Anomaly detection for yield improvement in glass production

Haruo Yonemori[1], Kenichi Arai[2], Hironobu Yamamichi[3], Ichiro Sakata[4], and Makoto Imamura[5]

[1,3,4]*AGC Inc., Yokohama, Kanagawa, 230-0045, Japan*
haruo.yonemori@agc.com
hironobu.yamamiti@agc.com
ichiro.sakata@agc.com

[2]*AGC Inc., Chiyoda-ku, Tokyo,100-8405, Japan*
kenichi.ka.arai@agc.com

[4]*Tokai University, Minato-ku, Tokyo,108-0074, Japan*
imamura@tsc.u-tokai.ac.jp

ABSTRACT

Predictive maintenance using manufacturing sensor data has attracted attention for reducing defects and selecting appropriate actions. This paper proposes an anomaly detection method using lasso regression and group-wise variable selection based on FTA（Fault Tree Analysis） domain knowledge. We evaluated our approach using real factory data and found that its precision and false positive rate are 66% and 30%, respectively. Moreover, we validate that the visualization of the contribution rate for anomaly detection is helpful for factory maintenance.

1. INTRODUCTION

Flat glass manufacturing facilities consist of melting furnace that melts raw materials at high temperature, float bath that form flat glass on molten tin, and annealing furnace that cool glass gradually. These facilities are hot and sealed, and it is difficult to monitor their internal conditions directly, so they are managed using various types of sensing information. At the startup of the production line, the production equipment is set to an appropriate state to prevent the production of defects. However, as glass production continues, the equipment condition gradually deviates from the appropriate production conditions, and defects may occur. Therefore, we have decided to develop an online detection method for detecting signs of abnormalities in manufacturing equipment based on sensing information, so that appropriate equipment maintenance actions can be taken based on early detection of abnormal conditions of the equipment.

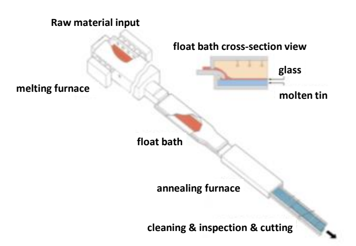


Figure 1 Glass production facility (from AGC HP)

2. ONLINE ABNORMALITY SIGN DETECTION METHOD

2.1. Flow of Proposal Method

Figure 2 shows the overall structure of the abnormality sign detection method. Process data is periodically transferred from the manufacturing line to the database. The new abnormality detection method obtains process data from the database and outputs a health index (abnormal degree) to the database. When the visualized health index obtained from the database indicates an abnormality, appropriate manufacturing actions are taken at the factory process site.

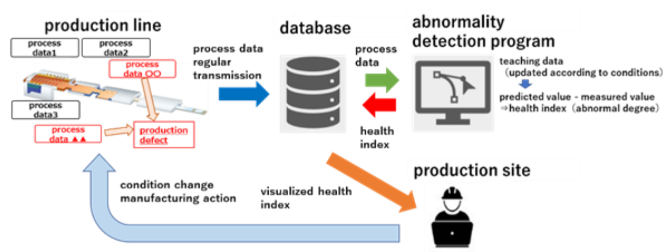


Figure 2: Overall structure of the detection method for abnormal signs

Figure 3 shows the health index calculation flow for the abnormality level. Using process data under normal quality conditions as training data, a prediction equation is created using the LASSO model, and the health index is calculated from the residual difference between the predicted value and the actual measured value. Details are described in Chapter 2.4. In the predictive creation model study, in addition to LASSO, Auto-associative kernel regression model and Auto-encoder were tested. Among them, LASSO, which obtained the most consistent results, was adopted as the current model.

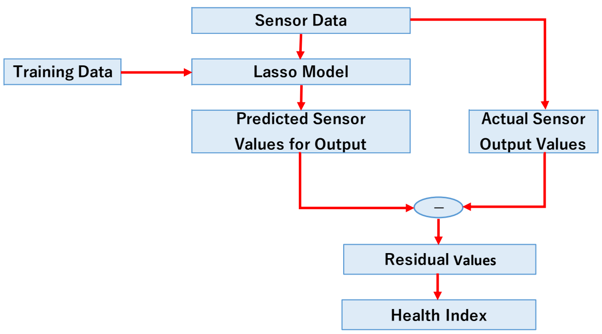


Figure 3: Health Index Calculation Method

2.2. Training Data and Estimation Goals

The goal was to create a method that can manage current production conditions not to deviate from the training data.

