To cite this version :

Abdoul Rahime DIALLO, Lazhar HOMRI, Jean-Yves DANTAN, Frédéric BONNET, Thomas BOEUF - Enhancing Fault Diagnosis in Process Industries with Internal Variables of Model Predictive Control - IFAC-PapersOnLine - Vol. 58, n°4, p.538-543 - 2024

Available online at www.sciencedirect.com

ScienceDirect

IFAC PapersOnLine 58-4 (2024) 538–543

Enhancing Fault Diagnosis in Process Industries with Internal Variables of Model Predictive Control

Abdoul Rahime Diallo* Lazhar Homri* Jean-Yves Dantan* Frédéric Bonnet Thomas Boeuf****

**Arts et Metiers Institute of Technology, Université de Lorraine, LCFC, 57070, Metz, France (e-mail : firstname.name@ensam.eu).*

***ArcelorMittal Research SA, APRC, Voie Romaine, BP 30320, 57283 Maizières les Metz, France (e-mail :firstname.name@arcelormittal.com)*

Abstract: This paper introduces the use of internal variables, estimated through Model Predictive Control (MPC), for fault detection and diagnosis in process industries. To do so, a data-driven methodology is proposed. Three reconstruction techniques - Principal Component Analysis (PCA), Kernel Independent Component Analysis (KICA), and Autoencoder (AE) - are compared using data sets that combine plant measurements with internal variables. The methodology was tested on a hot-dip galvanizing line dedicated to the production of automotive steel and compared to the use of only plant measurements for the development of the reconstruction methods. The results showed that the incorporation of internal variables significantly enhances the overall fault detection rate. Finally, contribution plots were used to identify the faulty sensor.

Keywords: Process monitoring, Fault detection, Fault diagnosis, Machine learning, Steel industry

1. INTRODUCTION

Process industries, also known as manufacturing industries, transform raw materials into products through physical and chemical phenomena, as opposed to discrete industries, which focus on assembling distinct, countable items. Process industries, which typically include sectors such as chemicals, food and beverages, pharmaceuticals, oil refining, and metal industry, are characterized by continuous or batch production processes (Kadlec et al., 2009). Meanwhile, assembly lines in the automotive industry are examples of discrete industries.

Process industries are characterized by complex and integrated operations, which require sophisticated approaches for quality and process monitoring. Kano & Nakagawa (2008), considered that enhancing product quality in process industries fundamentally relies on predicting product quality from operational conditions, identifying optimal operational conditions, and detecting and diagnosing faults. These three objectives encompass the majority of research efforts in process industry monitoring.

Even if process industries are very different, the monitoring issues are very similar (Kadlec et al., 2009; Kano & Nakagawa, 2008). Therefore, in this paper, we focus on galvanizing lines which are an excellent example of complex process industries. As such, all the aforementioned objectives for monitoring galvanizing lines can be found in the literature.

Firstly, mechanical properties, key indicators of the quality of galvanized steel, are not measurable in real-time. Quality assessment typically awaits test results from the steel strip's head or tail, which are known several hours after the end of galvanization, thus precluding adjustments to operational conditions based on achieved quality (Wang et al., 2022). Consequently, significant research has been conducted to predict the mechanical properties based on the process parameters and the product characteristics. Artificial neural networks have been widely used for this purpose (Lalam et al., 2019; Wang et al., 2022). Orta et al. (2020) found that incorporating an analytical model of recrystallization annealing as an input to the neural network, alongside process parameters and steel's chemical characteristics, enhances prediction accuracy.

Quality monitoring and assessment of galvanizing lines involves also deriving better operational conditions. This is particularly challenging due to product characteristic variations and uncertainties, furnace inertia, and disturbances, making it difficult to maintain uniform operational parameters throughout a steel strip's treatment (Sanz-Garcia et al., 2015). Inconsistencies in mechanical properties along a steel strip are a major customer complaint (Colla et al., 2020), leading to the implementation of MPC based on analytical (Strommer et al., 2018) or data-driven (Cho et al., 2023) models for controlling galvanizing lines.

