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A SIMULATION-BASED QUALITY VARIANCE CONTROL SYSTEM FOR THE ENVIRONMENT-SENSITIVE PROCESS MANUFACTURING INDUSTRY

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ABSTRACT

Optimizing the process parameters with respect to the future environmental conditions is an immediate challenge for environment-sensitive process manufacturing industry to achieve more consistent production quality. In this paper, we propose a simulation-based quality variance control system consisted of three core components: an indoor environment calibration module, a quality prediction module and a simulation engine. We then demonstrate the use of this system by analyzing a typical manufacturing process consisted of four sub-processes. The studies show that the proposed system can achieve better performances by integrating a future indoor environment calibration module than that of without such module. In addition, the simulation-based method can provide more acceptable outcome which outperforms the collaborative filtering algorithm. Such system is feasible to be applied in real industry scenarios which are sensitive to environmental changes to precisely control the quality variances.

1 INTRODUCTION

Quality is the most important factor related to the decision of the selection among competing products and services (Montgomery 2007). Consequently, the consistency of high quality is key to the production competitiveness and business success. This paper proposes a simulation-based method for process parameters optimization to achieve a precise quality control in an environment-sensitive process manufacturing industry.

The quality indicator of the environment-sensitive manufacturing process studied in this paper is impacted by two groups of parameters, i.e., process-control parameters and environmental parameters, the latter of which are highly related to the outdoor weather due to the air convection between the indoor and outdoor. The consistent indoor environment can only be sustained with large investments into the constant temperature and humidity system. For those factories that decide not to do so, how to play against the future outdoor weather changing calls for a solution. Usually, one single manufacturing process takes about 4 to 24 hours to complete and the process parameters must be set at the beginning and is barely mitigable. For example, if we take the output moisture as the quality indicator, the outdoor weather is sunny when the production for a particular batch is launched. As this batch manufacturing goes on and it finishes some of its preceding sub-processes, the outdoor weather changes dramatically from sunny to heavy rain, the resulted quality could be far inferior to the target if the process parameters are decided based on the previous sunny weather rather than considering the weather dynamics during the batch production. The reason is that in the sunny weather, the temperature is high and the relative humidity is low, more moisture would loss while in a rainy day less moisture would loss during the manufacturing processes.

Traditionally, engineers determine the process-control parameters based on their experience or intuition. However, the practice shows that this experience-based way does not work efficiently. Two reasons may lead to such an inconsistent control in practices. The first one is that the human experience is rather qualitative than quantitative, and hard to take all the complexity into consideration. The second one is that the future indoor environment is hardly predictable, which affected by the heat and steam given out by manufacturing itself.

Luckily, the process under concern is intensely instrumented with sensors and stream data are collected and uploaded every 10 seconds. These data make quantitative models for production quality control possible. In this study, we establish a simulation-based quality variance control system consisted of three core components: an indoor environment calibration module, a quality prediction module, and a simulation engine.

The indoor environment calibration module predicts the future environmental parameters (the temperature and relative humidity) around the manufacturing line using the outdoor city weather forecast and the manufacturing configuration, which consequently serve as the exogenous parameters to impact the manufacturing quality, together with other parameters set by the on-site technicians. The quality prediction module fits a mathematical model to precisely quantify the impacts of the process and environmental parameters on the quality indicator. Based on the quality prediction model, the simulation engine simulates the feasible combinations of the process parameters, and single out the optimal one to maintain the target quality persistently.

To demonstrate the method's feasibility and validity, a performance measurement was proposed and numerical studies were conducted. The results show that our method is superior to not only the average prediction level in the process manufacturing industry, but also the collaborative filtering algorithm in which the process parameters are optimized referring to the most similar well-controlled historical records. This study contributes to the literatures by proposing an effective simulation-based quality variance control system integrating an indoor environment calibration model to achieve the precise production. Furthermore, the prediction of indoor weather based on city climate forecast enables our parameters optimization with foreseeing insights, given the whole processing of a batch can last from four to 24 hours or even more.

The rest of the paper is organized as follows. Section 2 provides a literature review related to our study. Section 3 is the description of the simulation-based quality variance control methodology. Section 4 details the numerical studies to verify the proposed methodology and section 5 concludes the paper.

