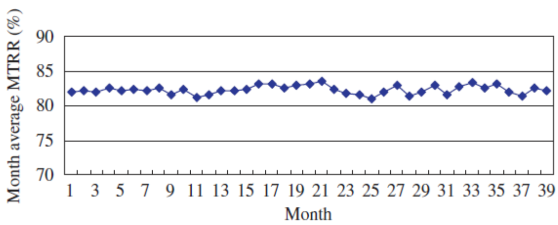


Fig. 6. Trend of monthly average MTRR for three years

principle analysis should be combined with data-driven, operational knowledge and intelligent methods should be used. For example, a novel tension fault diagnosis method for cold rolling continuous annealing processes has been reported in Liu et al [2011] by using the process data, where first principle analysis has been effectively combined with the well-known principal component analysis.

6.4 Multi-Objective Optimal Decision-making for Operational Indices

The objective of optimal operational control of industrial processes is to make the actual operational indices as close as possible to their optimized values. This means that the decision-making of the targeted values of operational indices is very important. These operational indices are closely linked to the production indices, namely the product quality, product quantity and production cost of the whole production line. The dynamic model between the operational indices and the production indices is generally difficult to be established using first principle analysis. Such model exhibits different characteristics for different industrial sectors and are also subjected to frequent variations of production conditions in terms of the changes in raw material composition and wear and tear of relevant production equipment. Therefore, the optimal decision making for operational indices is in fact a multi-objective and dynamical optimization problem for systems which is difficult to be modelled mathematically. This requires research on multi-objective intelligent optimization. For instant, a multi-objective evolutionary computing algorithm (Yu et al [2011]) has been combined with gradient approach so as to obtain the performance indices for mineral processing plant in terms of its concentrated grade, composition of raw materials and resources and product quantity of the concentrated grades.

6.5 Operational Closed-loop Feedback Control Under Hybrid Networking Environment

To ensure the reliability of the operational control for industrial plants, its operational optimization and control are realized by a two-layered structure, namely the control loops layer and the setting control layer. The input and output signals of the control loops are transmitted via device networks and the signals for setting control layer are transmitted using industrial Ethernet. Although there exist data transmission delay and package drop-off for Ethernet, this effect caused by such networking environment can be ignored when performing open loop optimal operation and control. For example, RTO method uses open-loop mode to produce control loop set points for chemical processes. However, to overcome the hybrid complexity for industrial plant, the optimal operational control should be realized in a closed loop format. Therefore, it is necessary to consider the impact of data transmission delay and package drop-off. In Chai et at [2012], integrated network based model predictive control for set point compensation in industrial processes has been preliminarily studied. Indeed, the operational closed loop feedback control under integrated network will constitute a new direction of research.

6.6 Dynamic and Static Performance Analysis for the Operational Control

Operational control not only makes the operational indices inside their targeted ranges finally, but also keeps these indices always inside the targeted range. This requires both the stability and the desired dynamic performance of the optimal operational control system. Since RTO adopts an open loop optimization, it does not affect the stability of the system. However, for optimal operational control system for complex industrial processes, since it uses closed loop feedback optimization the stability of the system needs to be considered. The stability of the system should also consider the effect of the tracking errors between the controlled variables and their set points of control loops. Since the dynamics of such a system cannot be modeled mathematically, existing tools on stability analysis cannot be readily used. Therefore, it is necessary to develop a novel kind of instrument for the analysis of the dynamic and static characteristics for operational control systems, where analytical methods should be combined with experimental approaches. This constitutes one of the possible approaches to validate the dynamic and static characteristics for the proposed optimal operational control system adopting experimental research method.

7. CONCLUSIONS

In response to the fast development of process industries and the requirements of industrial informatization in China, the objective of process control is not only ensuring that controlled variables to track their set points as closely as possible, but also requiring the optimal operational control of industrial plant. Under the national funded fundamental research program in China, a research project has been carried out to realize closed loop optimal operational control for complex industrial processes whose mathematical models are difficult to be established. The operational control strategy proposed in this project combines optimization with feedback, operational indices prediction with self-tuning, and the diagnosis of fault operating conditions with self-recovery control. Moreover, for specific industrial plants, relevant design methods have been proposed using data driven and intelligent methodologies. By taking the shaft furnace as a benchmark, the proposed optimal operational control methods is described together with both simulation results on a hybrid simulation system and its real applications to 22 shaft furnace in hematite ore mineral processing factory in China. The experimental results have clearly shown that the proposed method can constitute one of new approaches to solve the optimal operational control for complex industrial plants. Future issues and research methodologies on the optimal operational control for complex industrial processes are listed.

REFERENCES

S. Engell. Feedback control for optimal process operation. *Journal of Process Control*, 17:203–219, 2007.

M.L. Darby, M. Nikolaou, J. Jones and D. Nicholson. RTO: An overview and assessment of current practice. *Journal of Process Control*, 21:874–884, 2011.

R. Scattolini. Architectures for distributed and hierarchical model predictive control-A review. *Journal of Process Control*, 19:723–731, 2009.

M. Mehmet and F. Doyle. Real-time optimization of the pulp mill benchmark problem. *Computers and Chemical Engineering*, 32:789–804, 2008.

J. Hasikos, H. Sarimveis, P.L. Zervas, N.C. Markatos. Operational optimization and real-time control of fuel-cell systems. *Journal of Power Sources*, 193:258–268, 2009.

J. Jaschke, S. Skogestad. NCO tracking and self-optimizing control in the context of real-time optimization. *Journal of Process Control*, 21:1047–1416, 2011.

P. Tatjewski. Advanced control and on-line process optimization in multilayer structures. *Annual Reviews in Control*, 32:71–85, 2008.