The final aspect of galvanizing line monitoring focuses on fault diagnosis, primarily concerning roll faults. Steel strip transport through the lengthy galvanization process is facilitated by rolls, which also maintain tension essential for strip flatness. Tension meters placed along the line measure strip tension, regulating the dancer roll angle, rotation speed, and transport rolls' current in a closed-loop system (Liu et al., 2011). Despite this, tension faults can occur, potentially leading to catastrophic consequences such as strip breakage, causing over 24-hour production halts and equipment damage (Qiang Liu et al., 2013). To detect the occurrence of tension faults, multivariate statistical methods have been applied, using techniques such as PCA, Partial Least Squares (PLS), Canonical Correlation Analysis, ICA, and their non-linear or

10.1016/j.ifacol.2024.07.274

dynamic variants (Liu et al., 2018). To identify the roll at the origin of the tension fault, contribution plots are used.

However, beyond tension faults, sensor (*e.g.* temperature) or process actuator faults in furnaces and cooling chambers, or other process elements in galvanizing lines remain unaddressed. Detecting sensor and actuator faults in galvanizing lines is challenging due to the coupling of metallurgical, thermal, and mechanical phenomena, as well as the extensive range of diverse products, resulting in transition phenomena. Furthermore, the variation of certain product characteristics along a strip, such as emissivity, can cause significant fluctuations in measured values even under steady-state conditions.

Additionally, research on predicting mechanical properties and determining optimal operating conditions to enhance quality has resulted in the adoption of MPC for controlling galvanizing lines. This implementation has led to improved product reproducibility and reduced instances of non-quality. However, when faults are present, MPC tends to mask the appearance of some or propagate others, thus delaying their detection or complicating the identification of the root cause (Sotomayor & Odloak, 2005). Meanwhile, unmeasurable internal variables, calculated by MPCs alongside product quality predictions, contain valuable diagnostic information but are seldom reported in factory databases.

Fault detection and diagnosis methods are often classified into three categories: model-based, data-based, and knowledge-based. Data-driven methods have gained widespread acceptance in process industries due to the complexity of analytical models, the poor performance of knowledge-based methods as process size increases, and the availability of massive data in process industries (Adil et al., 2016). Reconstruction methods, also referred to as latent variables methods, are the most extensively employed among data-based methods for fault diagnosis in process industries (Lakshmi Priya Palla & Kumar Pani, 2023). These methods are optimal because they only necessitate normal process operating data to be implemented. In fact, historical fault data are rarely present in process industries (Li et al., 2020).

Consequently, this paper proposes a new methodology based on MPC logs to enhance sensor data for fault detection and diagnosis through reconstruction methods. The proposed methodology is employed to diagnose sensor faults on a galvanizing line. To validate the benefits of adding internal variables and MPC predictions, the reconstruction methods are applied without and with these parameters.

The rest of the paper is organized as follows. Section 2 describes typical reconstruction methods, including PCA, ICA, and AE. Section 3 presents the proposed methodology, covering the combination of internal variables with plant measurement, as well as the fine-tuning of the detection threshold. Application results in a hot-dip galvanizing line are presented in Section 4. Finally, Section 5 summarizes the conclusions and perspectives.

2. RECONSTRUCTION METHOD FOR FAULT DETECTION AND DIAGNOSIS

Fault detection through reconstruction methods is a three-step process. Firstly, data dimensionality is reduced. Secondly, the data is reconstructed from the latent space. Lastly, a detection index and threshold are used to classify new observations as either fault-free or faulty. The reconstruction error serves as the most commonly employed detection index. In certain studies, particularly ones based on multivariate statistical process monitoring techniques, such as PCA, ICA, and PLS, this index is synonymous with the square prediction error or Q-statistic. Its definition is based on the norm of the difference between the observation and its reconstruction using the model. In essence, it evaluates the quality of the reconstruction of an observation. Thus, although the general principle of these methods is identical, they differ in the way they achieve dimension reduction. In the following, we will briefly present the functional principle of three reconstruction methods. The presentation is based on (Qin, 2012) for PCA, (Lakshmi Priya Palla & Kumar Pani, 2023) for ICA, and (Yang et al., 2022) for AE.