2 LITERATURE REVIEW

Process manufacturing is a branch of manufacturing that converts highly variable raw materials into consistent quality finished goods in bulk quantities using formulas and recipes, as opposed to discrete manufacturing, which deals with countable units. The nature of the processing manufacturing, converting/transforming the raw materials, makes the end product unable to be unassembled to its original contents. If quality problems happen, the loss of the raw materials will not be redeemed.

To reduce the quality variance, optimizing the process parameters is recognized as one of the most important steps (Mok and Kwong 2002). It should adapt to not only the variable raw materials but also the changeable manufacturing environment, especially in an environment-sensitive manufacturing. The environmental change would also cause large quality variance if the process parameters cannot be adjusted accordingly.

As the widely deployment of the data collected sensors, vast troves of process data recording the values of parameters and the corresponding quality indicators have been collected in the real manufacturing process. With these data on hands, two group of data-driven methods have been adopted for parameters optimization to control the quality variance.

The first group method finds out the most similar historical records in which the quality indicators are well-controlled, and optimizes the parameter values referring to these well-controlled records. This method does not measure the quantitative impact of the parameters on the quality indicator and focuses on learning from the historical experience on parameters setting. Based on this idea, a number of recommendation approaches, e.g. the collaborative filtering (CF), knowledge-based algorithm, are proposed to give the most reasonable parameters recommendation (Ricci et al. 2011; Tarus et al. 2017). Chai et al. (2017) proposed a CF algorithm to optimize the process parameters for quality variance control in an environment-sensitive process manufacturing industry and demonstrated that the CF algorithm can be effectively applied in the manufacturing domain to achieve a precise production.

The other group of method establishes mathematical models to quantify the parameters' impact on the quality indicators and optimizes the parameters based on the built models. At the beginning when little data about the manufacturing process are known, the design of the experiment (DOE) is conducted to examine the effects of the process parameters on the output quality. A number of experiments with different levels of the parameters are designed and conducted to gain the corresponding values of the quality measurement. After getting these data, mathematical models such as regression models (Kim and Park 2011), machine learning models (Chen et al. 2009) are built to describe the numerical relationship between the parameters and the quality characteristics. As the manufacturing continues day by day, more and more real data are collected and the models can be updated with the higher accuracy. Based on the built models, optimization algorithms, such as the genetic algorithm (Cook et al. 2000), neural networks (Chen et al. 2009) as well as simulation based methods (Jahangirian et al. 2010; Negahban and Smith 2014; Thengvall et al. 2016) have been proposed to optimize the parameters to achieve the target quality.

However, in an environment-sensitive manufacturing system, the two methods face the same challenge that the future indoor environment is unknown and uncontrollable which makes the recommendation and the optimization hardly to be implemented before predicting the future indoor environment. Although, a bunch of literatures have explicated the indoor environment prediction (Rohdin and Moshfegh 2007; Thomas and Soleimani-Mohseni 2007; Mustafaraj et al. 2011), very rare literatures were related to the manufacturing domain, especially when integrated into a simulation-based system for the parameters optimization to control the quality variance.

3 SIMULATION-BASED QUALITY VARIANCE CONTROL SYSTEM

The simulation-based quality variance control system consists of three core components: indoor environment calibration module, quality prediction module, and simulation engine, as shown in Figure 1. We will elaborate the three components in the following sections.

