Implementation of Control Structure for Steel Pickling Process using Model Predictive Controller

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Abstract: This paper addresses the suitable control structure for a pickling process. Each pickling tank is modeled based on machine learning using recurrent neural network structure. In the steel pickling process, four pickling tanks are addressed. To control the acid concentration of the four pickling tanks effectively, each model predictive controller that controls two pickling tanks is designed. In addition, by designing the model predictive controller that considers the characteristics of the steel type, a suitable structure that can wash the oxide scale on the steel surface is proposed. The simulation results show the validity of the proposed structure and controller.

Keywords: Steel pickling process, process control, pickling tank, acid concentration control

1. INTRODUCTION

An oxide scale is generated on the steel surface after the hot rolling process in the steel production process. The oxide scale can be removed using the acid solution in the cold rolling process. This process is called the steel pickling process (Fig 1). To produce high-quality steel, the steel pickling process is essential. The tanks containing different acid concentrations are used in the steel pickling process. To get rid of the oxide scale on the steel surface, the steel strip with the oxide scale is soaked while passing from the high acid concentration tank to the low acid concentration tank. At this time, the acid is consumed and the acid concentration of each tank decreases. Therefore, additional acid solutions should be added to maintain a stable pickling process. If the concentration of the acid solution in the pickling tank is too high, the steel product may be damaged, and if it is too low, the oxide scale may not be removed cleanly. Therefore, it is essential to maintain the acid concentration of the pickling tank.

To control the steel pickling process, it is necessary to identify the properties and the system dynamics of the pickling tanks. A systematic method for modeling and parameter verification for a process with nonlinearity is not established. For this reason, many researchers studied to overcome these problems by utilizing machine learning (Alhajeri et al. (2021); Shokry et al. (2021); Zhu et al. (2018); Hosen et al. (2021)). A variety of machine learning structures such as auto-encoder (AE), multi-layer perceptron (MLP), convolutional neural network (CNN), and recurrent neural network (RNN) are used for nonlinear system identification. Among these methods, RNN is a type of artificial neural network in which the hidden node is connected to a directional edge to form a circulating structure. The result of the hidden layer of the RNN is linked back into the input of the same hidden layer. This characteristic makes a feature of RNN that allows consideration of time. The ability to judge sequential order can be particularly helpful in dealing with sequence data such as time data. In the steel pickling process, the acid concentration of the pickling tank is time sequence data. Therefore, RNN is a suitable learning structure to model the pickling process.

The model predictive control (MPC) has received much attention in control societies because of its online handling capability of input and output constraints and many applications to industrial processing systems as well as its good tracking performance (Yu et al. (2019); Hakimzadeh and Ghaffari (2020); Xie et al. (2021)). In particular, some researchers used MPC to control the acid concentration of the pickling tank based on the pickling tank modeled using a neural network structure. Daosud et al. (2005) tested and implemented a neural network direct inverse control strategy for controlling the concentrations of pickling tanks in a steel pickling process. Kittisupakorn et al. (2009) studied the multi-layer feedforward neural network to model the steel pickling process. These papers considered the pickling process with three pickling tanks. However, different control structure is needed for the pickling process structure with four pickling tanks.

This paper implements a pickling process structure with two model predictive controllers for four pickling tanks. Each pickling tank is modeled based on machine learning using RNN structure. Also, this paper proposes a process control structure choosing the suitable model predictive controller depending on steel type.

⋆ Sponsor and financial support acknowledgment goes here. Paper titles should be written in uppercase and lowercase letters, not all uppercase.