2.1 Principal component analysis

PCA reduces the dimensionality of a data set by transforming the original data X into a new set of variables, the principal components, which are orthogonal and capture the most variance in the data. Mathematically, this is achieved through eigenvalue decomposition of the covariance matrix Σ of X, where $\Sigma = \frac{1}{n-1} X^T X$ and n is the number of samples.

The original data X can be approximated by projecting it onto the first k principal components. If V_k denotes the matrix containing the first k eigenvectors, the projection Z is given by $Z = XV_k$. The reconstruction $\hat{X}$ from the latent space is $\hat{X} = ZV_k{}^T$.

2.2 Independent component analysis

ICA aims to represent a multivariate data set X as a combination of independent non-Gaussian signals or components. This is achieved by finding a separating matrix W such that $S = WX$ approximates the independent components, where S is the matrix of source signals assumed to be statistically independent. Since ICA assumes that the data are mixtures of independent sources, reconstruction involves the inverse operation. If W is the unmixing matrix, the approximation of the original data $\hat{X}$ can be obtained as $\hat{X} = W^{-1}S$.

2.3 Autoencoder

An AE consists of two parts: an encoder and a decoder. The encoder maps the input data X to a latent space representation Z using a function f, i.e., $Z = f(X)$. The dimensionality of Z is typically less than that of X, achieving dimensionality reduction. The decoder part of the AE aims to reconstruct the input data from the latent representation. It uses a function g to map Z back to the original data space, producing the reconstructed data $\hat{X}$, where $\hat{X} = g(Z)$. The AE is trained to minimize the difference between X and $\hat{X}$, often using the mean squared error as the loss function.

3. COMBINING INTERNAL VARIABLES WITH PLANT MEASUREMENT FOR FAULT DIAGNOSIS

The methodology adopted in this article involves two main stages. The first involves extracting internal variables from the MPC logs and merging them with the plant measurements. The second stage consists of training the reconstruction models, setting the detection threshold, and then evaluating the detection system.

MPC is a sophisticated control algorithm widely employed in process industries due to its ability to handle multivariable control problems with constraints. At its core, MPC uses a mathematical or empirical model to predict the future behavior of a process over a defined prediction horizon. This model incorporates various inputs, including setpoints, process measurements, and the targeted quality, to forecast process outputs (Figure 1). Estimated process outputs are of two types. The first type is internal variables, which are physical quantities that cannot be measured by sensors, but are essential for process control. Examples include enthalpy or phase fractions in galvanizing processes. The second type is product quality, which is also not measurable in real-time, but is assessed in the laboratory through destructive testing. The quality assessed in the laboratory is not known until well after production has been completed. As a result, it cannot be used for real-time fault detection and diagnosis. Instead, we propose to use the quality estimated in real-time by the MPC. In the remainder of this article, for the sake of language simplicity, we will use the term internal variable to designate both the internal variables and the quality estimated by the MPC.

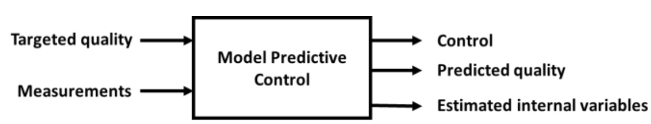

Figure 1. Simplified block diagram of MPC

Internal variables are rarely stored in production databases. Therefore, an essential step in their integration into a fault detection and diagnosis system is their extraction from MPC logs. The obtained data are then merged with sensor measurements to create a learning database for reconstruction methods as shown in Figure 2.