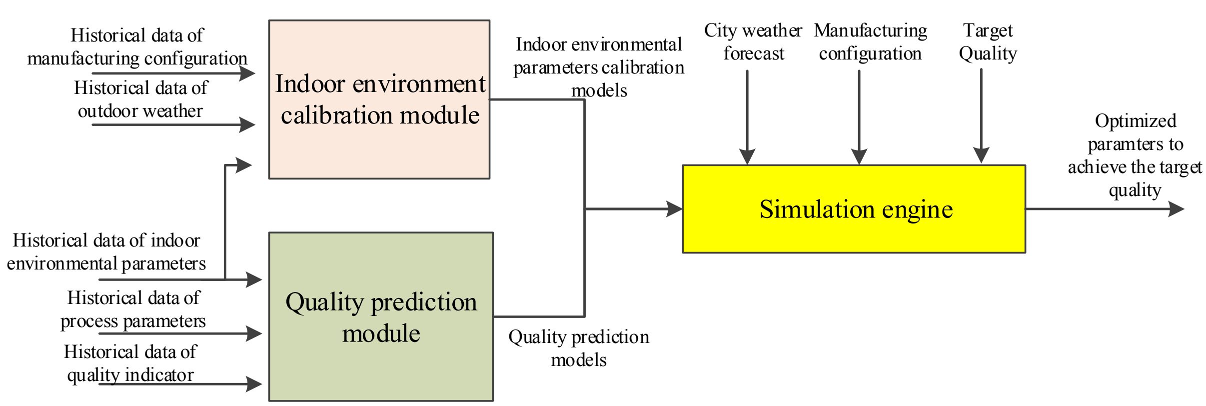

Figure 1: The simulation-based quality variance control system.

3.1 Indoor environment calibration module

The indoor environment calibration module aims to establish a mathematical model to calibrate the indoor environment around the manufacturing line. The impact factors of the future indoor environment include not only the future outdoor weather but also the manufacturing process itself. For example, the manufacturing process emits both heat and steam into the surroundings and the temperature and humidity goes higher and higher as the manufacturing continues. When the manufacturing operations stop, the indoor temperature and humidity goes down slowly before reaching a balance with the outdoor. Hence, in the calibration module, we consider two groups of parameters: the outdoor weather and the manufacturing configurations. The prediction model is given as follow:

$$E_c = f(W_c, W_s, W_{avg}, t_p, t_s) \tag{1}$$

E_c stands for the indoor environment value (the temperature and relative humidity) to be predicted for a given location at a given time point t. We have a great number of E_c located at different location of the manufacturing line at different time point to be predicted. Instead of only considering the outdoor weather at the given time point W_c, we also consider the outdoor weather when the manufacturing starts at that day: W_s, and the average outdoor weather 1 day before the given time point t: W_{avg}. The W_s is one of the outdoor weather values included in calculating the average outdoor weather W_{avg}. This kind of parameters extension aims to better and precisely describe the indoor environment change dynamics than just considering the outdoor weather at the given time point t. It is demonstrated to be more efficiently and can largely improve the model calibration accuracy through numerical studies.

As for the manufacturing configurations, we consider the production time t_p and the production stop time t_s between the given time point with the latest manufacturing start time or the latest manufacturing stop time separately.

The model can be trained as regression or machine learning models, such as neural network or support vector regression. Since we can train multiple models, we need to choose the best one with the minimum calibration error as the input of the simulation engine to reduce the quality control variance brought by the indoor environment calibration model. The best model selection method is similar as the one stated in the quality prediction module.

3.2 Quality prediction module

The quality prediction module tries best to mathematically describe the dynamics between the quality indicator and the parameters. This module takes the historical data of the environmental parameters, the process parameters and the quality indicator to fit models in order to predict quality when the process and environmental parameters are given.

Similar with the indoor environment calibration module, we also have multiple options to fit the quality prediction model and the best one should be selected as the quality prediction model. We calculate the Mean Absolute Error (MAE) which is widely used as simple while robust computational measures for each model and the one with the least MAE is selected as the best quality prediction model (Willmott and Matsuura 2005; Willmott et al. 2009).

The MAE calculates the mean absolute error between the true value d_t and the prediction y_t across all observations of the testing set. n is the number of records in the testing set.

$$\text{MAE} = \frac{\sum_{t=1}^{n}(|d_t - y_t|)}{n} \tag{2}$$

3.3 Simulation engine

The simulation engine uses the continuous simulation method to find out the best parameters setting based on the quality prediction model. A continuous simulation applies a continuous function using real numbers to represent a continuously changing system. More specifically, in our simulation, the continuous function is the quality prediction model, and the real numbers are the values of the parameters needed to be optimized. By simulating different values of the parameters, the quality can be evaluated and the most suitable parameters can be selected to achieve the target quality.

The simulation engine takes the quality prediction model, the indoor environment calibration model, and the value of the outdoor weather forecast, the manufacturing configurations, and the target quality to simulate the parameters needed to be optimized to find out the most suitable one to maintain the target quality persistently. The workflow of the simulation engine is shown as Figure 2.