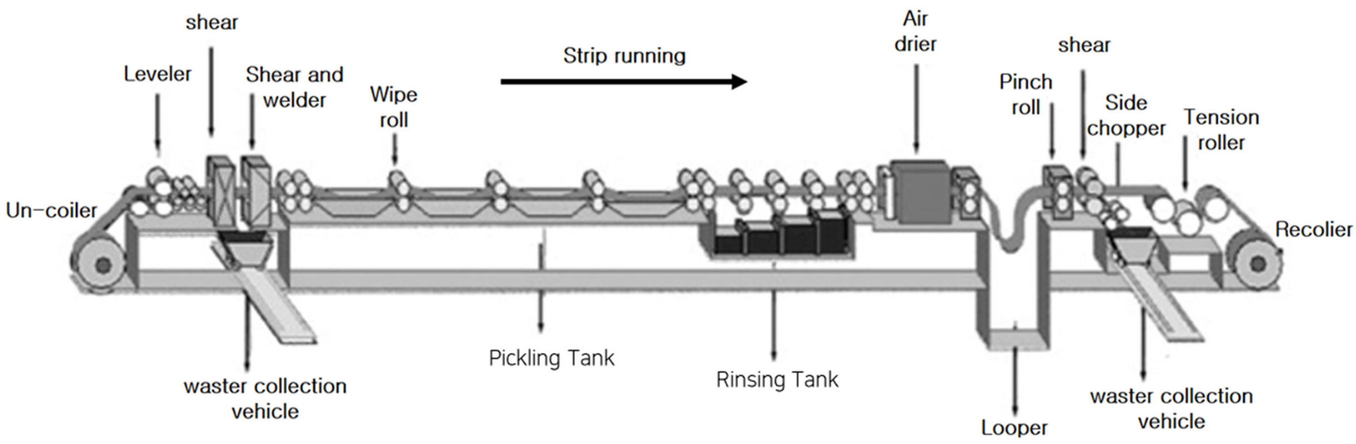

Fig. 1. Steel pickling process in cold rolling process

2. STEEL PICKLING PROCESS MODELING

This section presents the modeling of steel pickling process.

2.1 Nonlinear system identification

When expressing a general dynamic system, it is expressed in the form of input and output relationship, or state-space. Nonlinear system modeling based on input and output relationship is similar to the process in which artificial neural networks deduce the input and output relationship. General artificial neural networks use various neural network layers to express the nonlinearity of the relationship between input and output. The input and output relationship expressed as an artificial neural network is expressed as follows:

$$y(k) = \Pi_{i=1}^{N} g_i(W_i o_{NN,i-1}(k)), \quad (1)$$

where N is a number of the layer in neural networks, W_i is weight of ith layer, g_i is a nonlinear mapping function of each layer and o_0 is an output of the previous layer. When $i = 1$, $o_{NN,0}$ is $x(k)$. $x(k)$ and $y(k)$ are training input and output, respectively. The relationship between input and output in the case of nonlinear systems affected by past inputs and outputs can be expressed as follows:

$$\begin{aligned} y(k) = h(&u(k), u(k-1), u(k-2), \cdots, u(k-N), \\ &y(k-1), y(k-2), \cdots, y(k-M)), \end{aligned}$$

where h represents nonlinearity of an unknown nonlinear system, $u(k)$ is the input of nonlinear system, $y(k)$ is the measured output of the nonlinear system, and M, N is the time dependency of system. The Machine learning using the RNN structure can obtain h. This means that W_i and g_i in (1) are found and the nonlinear identification is completed.

2.2 Steel pickling process model

This paper addresses the steel pickling process that consists of four pickling tanks. The steel strip moves from tank 1 to tank 4, and the acid solution flows from tank 4 to tank 1.

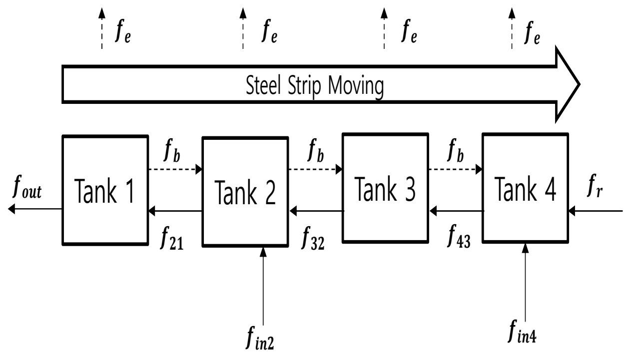

Fig. 2. Flows of the acid solution in the steel pickling process

Table 1. Flows description

Parameter	Description
f_{ij}	Flow from tank i to tank j
$f_{in2,4}$	Fresh acid solution flow from outside to Tank 2,4
f_b	Flow that moves together when steel strip moves.
f_e	Flow of evaporation
f_r	Flow from rinse tank
f_{out}	Flow to out

Fig 2 shows the flows of the acid solutions in the steel pickling process. The information about the parameters used in Fig 2 is shown in Table 1 where flow means the flow rate of the acid solution and the unit of flow is L/min. Since f_b and f_e are small values, we ignore them in this paper.