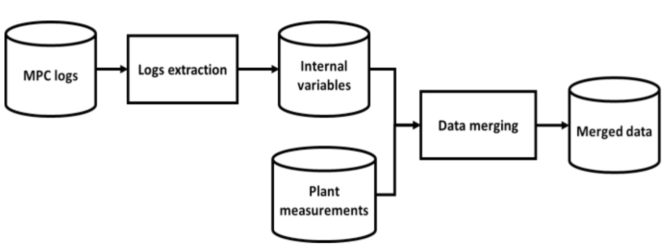

Figure 2. Combining internal variables with plant measurements

To implement the fault detection system, we proceed in three stages. The first is to train the reconstruction models. Next, we set the detection threshold for each model, and finally, we evaluate the detection system consisting of the reconstruction model and its detection threshold (Figure 3). For this purpose, fault-free data are subdivided into three parts, while faulty data are divided into two parts.

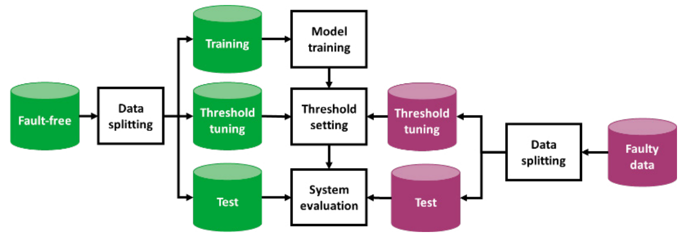

Figure 3. Development of fault detection models

The second segment of the fault-free data and the first segment of the faulty data are used to set the detection threshold. This approach enables verification that the reconstruction error of the unused fault-free data matches the distribution of the reconstruction error of the training data. Incorporating faulty data in setting the threshold allows for adjustment of the detection threshold based on the estimated distribution of the faulty data reconstruction error. For instance, if the reconstruction error distributions of fault-free and faulty data do not overlap, setting the detection limit at 95% or 99% confidence will produce superfluous false alarms. It may also entail prioritizing the detection of one fault over another and adjusting the detection threshold correspondingly. It is worth noting that the impact of some faults may be more severe than others. It could also include giving priority to specific products whose quality is more vulnerable to faults when optimizing the detection threshold. Finally, fault-free and faulty test data are used to evaluate the fault detection system.

4. Case Study

4.1 Process description

The galvanization line under consideration in this study plays an essential role in the manufacture of steel for automotive applications. The line comprises several components essential to ensure the production of high-quality galvanized steel. The sequential process starts with the entry section, followed by an annealing furnace, a zinc bath, vertical cooling, horizontal cooling, and a skin-pass station, and culminates in the exit section.

The annealing furnace, a critical stage in the process, subjects the steel to controlled heating and cooling cycles to optimize its mechanical properties. In this study, we focus on the cooling phase of the annealing furnace. This segment is of the utmost importance, as it significantly influences the final characteristics of the galvanized steel.

An MPC system is already deployed for precise control of the cooling process. It ensures that the cooling control is dynamically adjusted to adapt to disturbances and meet the stringent specifications required for automotive-grade galvanized steel. In the following subsections, reconstruction methods for sensor fault detection and diagnosis are compared in the context of this crucial phase of the galvanizing process.

4.2 Data gathering

The product characteristics of the 71 most commonly produced steel strips over one year are used in this study. The cooling process during the annealing of these strips with 625 different actuator configurations is simulated using the MPC deployed on the galvanizing line and an analytical model that simulates the cooling operation. Hence the fault-free database contains 44,375 samples, with 37 plant measurements and 15 internal variables extracted from the MPC logs.

Similarly, the MPC and the plant model are used to simulate a fault database. The simulated faults, proposed by the engineers of the line, are described in Table 1.

Table 1. Fault types

Fault	Description
Fault 1	Negative bias on the measurement of one of the steel's chemical characteristics
Fault 2	Positive bias on the measurement of one of the steel's chemical characteristics
Fault 3	Negative bias on the measurement of the soaking temperature
Fault 4	Positive bias on the measurement of the soaking temperature
Fault 5	Negative bias on the measurement of the snout temperature
Fault 6	Positive bias on the measurement of the snout temperature