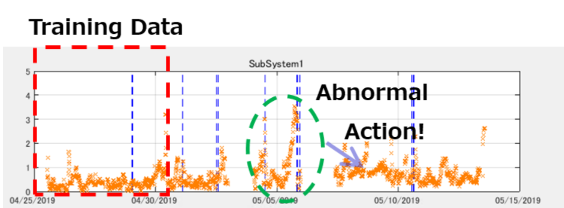


Figure 4: Training data and anomaly data

The sensed process data used were stored in a database at a sampling rate of once every 10 minutes. The health index was calculated at the same time intervals and monitored online during production to allow for proactive response when abnormal signs were detected. The target detection time for abnormal signs was set to 2 hours before an abnormality occurred.

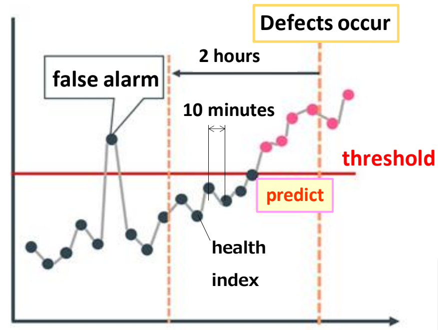


Figure 5: Health Index Schematic Graph

2.3. Variable Selection Based on Causal Analysis

The defects that were the subject of this anomaly detection method had many factors and had been a problem for a long time. First, FTA was used to analyze the causal relationships that generate the defects, and to estimate the "physical quantity" that causes the defect and the "location" where the defect is generated.

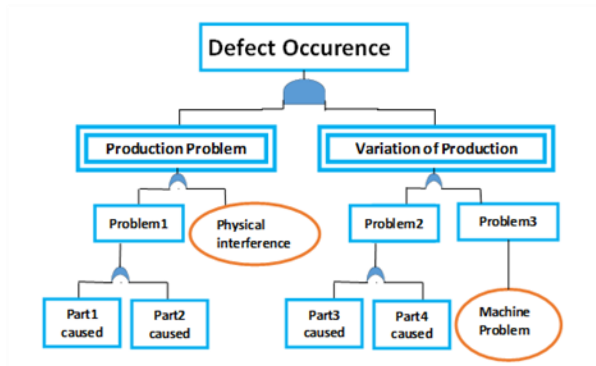


Figure 6: Causal analysis resulting in glass defects (FTA)

From the FTA, the important sensor groups and the objective and explanatory variables of the regression analysis were determined for each failure cause classification (Figure 7). Failure causes were categorized by location (Part 1-4) and by the four variables (a measured control value, an external measurement, a control setpoint, an internal measurement), finally creating 10 variable groups. In the glass process flow, Part 1 ~ 4 of the four equipment sometimes make defects. Glass is being transported from Part 1 upstream of the process to Part 4 downstream of the process continuously. Also, each facility has a control device, which controls variables to be managed during operation and measures whether they can be controlled correctly. Furthermore, many variables inside the equipment and outside the equipment have also been measured. And the causal relationship to the current anomaly can be explained with 4 variables among them using LASSO regression and domain knowledge. The 4 variables are actual control measurement values, control set values, internal measurements, and external measurements.

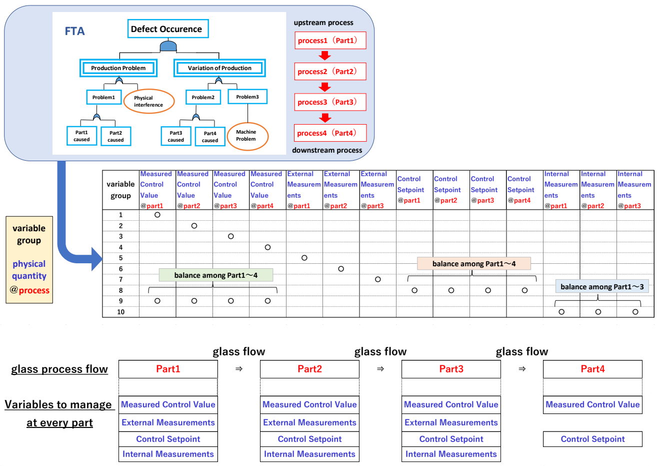


Figure 7: Contents of each variable group

The health index was calculated for each of these groups, and the largest health index (means highest abnormality) from the group was the OverAll health index. In the production site, when the OverAll health index exceeded the threshold, it was determined to be abnormal