2.3 Pickling tank modeling

This paper uses the RNN structure (Fig 3) to model the pickling tanks. The number of hidden neurons is 10 and the number of delays is 5. The Levenberg-Marquardt algorithm is used to learn the model. Our dataset is composed of approximately 15 days of pickling process data from a real plant. To train the pickling tank model, train, validation, and test set with 70%, 15%, and 15%

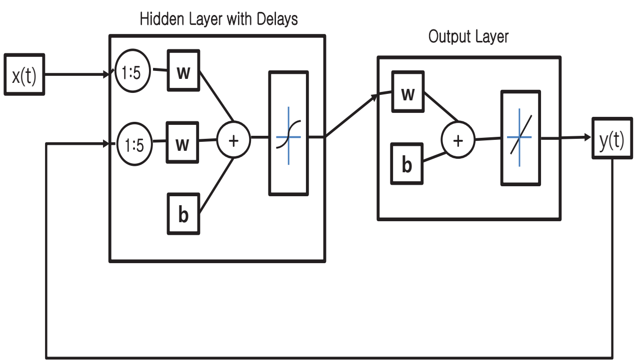

Fig. 3. RNN structure

ratio used. The input is f_{out}, f_{21}, f_{32}, f_{43}, f_{in2} and f_{in4}, and the output is the acid concentration of each tank.

3. CONTROL FOR STEEL PICKLING PROCESS

Since the steel pickling process has a large nonlinearity and multivariable interactions, it is difficult to control by using conventional controllers. This section addresses the sutable control structure for the steel pickling process and controller according to steel type.

3.1 Model predictive control

Let us consider the following cost function:

$$J_k = \sum_{i=1}^{N} \sum_{j=1}^{p} \{W_i[y_{r,i}(k+1|k) - y_i(k+j|k)]\}^2,$$

where k is the current control interval, $y_{r,i}$ is the reference acid concentration of target tank i, y_i is the acid concentration of tank i, p is the prediction horizon, N is the number of pickling tank, and $W_{i,j}$ is the tuning weight for ith plant output at jth prediction horizon step. Then, by solving the following minimizing problem, we can design the controller that tracks the reference acid solution concentration of the pickling tank.

$$min_{u(k+1),\cdots,u(k+m)} J_k,$$

where, m is control horizon.

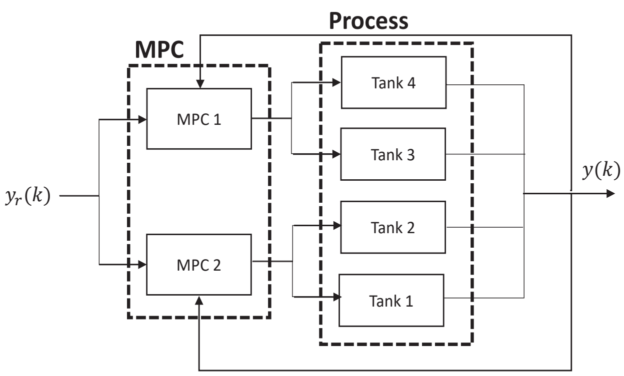

Fig. 4. MPC structure for steel pickling process

Then, let us consider the number of the MPC controller in the steel pickling process. In Fig 2, each pickling tank has flow from previous tank. Tank 2 and tank 4 have additional input flow (f_{in2}, f_{in4}). Therefore, it is an efficient control structure to control two tanks with one MPC controller by considering f_{in2} and f_{in4}. Fig 4 shows MPC structure for the steel pickling process, where $y_r(k)$ is the augmented vector of $y_{r,i}(k)$ for all $i \in [1, 4]$, and $y(K)$ is the augmented vector of the acid concentration of four tanks.

3.2 Controller according to steel type

In this paper, it is assumed that the amount of oxide scale generated on the surface is different because it has different chemical properties depending on the steel type. Each steel type has a different acid consumption, so it is efficient to design an appropriate MPC controller according to the steel type in process with strong nonlinearity.