The first two faults are related to the measurement of the same chemical characteristic of the steel strip. Measurements of chemical properties are taken during continuous casting and are then reused by the MPC of the galvanizing line to calculate the output of the cooling actuators. Faults in chemical measurements can affect steel quality but are difficult to detect. Two distinct faults are considered, depending on the direction of the bias. Since the cooling process generates distinct responses, the aim is to assess the ability of diagnostic models to determine the direction of sensor bias. Similarly, two faults are retained for the soaking pyrometer and two faults for the snout pyrometer. The soaking pyrometer measures the temperature of the steel strip as it enters the cooling process. This measurement is an input to the MPC. A fault in this pyrometer therefore distorts the calculations made by the MPC. The snout pyrometer measures the strip temperature at the end of the cooling process. The snout temperature is one of the target variables of the MPC.

4.3 Fault detection

The fault-free and faulty databases were used as described in Section 3 to implement reconstruction methods for fault detection. To determine the effectiveness of incorporating internal variables, two scenarios were examined. The first scenario involved creating three reconstruction models by solely utilizing plant measurements. In the second scenario, the reconstruction models were constructed using both plant measurements and internal variables. The three models compared each time are PCA, KICA, and AE. A Hermite polynomial kernel was used for the KICA. The company's goal is to limit the number of false alarms and to maximize the detection rate of Fault 1 and Fault 2. The detection threshold was set accordingly in both cases. Table 2 displays the Missed Detection Rate (MDR), *i.e.,* the percentage of faulty samples considered to be normal, in the test set for each of the three models in Scenario 1, while Table 3 presents the MDR for all three models in Scenario 2. It is noteworthy that there were no false alarms in the test data for both scenarios considered across all three models. There were 35,500 samples for each fault in the test set.

Table 2. MDR (%) without internal variables

Fault	PCA	KICA	AE
Fault 1	98.64	73.49	28.36
Fault 2	91.64	75.9	7.8
Fault 3	99.7	98.52	40.06
Fault 4	98.31	96.2	59.68
Fault 5	98.59	99.45	56.76
Fault 6	99.21	96.65	66.22

Comparing the two tables, it can be seen that the inclusion of internal variables leads to a significant improvement in the fault detection rate for all three models, except for KICA for Fault 5 and Fault 6. For instance, in the second scenario, despite the implementation of a high detection threshold to prevent false alarms, the KICA and the AE were able to identify all instances of Fault 1 and Fault 2 in the test data.

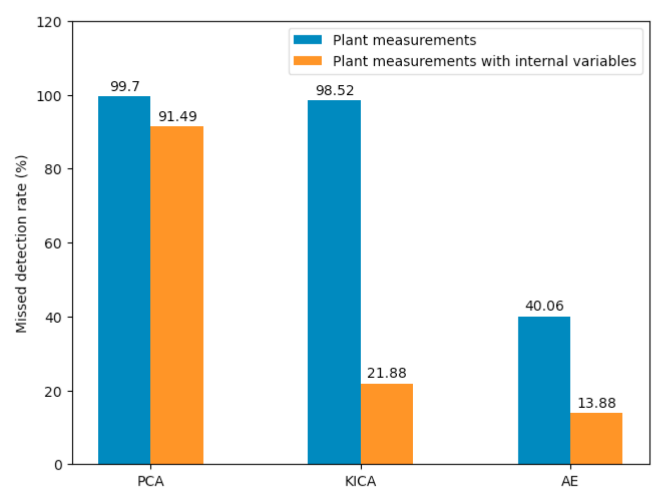

Figure 4. Comparison of MDR of Fault 3 with and without internal variables

Although no model successfully detected all occurrences of Fault 3 and Fault 4, as shown in Figure 4, there was a significant decrease in MDR. KICA and AE exhibited a significant improvement in their detection rate. The MDR is divided by approximately four and three, respectively, when transitioning from the first scenario to the second scenario.

The improvement observed for the other faults for PCA, and AE was maintained for the last pair of faults, while the performance of KICA stagnated or even deteriorated. These two faults concern the variable controlled by the MPC with a predefined target. The MPC reacted by adjusting the actuator commands when the target was not met, making the detection of this fault more complex.