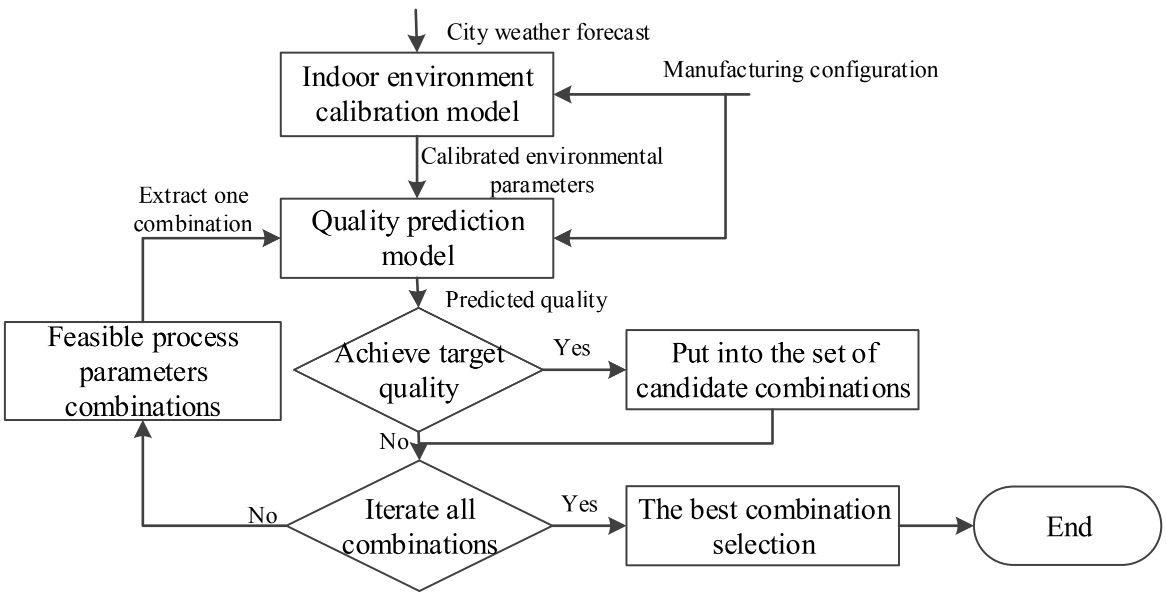

Figure 2: Workflow of the simulation engine.

In the first step, the indoor environment calibration model takes the input of outdoor weather forecast and manufacturing configurations to predict the environmental parameters. After that, the quality prediction model uses the output of the first step, also the manufacturing configurations and one feasible combination of the process parameters to predict the corresponding quality. If the predicted quality meets the target quality, we put this combination into the set of candidate combination and check whether the all feasible combinations have been iterated. If not, the iteration continues until each combination has been iterated once. After all iterations, the best process parameters combination selection strategy is adopted to select one best combination as the final parameters optimization result.

Note that the set of feasible process parameters combination are determined by the simulation configurations: the upper and low bound, and the simulation step length for each parameter.

In practice, each process parameter has an anticipated control value and we hope the minimum adjustment is expected for each parameter to adapt to the environmental change. We define D_c as the value deviation of parameters combination c from the expected control value. Let s_{ci} is the value of parameter i in combination c and e_i is the expected value for the parameter i. w_i is measures the control difficulty of parameter i. The deviation is defined as

$$D_c = \sum_{i \in I} w_i (s_{ci} - e_i)^2 \tag{3}$$

The parameters selection strategy is to select the process parameters combination with minimum weighted deviation from the anticipated control value as the final output optimized parameters option.

3.4 Parameters optimization performance measurement

This section proposes a measurement to evaluate the parameters optimization results. Apparently, the best evaluation approach is to apply the methodology into the real manufacturing line. By observing the difference of the real quality and target quality, the performance can be directly evaluated. However, this approach is often costly and also impractical for the factory to adopt before we can demonstrate the usage of the method.

