2024 European Control Conference (ECC)
June 25-28, 2024. Stockholm, Sweden

An Optimal Control Method for Operation Status Migration in the Process Manufacturing Industry

Xulong Zhang, Yonggang Li, Bei Sun*, and Shengyu Liu

Abstract—**The process manufacturing industry plays a pivotal role in the manufacturing industry. It is characterized by frequent fluctuations in inlet conditions, frequent changes in operating conditions, and numerous random disturbances. It is challenging to achieve the optimal operation of the whole process by ignoring the changes in operation status and only requiring the key technical indicator to be close to the optimal setpoint. To this end, this paper proposes an optimal control method for operation status migration in the process manufacturing industry. First, a method for defining and classifying operation statuses based on mechanism knowledge is proposed. Then, construct a nonlinear process description model and propose an online spatiotemporal recognition method for operation status. Finally, with the objectives of minimal consumption, system stability, and approach to the optimal setpoint, an optimal control model for optimal migration of operation statuses is constructed to obtain the optimal control quantities and achieve optimal operation. The experimental results show that the proposed method can reduce resource consumption by finding the optimal migration path of the operation status to ensure system stability and product quality, which is of great significance for actual production.**

Keywords—mechanism knowledge, optimal control, operation status migration, process manufacturing industry

I. INTRODUCTION

The process manufacturing industry is an essential pillar of the industrial sector. Through global optimization, the optimal setpoint of each unit process and equipment can be set. Affected by frequent changes in inlet conditions and operating parameters, its internal operation status changes frequently. It is often difficult to make the process run at the optimal status only by considering the controlled variable close to the final optimal setpoint and ignoring the changes in its internal operation status. How to make the whole process approach the optimal setpoint smoothly and economically by adjusting the control quantity in each sub-interval reasonably is an urgent problem to be solved.

Optimal control is a method of optimizing the process by optimizing the control quantity in each interval, which is widely used in the optimal operation of industrial processes.

Ashoori et al. discussed model predictive control (MPC) based on a detailed unstructured model for penicillin production in a fed-batch fermenter by constructing different cost functions for better control[1]. Logist et al. leveraged advanced deterministic techniques to reconcile multiple conflicting goals optimally[2]. Song et al. proposed multiple actor-critic structures for optimal industrial process control[3]. Sun et al. established a two-layer receding horizon framework for developing a data-driven optimal control[4]. Chen et al. proposed an optimal control algorithm based on off-strategy reinforcement learning to achieve precise control of ion concentration in the goethite iron removal process[5].

Some of the above literature used optimal control to study the coordination among different control objectives. The rest of the literature emphasized obtaining the control quantity through optimal control to realize the optimal operation of the process. However, they did not take into account the change in the operation status during the optimization. It would be unreasonable for the process manufacturing industry and may lead to fluctuations in operation statuses and unqualified products. In recent years, some scholars have also researched optimal control under multiple operation statuses (working conditions) in the process manufacturing industry.

Liang et al. proposed a transfer predictive control method based on inter-domain mapping learning to control the roasting process under multiple operating conditions[6]. Liu et al. proposed an integrated optimal control method based on temporal causal network and reinforcement learning, which realizes the optimal operation of the entire process by solving the optimal electrolyte temperature under multiple working conditions[7].

The above literature considered the multiple operation statuses (working conditions) in the process manufacturing industry but did not consider the optimal migration problem.

Xie et al. proposed a method to obtain the optimal working condition migration path for the copper flash smelting process[8]. Although the working condition migration was considered in this manuscript, the definition of the working condition was not based on the mechanism knowledge. When

Manuscript received October 17, 2023. This work was supported by the National Key R&D Program of China (Grant No. 2020YFB1713700), National Natural Science Foundation of China (62273362), and Fundamental Research Funds for the Central Universities of Central South University (1053320210632).

Xulong Zhang is with the School of Automation, Central South University, Changsha, China, and is currently a visiting PhD student with the Department of Engineering, King's College London, London, United Kingdom. (e-mail: zhangxulong@csu.edu.cn / xulong.zhang@kcl.ac.uk).

Yonggang Li is with the School of Automation, Central South University, Changsha, China (e-mail: liyonggang@csu.edu.cn).