Table 3. MDR (%) when internal variables are used

Fault	PCA	KICA	AE
Fault 1	88.09	0	0
Fault 2	89.83	0	0
Fault 3	91.49	21.88	13.88
Fault 4	89.71	27.76	26.86
Fault 5	85.15	99.97	46.62
Fault 6	65.54	99.93	23.15

Overall, the AE outperforms the other models with the lowest MDR in both scenarios. It is followed by KICA, which has a lower MDR than PCA, except for the two faults involving the controlled variable. This can be attributed to the non-linear nature of the galvanizing process, which is in contrast to the linear model employed by PCA. Moreover, PCA assumes a Gaussian distribution of data, which has not been verified by the collected data on the process. Therefore, in this study, the AE will be utilized to diagnose the detected faults.

4.4 Fault diagnosis

The objective of this section is to identify the faulty sensor and its bias (whether it is negatively or positively biased). This was achieved through the use of contribution plots which helped to determine and display the contribution of each variable to the reconstruction error through bar graphs.

For instance, Figure 5.a illustrates the contribution plot for a sample in the fault-free test data. All variables have minimal contributions, particularly in contrast to Figure 5.c and Figure 5.d where KC1, the variable measured by the faulty sensor, exhibits the highest contribution in absolute value. Figure 5.c and Figure 5.d represent the contributions of the variables for a sample in the Fault 1 and Fault 2 test data, respectively. It is worth noting that KC1 has a negative contribution for the sample of Fault 1, but a positive one for the sample of Fault 2. Therefore, the simulated bias sign has been recovered.

Figure 5.b demonstrates that the observations on one sample are consistent with all the samples in the test data. Moreover, the KC1 variable has a contribution around zero for all fault-free data samples. In addition, all Fault 1 data samples exhibit a KC1 contribution of less than -1, whereas the Fault 2 data samples exhibit a KC1 contribution of greater than 1.

Finally, it is of interest to evaluate the contribution of KC1 data to the reconstruction error of the remaining faults. In fact, if the contribution of this variable to the reconstruction error of the other faults is as high as its contribution to the reconstruction error of Fault 1 and Fault 2, then it cannot be used to isolate the latter two faults. Thus, Figure 6 compares the contribution of KC1 to the reconstruction error of the fault-free data and that of the six studied faults. The results indicated that while the contribution of KC1 to the reconstruction error of some faulty samples was not null, specifically Fault 5 and Fault 6, it was significantly smaller than for Fault 1 and Fault 2. In fact, there was no overlap between the distributions of Fault 1 and Fault 2 and the remaining faults.

Similarly, for all other faults, there existed a variable with the largest absolute contribution, whose sign was dependent on the simulated bias. This variable was used to isolate the faults from one another, whereas its contribution sign was used to establish the direction of the bias.