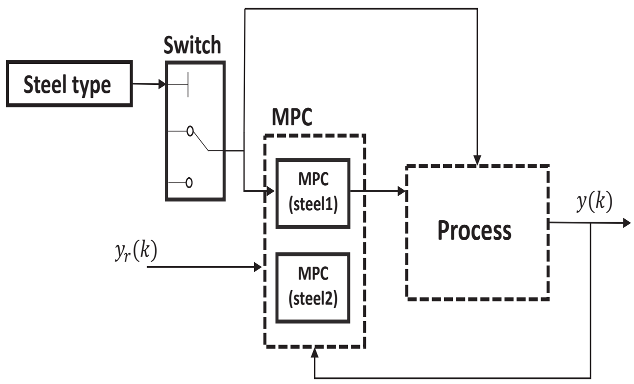

Fig. 5. Control structure for steel pickling process depending on steel type

Fig 5 is the proposed control structure for the steel pickling process depending on the steel type. Each MPC (steel type) is composed of two MPC controllers that control the acid concentration of the four tanks. In Fig 5, MPC(steel 1) and MPC(steel 2) are the suitable MPC controllers designed according to steel type 1 and type 2. In using this structure, the steel type is selected and information on the acid consumption is reflected in the process. Then, the process goes by automatically selecting the appropriate MPC for the steel type.

4. SIMULATION RESULTS

This section presents the simulation results based on the proposed steel pickling process structure. Also, in the process that cleaning the oxide scale on the surface of the different steel types, the performance of the control structure using fixed MPC controller and performance of control structure switching MPC controller which changes into the appropriate MPC controller for each steel type are compared.

In the simulation, the number of the steel types with different acid consumption is four and the reference value is set based on steel pickling process data from a real plant. Fig 6 shows the reference acid concentration, output