Bei Sun is with the School of Automation, Central South University, Changsha, China (corresponding author to provide phone: +8615111052394; e-mail: sunbei@csu.edu.cn).

Shengyu Liu is with the School of Automation, Central South University, Changsha, China (e-mail: 214611078@csu.edu.cn).

the inlet conditions change significantly, the definition of the working condition may deviate.

To this end, an optimal control method for operation status migration in the process manufacturing industry is proposed in this study. By studying the appropriate control quantity at each time interval, the operation status can be approached to the vicinity of the optimal setpoint stably and economically, and the resource consumption can be reduced under the premise of meeting the production requirements. The proposed method not only overcomes the inaccurate definition of operation status based on production data, but also constructs the optimal operation status migration path by continuously approaching the optimal setpoint, which can be applied to diverse process manufacturing industries. Specifically, it includes three parts:

(1) Define different operation statuses based on the proportion of reactants participating in the actual reaction and classify the operation statuses based on historical data.

(2) Construct a nonlinear process description model and propose an online recognition method of operation status based on spatiotemporal distance.

(3) Based on the optimal setpoint obtained from the global optimization (previous work [9]), combined with the optimal resource consumption and system stability, the optimal operation status migration model is established to obtain the optimal operation status migration path and the optimal control quantity at each moment.

The rest of this paper is organized as follows. Section II introduces the optimal control and operation status migration problem and its challenges in the process manufacturing industry, using the purification process in the zinc smelting process as an example. Section III introduces the optimal control method for operation status migration in the process manufacturing industry. The verification of the proposed method by simulations based on real production data generated from the industrial site is presented in Section IV. Conclusions are drawn in Section V.

II. Process Description and analysis

Zinc hydrometallurgy is a typical manufacturing process that mainly includes roasting, leaching, purification, and electrolysis. Among them, the purification process is a crucial process to ensure production safety and product quality, and its primary purpose is to remove the impurity ions contained in the neutral leachate to within the range required by the process.

The purification process mainly includes two sub-processes: copper removal and cobalt removal, which is shown in Fig. 1.

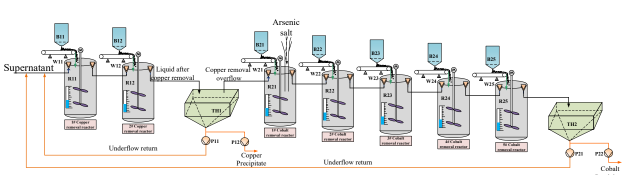


Fig. 1. Purification process.

The copper removal process includes two continuous reactors, and the removal of copper ions is mainly achieved through the following replacement reaction.

$$Cu^{2+}+Zn=Zn^{2+}+Cu \tag{1}$$

The cobalt removal process includes five continuous reactors, and the removal of cobalt ions is achieved by adding zinc powder and arsenic salt to react with cobalt ions.

$$HAsO_2+Co^{2+}+3H^{+}+2.5Zn=CoAs+2.5Zn^{2+}+2H_2O \tag{2}$$

In actual production, a certain amount of copper ions will promote the removal of cobalt ions, so the removal of cobalt ions is more complicated and more concerning for operators[10]. Considering that the main cobalt removal reaction takes place in the 1# cobalt removal reactor (More than 80% of the cobalt ions are removed in the 1# cobalt removal reactor), this study takes the 1# cobalt removal reactor as an example to study the optimal control method for operation status migration in the process manufacturing industry.

Considering actual production needs, the optimal setpoint of the key technical indicator (outlet cobalt ion concentration) can be obtained through global optimization[9]. In order to realize the optimal operation of the process, it is necessary to adjust the control quantity to make the controlled variable gradually approach and finally reach the optimal setpoint. Only considering how to make the controlled variable close to the optimal setpoint and ignoring the changes in the operation status during this process will lead to the operation status not always being optimal, affecting the final product quality and increasing resource consumption. Therefore, it is necessary to study the optimal migration of operation statuses during this process. Affected by changes in inlet conditions and operating parameters, the operation status inside the reactor changes frequently. Therefore, there are significant challenges in defining the operation status and achieving optimal migration of the operation status. It mainly includes:

(1) Difficult in defining the operation status

The mechanism of the manufacturing process is complex, and there are many disturbances. At the same time, considering the cascading characteristics of the process manufacturing industry, the operation status in the reactor changes frequently, so its definition is difficult.