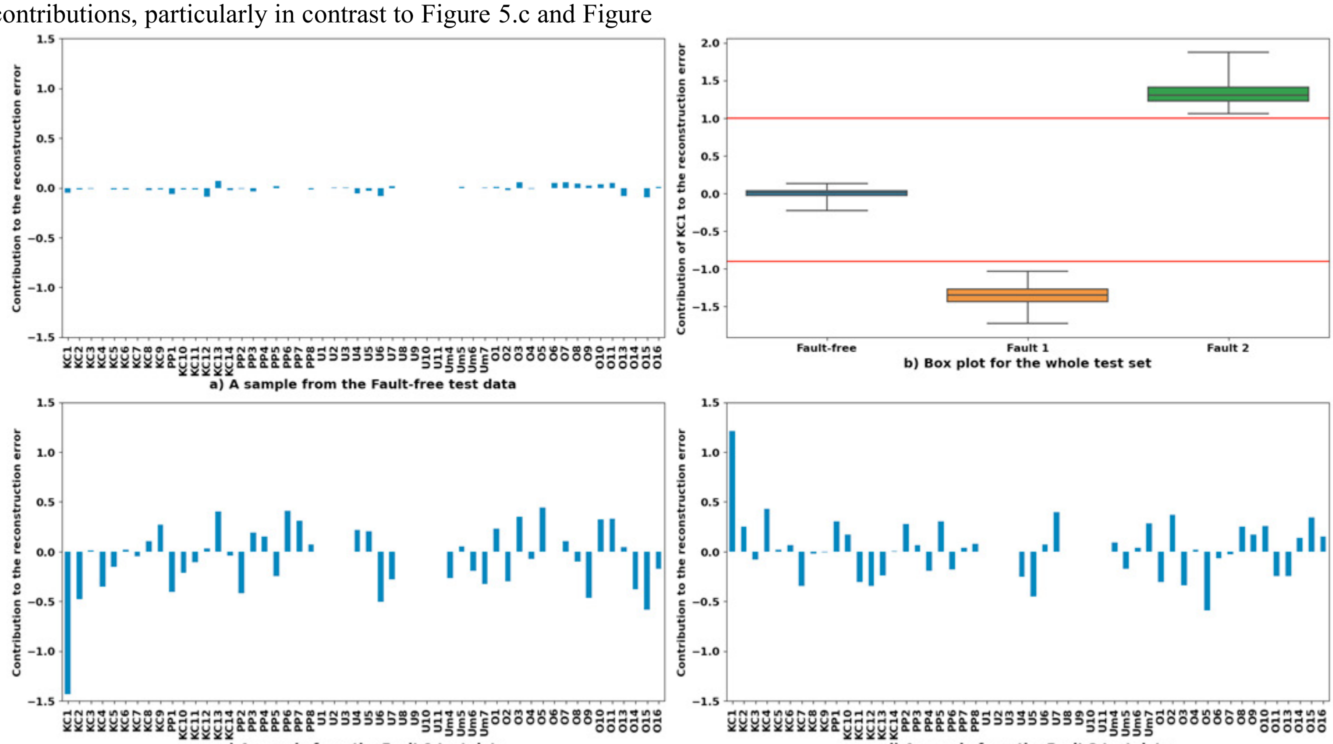

Figure 5. Contribution to the reconstruction error for a sample from, a) Fault-free data; c) Fault 1 data; d) Fault 2 data. b) Distribution of KC1's contribution

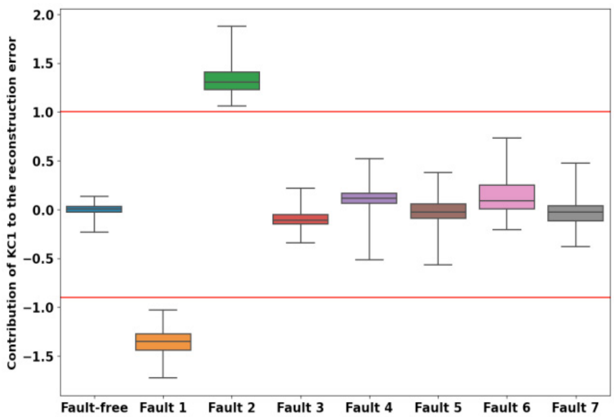

Figure 6. Contribution of KC1 to the reconstruction error for all the faults

5. CONCLUSIONS

Model predictive control is a widely adopted methodology in process industries. This study introduces an innovative approach to enhance the detection efficiency of reconstruction-based techniques. Specifically, internal variables obtained from MPC's operation are added to the plant measurements. The proposed approach was validated through experiments conducted on a galvanizing line. The findings indicated that the integration of internal variables substantially enhances the performance of reconstruction methods. The use of contribution plots in our approach offered two advantages. First, it allowed for precise fault isolation, improving the efficiency and accuracy of the diagnostic process. Second, it aided in detecting bias signals, contributing to a better understanding of underlying issues that led to faults. As a perspective, our research will concentrate on uncertainty quantification in fault detection. This requires the development of methods to better measure and account for the uncertainties inherent in process data and model predictions to further refine the reliability of the fault detection system.

REFERENCES

Adil, M., Abid, M., Khan, A. Q., Mustafa, G., & Ahmed, N. (2016). Exponential discriminant analysis for fault diagnosis. *Neurocomputing*, *171*, 1344–1353.