In this practice, we define a performance metrics method on all history batches based on cross validation. After conducting the cross validation, two group of values σ_{hi} and σ_{hy} are calculated referring to (4) and (5). σ_{hi} is the difference of the optimized value of parameter i with the real collected value for the history batch h; σ_{hy} is the difference of the target quality level with the real quality value of history batch h. P_{hi} is the actual value of the parameter i for the batch h and P_{fi} is the optimized value of the parameter i for the batch h.

$$\sigma_{hi} = P_{fi} - P_{hi} \tag{4}$$

$$\sigma_{hy} = P_{fy} - P_{hy} \tag{5}$$

$$\rho_{iy} = cor(\sigma_i, \sigma_y) \tag{6}$$

The correlation ρ_{iy} given in (6) is calculated as the performance metric to evaluate the optimization performance of the parameter i. If $|\rho_{iy}|$ is close to 1, it means that when parameter i is adjusted from real value p_{hi} to p_{fi} in the real manufacturing line, the quality would be more likely to be optimized to the target value for the historical batch h. In other words, the optimized results would be more reasonable, if $|\rho_{iy}|$ is more close to 1.

One limitation is that this performance metric can only measure performance for optimizing a single parameter each time. When two or more parameters are collaboratively optimized, this metric will no longer work. In this case, similar with the single parameters optimization, multiple correlation coefficient of the quality difference with the value difference of the process parameters can be calculated as the performance metric (Cohen et al. 2013). A higher coefficient indicates a better performance.

4 NUMERICAL STUDY

The primary objective of the numerical study is to demonstrate the feasibility and usage of the proposed simulation-based quality variance control system. In this section, we applied this method into a typical environment-sensitive process manufacturing line consisted of four sub-processes shown in Figure 3.

The first step is to moisten the raw material by adding water and steam. Then the moistened material is transferred and temporarily stored into a closed space for the upcoming process. After that, the chemical condiments in the recipes are added into the raw material in order for flavoring. Finally, the raw material are fully blended with the chemical condiments and stored for a relative long time period.

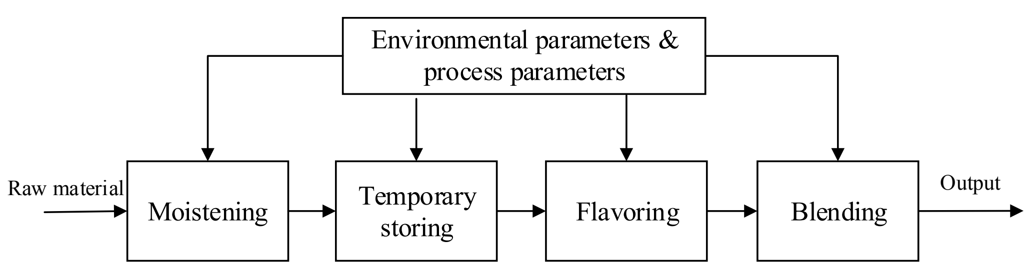

Figure 3: Four sub-processes of the studied manufacturing process.

The raw material usually flows in batch. The quality indicator under concern is the moisture content of the output. Totally, 31 parameters through the four sub-processes, including the process and environmental parameters, are considered. The process parameters, such as the adding amount of water and steam in the first step, have direct impact on the moisture content of the output. The moisture content would be higher if more water or steam are added. The environmental parameters have indirect influences. If the environmental humidity is low and the temperature is high, more moisture would loss through this process, especially in the temporary storing and blending steps due to long time exposing in the environment.

The process takes about 4 to 24 hours to complete one batch and all the process parameters must be set at the beginning of each batch. Due to the change of the outdoor weather over time, the indoor environment may vary a lot even in one batch. If the process parameters, cannot be set adaptively to the variation of the future environment, huge quality variance would be caused. For example, the outdoor weather is sunny at the beginning of batch. The temperature is high and humidity is modest, we may decide to add more water at the first step considering the possible large moisture loss during the manufacturing process. However, when the batch enters the third sub-process, the outdoor weather changes dramatically and a heavy rain comes which makes the humidity much higher. In this case, less moisture would loss in the third and fourth steps. The output moisture would be much higher than the target and a large quality variation is caused. Hence, the proposed simulation-based quality variance method is applied to optimize the process parameters to adapt to the environmental variation and thus to achieve a consistent quality.