(2) Difficult in establishing process model and identifying operation status online

Considering that the whole process contains a large number of process variables and there are coupling relationships among different variables, it is challenging to establish a nonlinear process description model. At the same time, because some technical indicators are difficult to obtain online, it is challenging to recognize the operation status online based on the definition.

(3) Difficult in determining the optimal operation status migration path

Considering the volatility of the process, the operation status changes frequently. It is challenging to migrate the operation status smoothly and economically to the optimal setpoint by adjusting the control quantity.

III. METHODOLOGY

In this study, an optimal control method for operation status migration in the process manufacturing industry is proposed. The overall framework is shown in Fig. 2. First, the zinc powder utilization performance index (ZPUPI) is proposed to evaluate the proportion of reactants participating in the actual reaction and used to define and classify the operation status; then, a nonlinear process description model is constructed, and an online recognition method of operation status based on spatiotemporal distance is proposed; finally, with the objectives of minimum consumption, system stability, and approach to the optimal setpoint, an optimal control method for operation status migration is proposed considering the smooth migration of operation status and production constraints. It is elaborated in Sections III.A to III.C.

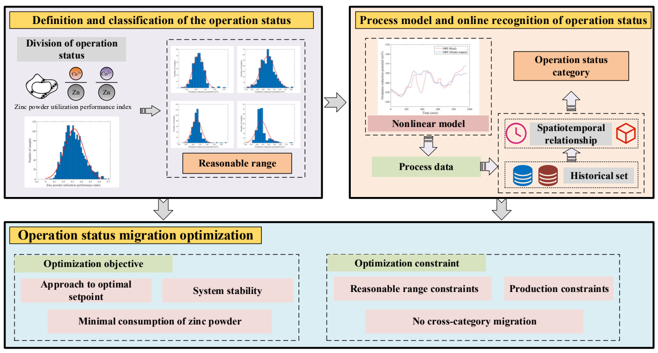


Fig. 2. Overall framework.

A. Definition and classification of operation status

In the 1# cobalt removal reactor, multiple oxidation-reduction reactions are carried out in parallel, and they promote and inhibit each other to form a dynamic balance. At the same time, considering the large volume of the hydrometallurgical reactor, the input reactants cannot completely participate in the actual reaction. The proportion of participation can reflect the degree of progress of each reaction to a certain extent, that is, the operation status in the reactor. In the 1# cobalt removal reactor, zinc powder is the main reactant. ZPUPI is proposed to evaluate the operation status in the reactor, which is shown in (3).

$$ZPUPI = \frac{zinc_{theory}}{zinc_{actual}} \tag{3}$$

where, $zinc_{theory}$ and $zinc_{actual}$ represent the amount of zinc powder theoretically required and actually consumed to remove certain impurities, respectively.

Considering the volume of the hydrometallurgical reactor and the average inlet flow rate, it takes around 2 hours for a certain amount of solution to flow from flowing into the reactor to flowing out of the reactor. At the same time, the test interval of the key technical indicators is also 2 hours. Therefore, this study takes 2 hours as an interval to calculate ZPUPI in each time interval. The actual production data of about 5,000 consecutive hours were taken for analysis, and ZPUPIs in about 2,500 time intervals were calculated. Its distribution is shown in Fig. 3.

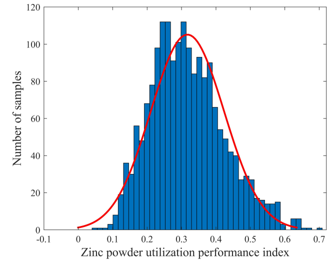


Fig. 3. Distribution of ZPUPI.

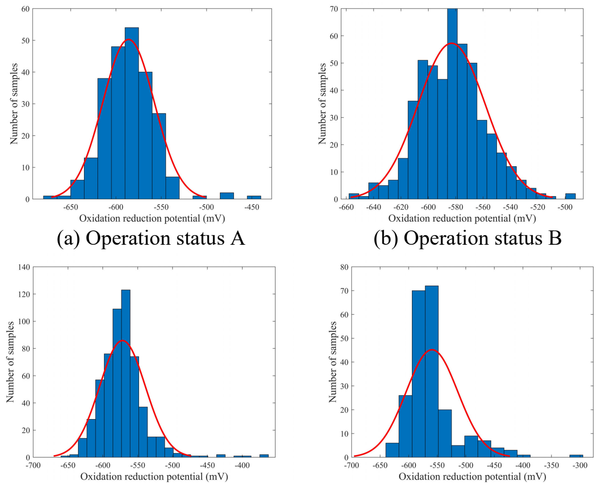
Fig. 3 shows that ZPUPIs calculated from historical data basically obey a normal distribution. Therefore, the operation status can be classified according to the distribution characteristics of ZPUPI combined with the key parameters of the normal distribution. The specific classification and corresponding parameter requirements are shown in Table I.