Cho, M., Ban, J., Seo, M., & Kim, S. W. (2023). Neural network MPC for heating section of annealing furnace. *Expert Systems With Applications*, *223*, 119869.

Colla, V., Cateni, S., Maddaloni, A., & Vignali, A. (2020). A modular machine-learning-based approach to improve tensile properties uniformity along hot dip galvanized steel strips for automotive applications. *Metals*, *10*(7), 1–23.

Kadlec, P., Gabrys, B., & Strandt, S. (2009). Data-driven Soft Sensors in the process industry. *Computers & Chemical Engineering*, *33*(4), 795–814.

Kano, M., & Nakagawa, Y. (2008). Data-based process monitoring, process control, and quality improvement: Recent developments and applications in steel industry. *Computers and Chemical Engineering*, *32*(1–2), 12–24.

Lakshmi Priya Palla, G., & Kumar Pani, A. (2023). Independent component analysis application for fault detection in process industries: Literature review and an application case study for fault detection in multiphase flow systems. *Measurement*, *209*, 112504.

Lalam, S., Tiwari, P. K., Sahoo, S., & Dalal, A. K. (2019). Online prediction and monitoring of mechanical properties of industrial galvanised steel coils using neural networks. *Ironmaking and Steelmaking*, *46*(1), 89–96.

Li, W., Gu, S., Zhang, X., & Chen, T. (2020). Transfer learning for process fault diagnosis: Knowledge transfer from simulation to physical processes. *Computers and Chemical Engineering*, *139*, 106904.

Liu, Q., Chai, T., & Qin, S. J. (2011). Fault Diagnosis of Continuous Annealing Processes Using Reconstruction-based Block Contribution. *IFAC Proceedings Volumes*, *44*(1), 4362–4367.

Liu, Q., Zhu, Q., Qin, S. J., & Chai, T. (2018). Dynamic concurrent kernel CCA for strip-thickness relevant fault diagnosis of continuous annealing processes. *Journal of Process Control*, *67*, 12–22.

Orta, A. H., Kayabasi, I., & Senol, M. (2020). Prediction of mechanical properties of cold rolled and continuous annealed steel grades via analytical model integrated neural networks. *Ironmaking & Steelmaking*, *47*(6), 596–605.

Qiang Liu, Qin, S. J., & Tianyou Chai. (2013). Decentralized Fault Diagnosis of Continuous Annealing Processes Based on Multilevel PCA. *IEEE Transactions on Automation Science and Engineering*, *10*(3), 687–698.

Qin, S. J. (2012). Survey on data-driven industrial process monitoring and diagnosis. *Annual Reviews in Control*, *36*(2), 220–234.

Sanz-Garcia, A., Fernandez-Ceniceros, J., Antonanzas-Torres, F., Pernia-Espinoza, A. V., & Martinez-de-Pison, F. J. (2015). GA-PARSIMONY: A GA-SVR approach with feature selection and parameter optimization to obtain parsimonious solutions for predicting temperature settings in a continuous annealing furnace. *Applied Soft Computing*, *35*, 13–28.

Sotomayor, O. A. Z., & Odloak, D. (2005). Observer-based fault diagnosis in chemical plants. *Chemical Engineering Journal*, *112*(1–3), 93–108.

Strommer, S., Niederer, M., Steinboeck, A., & Kugi, A. (2018). Hierarchical nonlinear optimization-based controller of a continuous strip annealing furnace. *Control Engineering Practice*, *73*, 40–55.

Wang, X., Wang, Y., & Tang, L. (2022). Strip Hardness Prediction in Continuous Annealing Using Multiobjective Sparse Nonlinear Ensemble Learning With Evolutionary Feature Selection. *IEEE Transactions on Automation Science and Engineering*, *19*(3), 2397–2411.

Yang, Z., Xu, B., Luo, W., & Chen, F. (2022). Autoencoder-based representation learning and its application in intelligent fault diagnosis: A review. Measurement, 189, 110460.