In the numerical study, five representative predictive models, including the linear regression model(lm) , the Lasso regression model (lasso), the neural network model (nnet), the support vector regression (svr) model and the combination prediction model (combin), are implemented and compared to choose the best one for both the indoor environment calibration and the quality prediction.

Besides, we also implemented and compared with the proposed collaborative filtering algorithm in which the process parameters are optimized referring to the most similar well-controlled historical records (Chai et al. 2017).

All the models and algorithms are implemented using “R”. The linear regression was implemented using the “MASS” package (Ripley 2016a). The backward stepwise method was adopting to automatically choose the best set of predictive variables using AIC criteria. The Lasso regression was implemented using the “glmnet” package (Hastie 2016) and regularization coefficient λ is automatically estimated. The neural network was implemented using the “nnet” package (Ripley 2016b) with a structure of one input layer, one hidden layer and one output layer. The support vector regression was implemented using “e1071” package (Meyer 2017) with the default setting. The combination prediction model combines the output of the previous four models linearly based on the prediction error of the four models.

There are totally 894 batches of data collected from 2015-01 to 2016-06 in a real process manufacturing line. The data set includes a rich variety of data types uploaded by sensors, sampling every 10 seconds. Data pre-processing was performed to get rid of the abnormal data and aggregate the data in batch.

Batch is the unit for parameters optimization. Cross validation was chosen to do the verification. One tenth batches are selected as the test data in each iteration. Totally 10 iterations were conducted to iterate all batches.

To verify the feasibility of the proposed method and evaluate the impact of the indoor environment calibration error, we also compared the following three environment scenarios.

(1) **Calibrated environment scenario:** We use the future calibrated environment to predict the quality in the test data. This scenario is a practical one and is recommended for practice use.
(2) **Actual measured environment scenario:** We use the future actual measured environment to predict the quality in the test data. This scenario is an impractical one in reality since the future

environment cannot be actually measured at the beginning of each batch. This scenario only acts as the best benchmark.

(3) **Batch start environment scenario:** We use the actual measured environment at the beginning of the batch as the future indoor environment to predict the quality in the test data. The scenario is adopted in practice by the factory engineers and acts as a practical benchmark to evaluate the performance improvement with an indoor environment calibration module.

4.1 Indoor environment calibration results analysis

As stated above, environmental parameters impose large impact on the final quality. If we can accurately predict the future indoor manufacturing environment, we can better set the process parameters adaptively. Each sub-process has one temperature and one relative humidity sensor to collect the real time environment data every 10s. Since the city forecast weather data is provided in hour, we aggregate the real time collected environmental data in hour and then to establish the calibration model.

Table 1 is the indoor environment calibration mean absolute errors defined in section 3.2 for the four sub-processes using five different models. The third column shows that the real collected values of the temperature and relative humidity vary in different sub-process due to different manufacturing operations. “svr” and “combin” models achieve almost the same performance and are both superior to other algorithms in all the four sub-processes in terms of both the temperature and relative humidity calibrations.

The system can intelligently choose and customize the calibration models for each sub-process in order to reach the best performance. We can also find that the average absolute prediction error is about 0.47℃ for the temperature and 2.33% for the relative humidity after choosing the best model.

Though the calibration error for the indoor manufacturing temperature and relative humidity is relative low, still the performance is hardly evaluated by only analyzing the calibration errors themselves. Only after analyzing the quality prediction results, can we evaluate the impact of the calibration performance.

Table 1: The comparison of indoor environment calibration errors across different prediction models in different sub-processes.