TABLE I
OPERATION STATUS CLASSIFICATION

Category	Range of ZPUPI
Operation status A	$ZPUPI \geq \mu+\sigma = 0.4237$
Operation status B	$0.3171 = \mu \leq ZPUPI < \mu+\sigma = 0.4237$
Operation status C	$0.2104 = \mu-\sigma \leq ZPUPI < \mu = 0.3171$
Operation status D	$ZPUPI < \mu-\sigma = 0.2104$

μ is the expectation of the normal distribution, which is 0.3171; σ is the standard deviation of the normal distribution, which is 0.1067.

Through the classification in Table I, the production data in each operation status can be obtained. For the 1# cobalt removal reactor, its operating goal is to reduce the outlet cobalt ion concentration to within a certain range (according to the process constraints). Due to the harsh production environment and the limitation of detection devices, it is often impossible to obtain the outlet cobalt ion concentration through online detection in actual production, so it cannot be used as a controlled variable. As mentioned above, the 1# cobalt removal reactor contains multiple parallel oxidation-reduction reactions, so the oxidation-reduction potential (ORP) can reflect the progress of each reaction to a certain extent, and it can be detected online, so it is used as a controlled variable. By adjusting the amount of zinc powder added, the ORP gradually approaches the optimal ORP setpoint (by establishing a conversion model between the optimal outlet cobalt concentration and the optimal ORP) to realize the optimal operation of the process. In order to ensure the rationality of ORP in each operation status in the subsequent optimal control, it is necessary to determine the reasonable range of ORP in each operation status. The distribution of the ORP average value in each time interval in each operation status is shown in Fig. 4.



(a) Operation status A (b) Operation status B

(c) Operation status C (d) Operation status D

Fig. 4. The distribution of the ORP average value in each time interval in each operation status.

It can be seen from Fig. 4 that the distributions of ORP in each operation status are close to the normal distribution. When the ORP is within one standard deviation from the expectation of normal distribution, it can be considered a more reasonable range in this category. The reasonable range of ORP in each operation status is shown in Table II.

TABLE II
REASONABLE RANGE OF ORP IN EACH OPERATION STATUS

Category	Reasonable range of ORP
Operation status A	$-614.5055 < ORP < -557.6327$
Operation status B	$-607.5860 < ORP < -558.3330$
Operation status C	$-604.7248 < ORP < -538.8988$
Operation status D	$-604.6840 < ORP < -513.6994$

B. Process model and online recognition of operation status

The process model is the basis of optimal control. In order to further study the optimal control method and the optimal operation status migration path, it is necessary to construct the process description model. It is mentioned in Section III.A that ORP can characterize the progress of each reaction to a certain extent, so a description model between inlet conditions, operating parameters, and ORP is constructed.

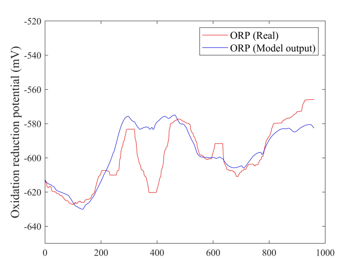


Fig. 5. Process description model.

The nonlinear auto-regressive model with exogenous inputs (NARX) fitting module in MATLAB was used to construct the process description model, and the continuous 960 mins data was used, of which 750 mins data was used as training, and 210 mins data was used as testing. The fitting results are shown in Fig. 5.

Operation statuses were defined and classified based on mechanism knowledge and historical data distributions in Section III.A. Due to some key technical indicators being challenging to detect online, the current operation status category cannot be determined according to the definition of the operation status when the system is running online. Therefore, it is necessary to construct an online recognition method for the operation status, that is, to determine the category of the current operation status by evaluating the similarity between the current operation status and the operation status of each category in the historical samples.