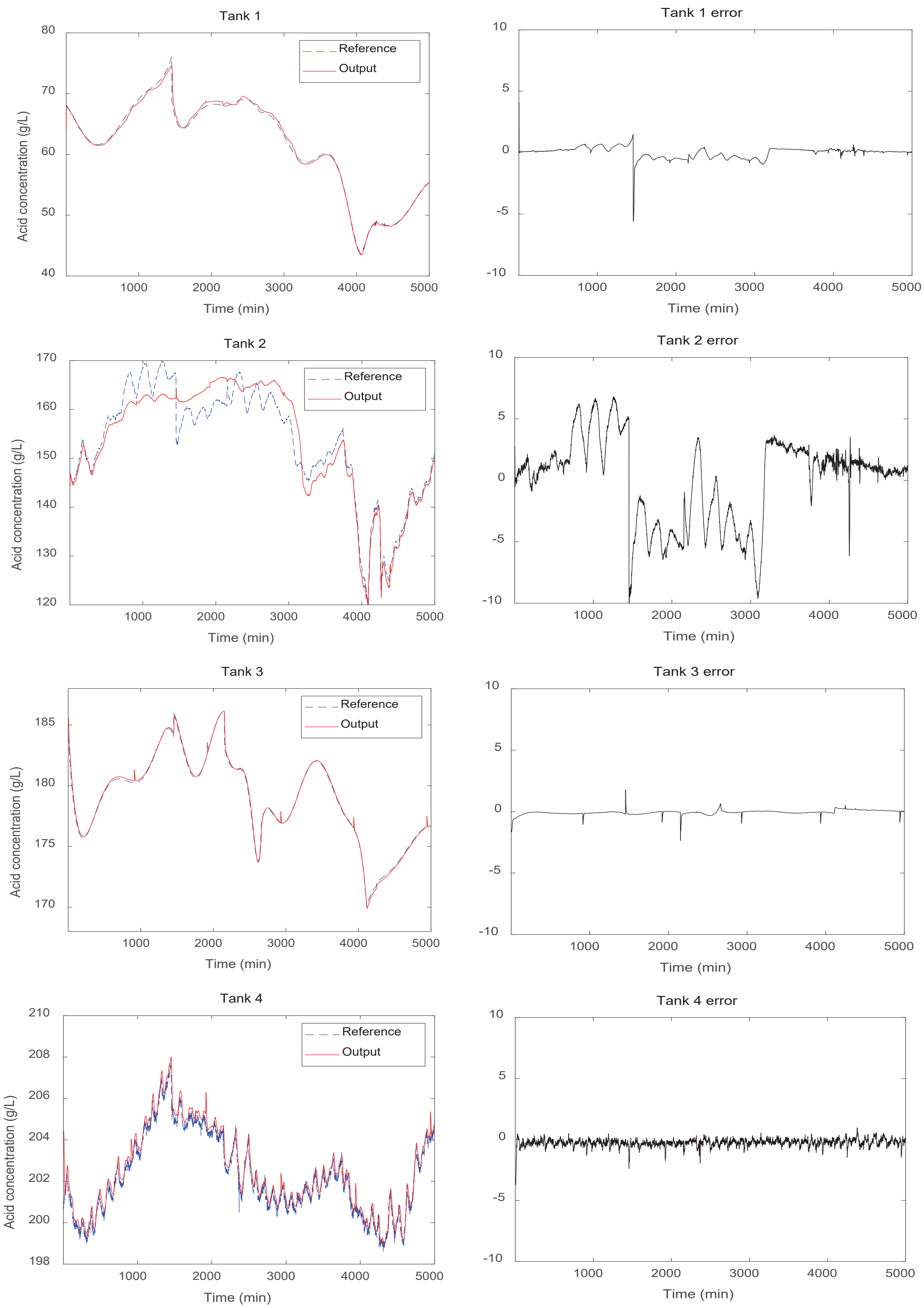

Fig. 6. Reference acid concentration, output acid concentration, and error of each tank