	Sub-process	**avg_actual_value**	**lasso**	**lm**	**nnet**	**svr**	**combin**
Temperature	Moistening	25.92	0.73	0.71	0.54	0.46	0.45
	Temporary storing	27.30	0.84	0.83	0.64	0.48	0.48
	Flavoring	25.44	0.71	0.70	0.94	0.44	0.44
	Blending	26.23	0.90	0.89	1.04	0.52	0.52
	Average	26.22	0.79	0.78	0.79	0.48	0.47*
Relative Humidity	Moistening	46.80	2.84	2.80	2.41	1.86	1.85
	Temporary storing	51.78	3.72	3.67	3.80	2.49	2.50
	Flavoring	49.28	3.12	3.08	3.64	2.05	2.03
	Blending	58.04	5.25	5.19	4.06	2.95	2.94
	Average	51.48	3.73	3.68	3.48	2.34	2.33*

4.2 Quality prediction results analysis

The performance of the proposed simulation-based quality variance control system primarily determined by the quality prediction model. The higher prediction accuracy, the better the process parameters optimization and hence the less variance of the quality control. In this section, we analyze the quality prediction results under the three defined environment scenarios and using the five predictive models.

Table 2 gives the quality prediction results. We can see that the prediction performance varies differently using different prediction model under different environment scenario. Besides, the gap using the indoor environment calibration model relative to the best benchmark varies 10%~20% under different prediction model. With this indoor environment calibration module, the prediction accuracy can also improve by 6%~20% comparing using the batch start temperature and relative humidity.

Among these five models, "combin" model is shown as the best model using the proposed criteria in section 3.2 for the calibrated environment scenario. The MAE is 0.1375%, far less than the quality variance requirement for this process, 0.5%. Figure 4 shows the output quality comparison of the actual moisture and the predicted moisture. The predicted values fit very well with the actual collected values. Figure 5 shows the prediction error distribution, 99.78% of the prediction error are within ±0.5%.

To sum up, a higher prediction accuracy can be achieved with integrating an indoor environment calibration model and we can predict the quality with a considerably high accuracy.

Table 2: The comparison of the quality prediction under different environment scenarios using different predictive models.

Scenario	**lm1**	**lasso**	**nnet**	**svr**	**combin**
Actual measured environment	0.1201%	0.1234%	0.1280%	0.1252%	0.1209%
Calibrated environment	0.1461%	0.1472%	0.1486%	0.1390%	0.1375%
Batch start environment	0.1581%	0.1565%	0.1696%	0.1632%	0.1638%
Gap[1]	21.65%	19.24%	16.13%	10.98%	13.73%
Improvement[1]	8.19%	6.35%	14.08%	17.47%	19.17%

Gap[1]= (Calibrated environment- Actual measured environment)/ Actual measured environment* 100%;
Improvement[1] =(Start batch environment - Calibrated environment)/ Calibrated environment * 100%.

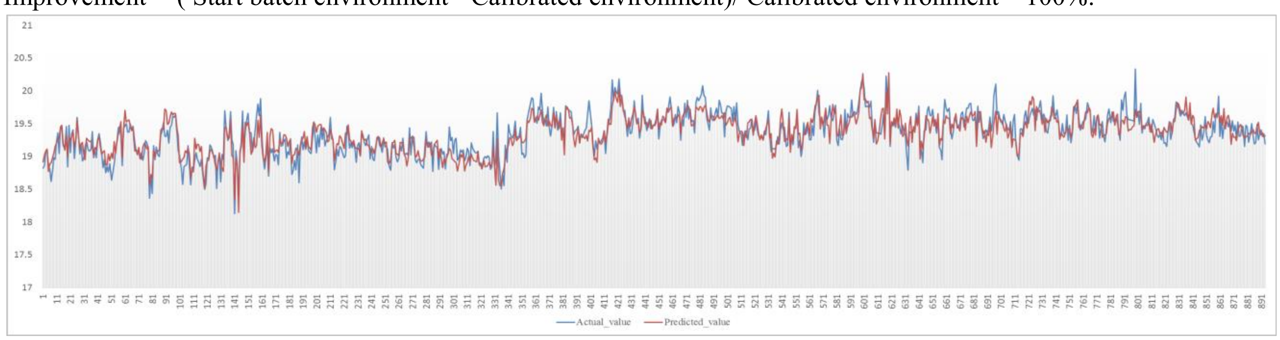

Figure 4: Comparison of the actual and the predicted output moisture using best prediction model.