Euclidean distance is a common method to judge sample similarity through spatial distance. However, changes in inlet conditions and operating parameters result in frequent changes in its operation status, and many new samples will be generated during operation. Samples that are further away from the current time will have less reference value to the present. Therefore, the time distance between historical and current samples also needs to be considered when evaluating similarity. To this end, this study proposes an online recognition method of operation status based on spatiotemporal distance, which determines the best matching sample by comprehensively considering the distance of time and space. The specific algorithm is shown in Algorithm 1.

Algorithm 1 Online operation status recognition method based on spatiotemporal distance

Step 1. Spatial distance calculation: Calculate the distance between the current sample and all historical samples, get the samples closest to the current sample in each operation status and sort them, take the two closest distances, and record the distances as d_1 and d_2 respectively, the corresponding categories are c_1, c_2 respectively, and their time orders in all samples in their respective categories are n_1, n_2 respectively.

Step 2. Spatial distance judgment: if $d_1 < a$ and $d_2 < a$ (a is the spatial distance judgment threshold, obtained according to production needs), go to *Step 3*; if $d_1 < a$ and $d_2 > a$, go to *Step 4*; if $d_1 > a$ and $d_2 < a$, go to *Step 5*.

Step 3. Time distance judgment: if $n_1 < 0.2 * m_{c_1}$ (m_{c_1}: the total number of samples in the c_1 category) and $n_2 > 0.2 * m_{c_2}$ (m_{c_2}: the total number of samples in the c_2 category), the current sample is considered to belong to c_2, otherwise, it is considered to belong to c_1.

Step 4. It can be considered to belong to c_1.

Step 5. It can be considered to belong to c_2.

C. Operation status migration optimization

Facing actual production needs and stability requirements, construct an optimization model for the optimal migration path of the operation status and obtain the control quantity in each time interval through optimal control to achieve optimal operation of the whole process.

i. Assumptions.

Considering the simplicity and practicality of the calculation, some reasonable assumptions need to be made before constructing the optimal control model.

(1) According to the volume of the hydrometallurgical reactor combined with the average inlet flow rate of the 1# cobalt removal reactor, it can be considered that the time required for a certain solution to flow from flowing into the reactor to flowing out of the reactor is approximately 2 hours.

(2) Considering the reaction time and the frequency of the optimal setting in previous studies, this study studies the optimal migration of operation statuses with a two-hour cycle.

(3) The migration of the operation status takes a certain amount of time. In order to simplify the solution and facilitate understanding, this study does not consider the migration time of the operation status and believes that the migration of the operation status can be completed instantly.

ii. Objectives.

In order to ensure the optimal operation of the process, the following objectives need to be considered at the same time.

(1) Approach to optimal setpoint (T_1)

In our previous research, the optimal ORP setpoint for each reactor was set every two hours according to the operation status of each reactor combined with the production goals. At the end of each time interval (2 hours, 120 mins), the ORP in the reactor needs to be as close as possible to the optimal ORP setpoint. It can be expressed as:

$$abs(xk_t - xk_{goal}) < \theta_1 (t = 116, 117, 118, 119, 120) \tag{4}$$

where, xk_i indicates the ORP at the t^{th} minute in a time interval, xk_{goal} indicates the optimal ORP setpoint corresponding to the current time interval, θ_1 indicates the acceptable deviation range between the current ORP and the optimal ORP setpoint, which is determined by the production requirements.

(2) System stability (T_2)

System stability is the key to ensuring product quality and production safety. In order to ensure that the system does not experience significant fluctuations, it is necessary to ensure that the fluctuations between the manipulated variable (zinc powder) and the controlled variable (ORP) between consecutive moments are less than a certain threshold. System stability objective can be expressed as:

$$u_t - u_{t-1} < \theta_2 ; xk_t - xk_{t-1} < \theta_3 (t = 2, 3, \cdots, 120) \tag{5}$$

where, u_t represent the amount of zinc powder added at t^{th} minute in a time interval, θ_2 and θ_3 represent the acceptable fluctuation thresholds of the amount of zinc powder added and ORP at adjacent moments in the production, respectively.