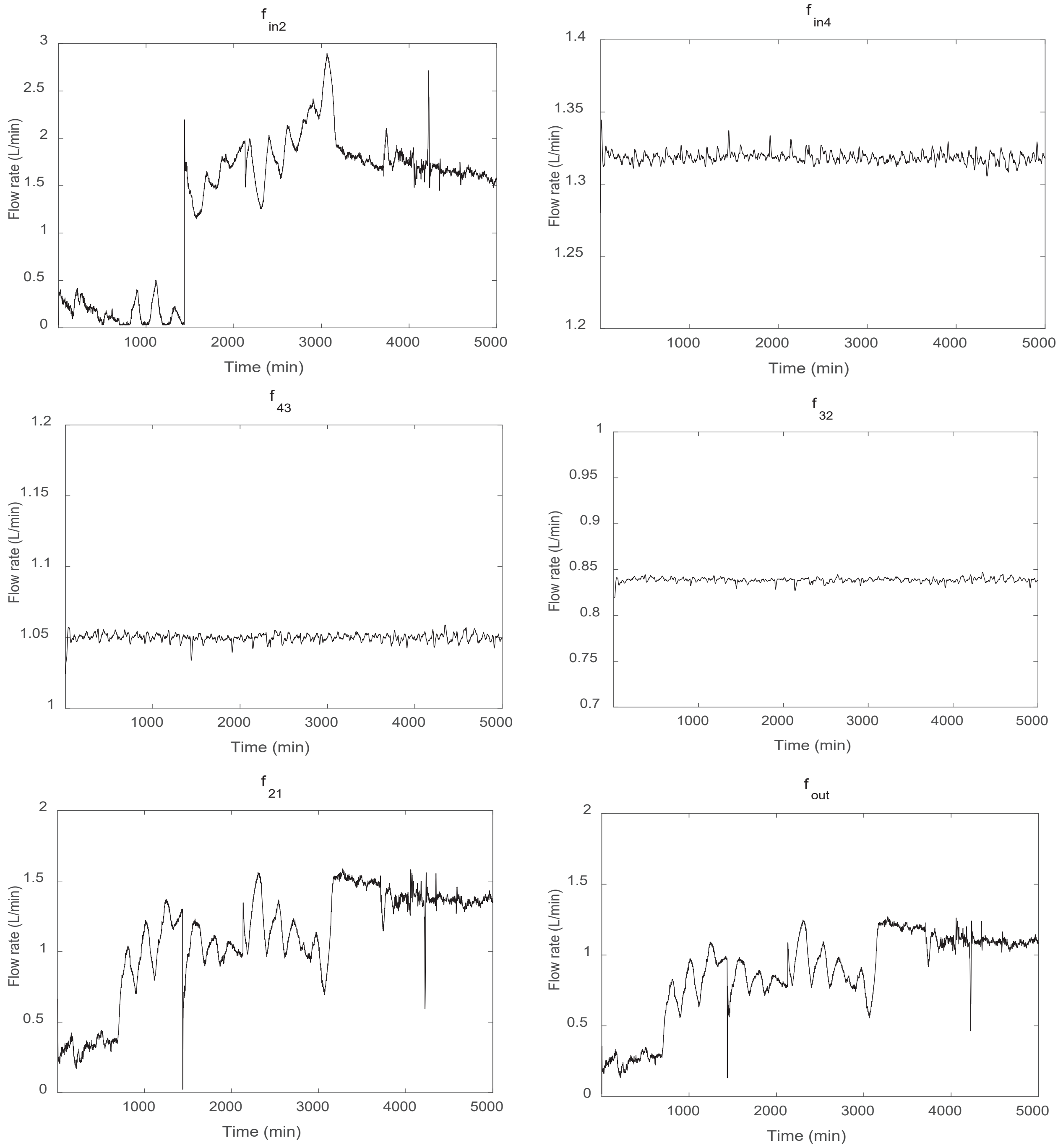

Fig. 7. Flows rate of input acid concentration

acid concentration controlled by switched MPC controller, and error of each tank and Fig 7 shows flows of input acid concentration. Since tank 2 and tank 4 have input about the fresh acid solution (f_{in2} and f_{in4}) from outside, there are some variations. In particular, tank2 has three flows involved, so errors appear larger than other tanks. Nevertheless, all four tanks significantly track reference well.

By comparing the RMSE of the fixed MPC and switched MPC, Table 2 shows that the proposed MPC structure that changes depending on the steel type is a more suitable control structure for pickling process.

Table 2. RMSE of fixed MPC and switched MPC

	Tank 1	Tank 2	Tank 3	Tank 4
Fixed MPC	0.5053	0.3034	5.2020	0.9929
Switched MPC	0.3402	0.2138	5.1750	0.9575

5. CONCLUSION

This paper addressed a control structure in the pickling process. The modeling of the pickling tank was learned using RNN structure. Also, considering the pickling process structure with four pickling tanks and steel types, the effective control structure is proposed. The simulation results showed better tracking performance.

ACKNOWLEDGEMENTS

This research was supported by the Basic Science Research Program through the National Research Foundation of Korea (NRF) funded by the Ministry of Science, ICT, and Future Planning (2020R1A2C2005709).

REFERENCES

Alhajeri, M.S., Wu, Z., Rincon, D., Albalawi, F., and Christofides, P.D. (2021). Machine-learning-based state estimation and predictive control of nonlinear processes. *Chemical Engineering Research and Design*, 167, 268–280.

Daosud, W., Thitiyasook, P., Arpornwichanop, A., Kittisupakorn, P., and Hussain, M.A. (2005). Neural network inverse model-based controller for the control of a steel pickling process. *Computers & Chemical Engineering*, 29(10), 2110–2119.

Hakimzadeh, A. and Ghaffari, V. (2020). Designing of nonfragile robust model predictive control for constrained uncertain systems and its application in process control. *Journal of Process Control*, 95, 86–97.

Hosen, M.A., Khosravi, A., Kabir, H.D., Johnstone, M., Creighton, D., Nahavandi, S., and Shi, P. (2021). Nn-based prediction interval for nonlinear processes controller. *International Journal of Control, Automation and Systems*, 1–14.

Kittisupakorn, P., Thitiyasook, P., Hussain, M.A., and Daosud, W. (2009). Neural network based model predictive control for a steel pickling process. *Journal of Process Control*, 19(4), 579–590.

Shokry, A., Medina-González, S., Baraldi, P., Zio, E., Moulines, E., and Espuña, A. (2021). A machine learning-based methodology for multi-parametric solution of chemical processes operation optimization under uncertainty. *Chemical Engineering Journal*, 425, 131632.

Xie, H., Wu, B., and Liu, W. (2021). Adaptive neural network model-based event-triggered attitude tracking control for spacecraft. *International Journal of Control, Automation and Systems*, 19(1), 172–185.

Yu, T., Zhao, J., Xu, Z., Chen, X., and Biegler, L.T. (2019). Sensitivity-based hierarchical distributed model predictive control of nonlinear processes. *Journal of Process Control*, 84, 146–167.

Zhu, Q.X., Wang, X., He, Y.L., and Xu, Y. (2018). An improved extreme learning machine integrated with nonlinear principal components and its application to modeling complex chemical processes. *Applied Thermal Engineering*, 130, 745–753.