V. Adetola and M. Guay. Integration of real-time optimization and model predictive control. *Journal of Process Control*, 20:125–133, 2010.

L.A. Alvarez and D. Odloak. Robust integration of real time optimization with linear model predictive control. *Computers and Chemical Engineering*, 34:1937–1944, 2010.

M. Wu, W. H. Gao, C.Y. He, J.H. She. Integrated intelligent control of gas mixing-and-pressurization process. *IEEE Transactions on Control System Technology*, 17: 68–77, 2009.

K.B. Bischoff, M.M. Denn. *Advances in Chemical Engineering*, Vol 26. San Diego: Academic Press, 2001.

S. Skogestad. Plantwide control: the search for the self-optimizing control structure. *Journal of Process Control*, 10:487–507, 2000.

W. Findeisen, F.N. Bailey, M. Bryds, K. Malinawski, P. Tatjewski and A. Wozniak . *Control and Coordination in Hierarchical Systems*, John Wiley, New York, 1980.

T.E. Marlin and A.N. Hrymak. Real-time operations and optimization of continuous processes, in Kantor, J. et al, *Fifth International Conference on Chemical Process Control*, AIChE Symp. Series 316, New York, 1997.

R. Nath and Z. Alzein. On-line dynamic optimization of olefins plants. *Computers & Chemical Engineering*, 24: 533–538, 2000.

J.C.M Hartmann. Distinguish between scheduling and planning models. *Hydrocarbon Processing* July: 93-100.

R.D. Bartusiak. NMPC: a platform for optimal control of feed- or product-flexible manufacturing, *Preprints International Workshop on Assessment and Future Directions of NMPC*, Freudenstadt, pp. 3-14.

S.J. Qin and T. Badgewell. A survey of industrial model predictive control technology. *Control Engineering Practice*, 11:733–764, 2003.

H.X. Li and S.P. Guan. Hybrid intelligent control strategy Supervising a DCS-controlled Batch Process. *IEEE Control Systems Magazine*, 21:36–48,2001.

Z.J. Wang, Q.D. Wu and T.Y. Chai. Optimal-setting control for complicated industrial processes and its application study, *Control Engineering Practice*, 12:65–74, 2004.

C.H. Yang, W.H. Gui, L. Kong. A two-stage intelligent optimization system for the raw slurry preparing process of alumina sintering production. *Engineering Applications of Artificial Intelligence*, 22:786–795, 2009.

M. Wu, C.-H. Xu, J.H. She and R. Yokoyama. Intelligent intergrated optimization and control system for lead-zinc sintering process. *Control Engineering Pracitcle*, 17: 280–290, 2009.

T.Y. Chai, J.L. Ding, H. Wang and C.Y. Su. Hybrid Intelligent Optimal Control Method for Operation of Complex Industrial Processes. *Acta Automation Sinica*, 34: 505–515, 2008.

T.Y. Chai, J.X. Liu, J.L. Ding and C.Y. Su. Hybrid Intelligent Control for Hematite High Intensity Magnetic Separating Process. *Measurement and Control*, 40: 171–175, 2007a.

P. Zhou, T.Y. Chai, J. Sun. Intelligence-based Supervisory Control for Optimizing the Operation of a DCS-Controlled Grinding System. *IEEE Transactions on Control Systems Technology*, 2012(Accepted).

P. Zhou, T.Y. Chai, H. Wang. Intelligent optimal-setting control for grinding circuits of mineral processing process. *IEEE Transactions on Automation Science and Engineering*, 6:730–743, 2009.

A.J. Yan, T.Y. Chai, H. Yue. Multivariable intelligent optimizing control approach for shaft furnace roasting process. *Acta Automation Sinica*, 32: 636–640, 2006.

F.H. Wu adn T.Y. Chai. Soft sensing method for magnetic tube recovery ratiovia fuzzy systems and neural networks. *Neurocomputing*, 73: 2489–2497, 2010.

T.Y. Chai F.H. Wu, J.L. Ding and C.Y. Su. Intelligent work-situation fault diagnosis and fault-tolerant system for roasting process of shaft furnace, *Proc of the ImechE, Part I, Journal of Systems and Control Engineering*, 221: 843–855, 2007b.

T.Y. Chai, J.L. Ding and F.H. Wu. Hybrid intelligent control for optimal operation of shaft furnace roasting process, *Control Engineering Practice*, 19: 264–275, 2011a.

J.L. Ding, T.Y. Chai and H. Wang. Offline modelling for product quality prediction of mineral processing using modelling error PDF shaping and entropy minimization. *IEEE Transactions on Neural Networks*, 22(3):408–419, 2011.

J.L. Ding, T.Y. Chai and H. Wang. Knowledge-based Global Operation of Mineral Processing Under Uncertainty. *IEEE Transactions on Industry Informatics*, 2012(Accepted).

T.Y. Chai, Y.J. Zhang, H. Wang, C.Y. Su and J. Sun. Data-based virtual unmodelled dynamics driven multivariable nonlinear adaptive switching control. *IEEE Transactions on Neural Networks*, 22(12): 2154–2172, 2011b.

Q. Liu, T.Y. Chai, H. Wang and S.J. Qin. Fault diagnosis of continuous annealing processes using reconstruction-based method, *IEEE Transactions on Neural Networks*, 22(12):2284–2295, 2011.

G. Yu, T.Y. Chai and X.C. Luo. Multi-objective Production Planning Optimization Using Hybrid Evolutionary Algorithms for Mineral Processing, *IEEE Transactions on Evolutionary Computation*, 15(4):487–514, 2011.

T.Y. Chai and L. Zhao. Integrated network based model predictive control for set point compensation in industrial processes. *IEEE Transactions on Industry Informatics*, 2012(Accepted).