(3) Minimal consumption of zinc powder (T_3)

Reducing the consumption of zinc powder on the premise of meeting the production requirements will help reduce the cost of the enterprise, which is of great significance for actual production.

iii. Constraints.

(1) No cross-category migration

Divide each time interval into six sub-intervals (each sub-interval is 20 mins), identify the operation status category of each sub-interval based on the method in Section III.B, and record the identified category as $c_i (i = 1, 2, \cdots, 6)$, considering the smoothness of operation status changes, it is required that the operation status cannot migrate across categories. Assuming that the operation statuses A, B, C, and D are respectively recorded as 1, 2, 3, and 4, it needs to meet:

$$abs(c_i - c_{i-1}) \le 1 (i = 2, 3, 4, 5, 6) \tag{6}$$

(2) Reasonable range constraints

ORP in every time interval needs to satisfy the reasonable ORP range of the corresponding category in Table II.

$$xk_{\min} < xk_t < xk_{\max} (t = 1, 2, \cdots 120) \tag{7}$$

where, $xk_{\max}$ and $xk_{\min}$ represent the acceptable maximum and minimum ORP of the current category, respectively.

(3) Production constraints

In actual production, the amount of manipulated variable (zinc powder) needs to be limited to the acceptable range of the process:

$$u_{\min} < u_t < u_{\max} (t = 1, 2, \cdots, 120) \tag{8}$$

where, $u_{\max}$ and $u_{\min}$ represent the acceptable maximum and minimum zinc powder added in production, respectively.

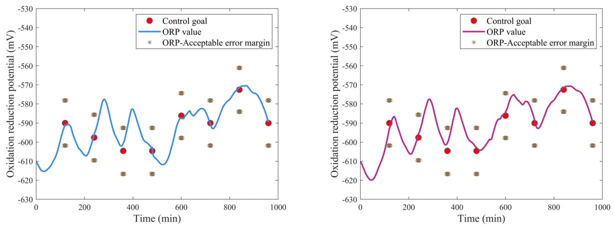
To sum up, the optimal control construction for operation status migration can be described as:

$$\begin{aligned} &\min(xk_t, u_t, c_i) = w_1 T_1 + w_2 T_2 + w_3 T_3 \\ &s.t.\ abs(c_i - c_{i-1}) \le 1 (i = 2, 3, 4, 5, 6) \\ &\quad xk_{\min} < xk_t < xk_{\max} (t = 1, 2, \cdots 120) \\ &\quad u_{\min} < u_t < u_{\max} (t = 1, 2, \cdots, 120) \end{aligned} \tag{9}$$

where, w_1, w_2, and w_3 respectively represent the weights corresponding to the three objectives, which are determined by production needs.

IV. Experimental results

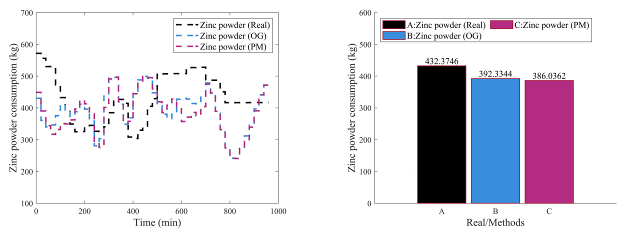
In this section, the proposed method was verified using the real production data of a large zinc smelter. The production data of 8 consecutive time intervals (960 mins) were used for verification. The method proposed in this paper (Proposed Method, PM) was compared with the method that ignores the operation status migration path and only considers the approach to the final optimal ORP setpoint (Only Goal, OG, later referred to as the comparison method). The control effects of the two methods are shown in Figs. 6(a) and 6(b), respectively.



(a) Control effect of PM (b) Control effect of OG

Fig. 6. Comparison of the control effects of the two methods.

It can be seen from Figs. 6(a) and 6(b) that the ORP values obtained by the two methods are close to or reach the optimal setpoint at all target points and are within the acceptable error margin of the production site, and the ORP fluctuations obtained by the proposed method are relatively smaller. The comparison of the amount of zinc powder added in each time interval and the average amount of zinc powder added of the proposed method, the comparison method, and the manual control are shown in Figs. 7(a) and 7(b), respectively.