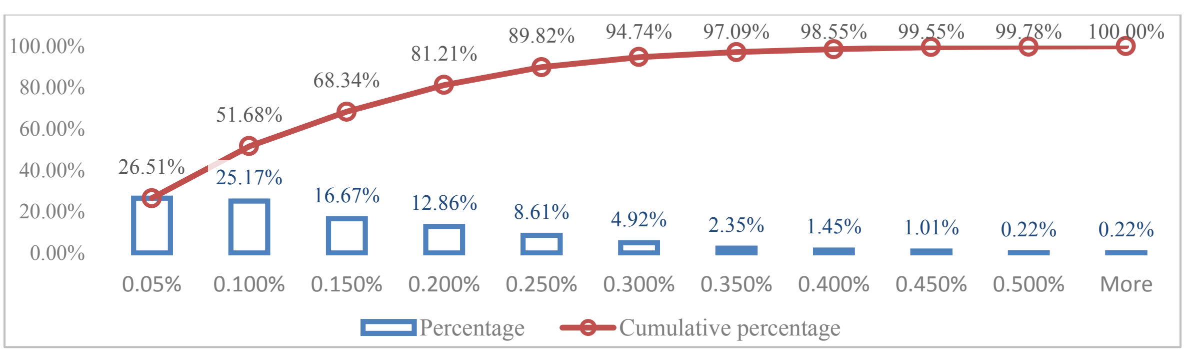

Figure 5: The absolute prediction error distribution using the best prediction model.

4.3 Process parameters optimization results analysis

This section optimizes the process parameters based on the quality prediction model. In this numerical study, adding amount of water is the leading parameter that dominates the impact on the moisture content of the output, and selected by the factory engineer for adjustment to adapt to the environmental variation. The primary goal of this numerical study is to determine the adding amount of water for each batch to achieve a consistent quality. The correlation defined in (6) for the process parameter of the water adding amount and the moisture content was calculated as the performance measurement after completing the cross validation. Besides, in this section, we compared the results with a proposed collaborative filtering algorithm.

Table 3 gives the process parameters optimization results. The correlation for the calibrated environment scenario is 0.783, showing a very strong correlation between the quality difference and the parameters difference. It means if we adjust the parameters from the real collected values to the optimized values, the quality is very likely to be optimized to the target quality. In other words, the parameter optimization results are reasonable enough and can provide useful guidance for the parameters setting in practice.

The gap shows that when using the calibrated environment, the performance only declines by about 7.12% and 4.80% comparing the actual environment for the simulation-based and collaborative filtering method separately. The improvement[1] shows that with an indoor environment calibration model, the performance can increase by 5.81% and 4.71% for the simulation-based and collaborative filtering method respectively. The improvement[2] shows that the proposed simulation-based method achieves better performance than the collaborative filtering algorithm. The improvement is roughly 6.68%.

In summary, the simulation-based quality variance control system can achieve a considerably acceptable outcome in terms of the quality prediction as well as the parameters optimization.

Table 3: The comparison parameter optimization results of the simulation-based method and collaborative filtering algorithm under two environment scenario.

Scenario	Simulation-based	collaborative filtering	Improvement[2]
Actual measured environment	0.843	0.771	9.34%
Calibrated environment	0.783	0.734	6.68%
Batch start environment	0.74	0.701	5.56%
Gap	7.66%	5.04%	
Improvement[1]	5.81%	4.71%	

Gap= (Actual measured environment - Calibrated environment)/ Calibrated environment *100%;
Improvement[1]= (Calibrated environment - Batch start environment)/ Batch start environment *100%;
Improvement[2]= (Simulation-based - Collaborative filtering)/ Collaborative filtering*100%.

5 CONCLUSION

In this paper, we proposed a simulation-based quality variance control system for process parameters optimization to achieve a consistent quality for the environment-sensitive process manufacturing industry. The system consists of three components: indoor environment calibration module, quality prediction module and simulation engine. We then demonstrate its usage through numerical studies of a typical process manufacturing. By comparing the performance of using the actual measured environment, the calibrated environment and the batch start environment in predicting the quality and optimizing the process-controlled parameters, the indoor environment calibration performance as well as feasibility of the proposed simulation-based framework have been verified. The proposed system is also proven to be superior to the collaborative filtering algorithm. To sum up, the proposed simulation-based quality variance control system can be effectively and efficiently applied to optimize the process parameters and precisely control the quality variance in an environment-sensitive process manufacturing industry.

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