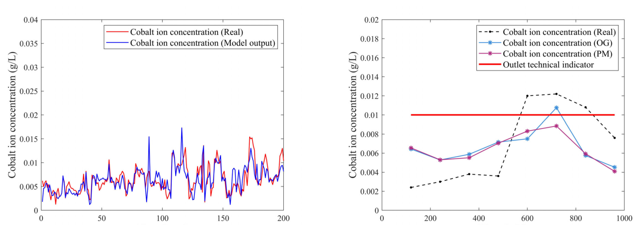


(a) Each time interval (b) Average value

Fig. 7. Comparison of the amount of zinc powder added.

It can be seen from Figs. 7(a) and 7(b) that the proposed method reduces zinc powder consumption while meeting the production requirements, which proves the effectiveness of the proposed method.

In order to further verify the control effect, the MATLAB neural network fitting app is used to establish a nonlinear model of the manipulated variable and outlet technical indicator. The training effect of the outlet technical indicator model is shown in Fig. 8(a). The testing effect of the proposed method, the comparison method, and the manual control in continuous 960 minutes is shown in Fig. 8(b).



(a) Outlet technical indicator model (b) Comparison of control effect.

Fig. 8. Outlet technical indicator model and the comparison of the outlet technical indicator control effect.

It can be seen from Fig. 8(b) that both the outlet technical indicator obtained by manual control and the comparison method exceeded the requirement, while the outlet technical indicator obtained by the proposed method met the actual production requirement, which further proves the necessity of researching optimal operation status migration and the effectiveness of the proposed method.

V. Conclusion

In the process manufacturing industry, the frequent fluctuations of the inlet conditions and operating parameters make it challenging to make the whole process run in the optimal status by only considering the final optimal setpoint and ignoring the changes in the operation status. To this end, this study proposed an optimal control method for operation status migration in the process manufacturing industry. By finding the optimal migration path of the operation status, the operation status is gradually migrated to the optimal setpoint. Actual production data was used for experimental verification. The results showed that the method proposed in this study can make the controlled variables gradually approach the final optimal setpoint and reduce resource consumption under the premise of meeting the production requirements. The proposed method is of great significance for the process manufacturing industry to improve product quality and reduce enterprise costs.

References

[1] A Ashoori, B Moshiri, A Khaki-Sedigh, et al., "Optimal control of a nonlinear fed-batch fermentation process using model predictive approach," *Journal of Process Control*, vol.19, July 2009, pp. 1162-1173.

[2] F Logist, B Houska, M Diehl, and JF Van Impe, "Robust multi-objective optimal control of uncertain (bio) chemical processes," *Chemical engineering science*, vol. 66, October 2011, pp. 4670-4682.

[3] R Song, F Lewis, Q Wei, et al., "Multiple actor-critic structures for continuous-time optimal control using input-output data," *IEEE Transactions on Neural Networks and Learning Systems*, vol. 26, February 2015, pp. 851-865.

[4] B Sun, M He, Y Wang, et al., "A data-driven optimal control approach for solution purification process," *Journal of Process Control*, vol. 68, August 2018, pp. 171-185.

[5] N Chen, S Luo, J Dai, B Luo, and W Gui, "Optimal control of iron-removal systems based on off-policy reinforcement learning," *IEEE Access*, vol. 8, August 2020, pp. 149730-149740.

[6] H Liang, C Yang, K Huang, D Wu, and W Gui, "A transfer predictive control method based on inter-domain mapping learning with application to industrial roasting process," *ISA transactions*, vol. 134, March 2023, pp. 472-480.

[7] T Liu, C Yang, C Zhou, et al., "Integrated Optimal Control for Electrolyte Temperature With Temporal Causal Network and Reinforcement Learning," *IEEE Transactions on Neural Networks and Learning Systems*, June 2023, pp. 1-13.

[8] Y Xie, J Liu, D Xu, et al., "Optimal control strategy of working condition transition for copper flash smelting process," *Control Engineering Practice*, vol. 46, January 2016, pp. 66-76.

[9] X Zhang, Y Li, W Chen, et al., "Self-organized cascade collaborative optimization method for associated unit processes," *Journal of Manufacturing Processes*, vol. 101, September 2023, pp. 322-338.

[10] B Sun, C Yang, Y Wang, et al., "A comprehensive hybrid first principles/machine learning modeling framework for complex industrial processes," *Journal of Process Control*, vol. 86, February 2020, pp. 30-43.