2.4. Analysis Anomaly Detection Algorithm

The original program of the method was commissioned to Predictronics Corp. and customized in-house at AGC. The HI (health index) was calculated by determining the residuals from the predicted values and the measured values that were obtained for each variable group. Furthermore, from each health index, the contribution of the variables used for each health index was calculated. The equations (1) ~ (5) are quoted from Training Materials (November 29, 2017) Using Process Data for Quality Improvement of PREDICTRONICS CORP.

$$Num\_STDEV = 1/\sqrt{\alpha} \quad ※ \quad \alpha = 0.03 \tag{1}$$

$$Residual_{Scaled} = \frac{(|Residual| - mean(|Residual_{Baseline}|))}{stdev(|Residual_{Baseline}|) \times Num\_STDEV} \tag{2}$$

($Residual_{Baseline}$ was calculated by training data only.)

$$Subsystem\_HI = max(Residual_{Scaled}) \tag{3}$$

(Subsystem_HI selected the variables with max residual in each variable group.)

$$Overall\_HI = max(Subsystem\_HI) \tag{4}$$

(Oveall_HI selected the variable group with max health index.)

$$Contribution_i = \frac{Residual_{scaled_i}}{\sum_{i=1}^{n} Residual_{scaled_i}} \tag{5}$$

(Residual = difference between predicted and measured values)

(Baseline = training data period)

(Subsystem = variable group)

(Overall_HI = maximum health index for all variable group)

(Contribution = each variable contribution to the health index in the variable group)

3. Evaluation

3.1. Evaluating the accuracy of detecting abnormal signs

Although the health index can be evaluated visually to some extent by drawing a graph, in addition, the precise rate and false positive rate were used as quantitative evaluation indicators. The definitions of each are shown in Figure 8. Measured values were classified into four categories (FP, TP, TN, and FN), and a higher precise rate was judged as more accurate predictive signs, while a lower false positive rate was judged as fewer false alarms.

Precise rate = TP/(FN+TP)

False positive rate = FP/(TN+FP)

		Predicted value	
		Negative(0)	Positive(1)
True value	Positive(1)	FP False Positive	TP True Positive
	Negative(0)	TN True Negative	FN False Negative

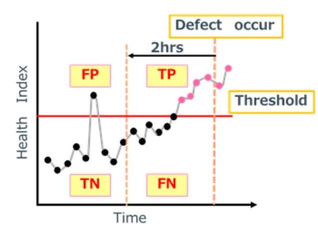


Figure 8 Definition of precise rate and false positive rate

Thresholds were set using ROC curves (Figure 9). Specifically, the threshold value was the value at which the difference between the precise rate and false positive rate of the Overall health index was the largest value. The intent was to maximize method performance in this way.

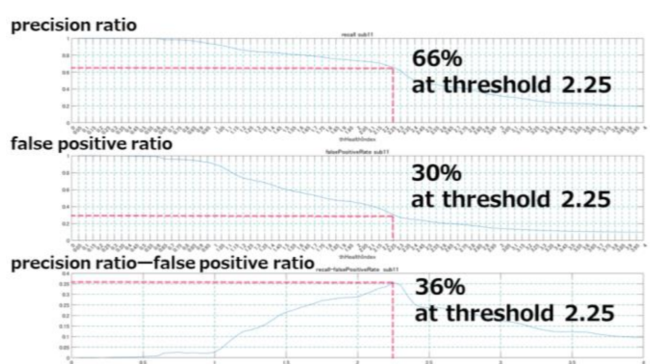


Figure 9 Determination of Overall H.I thresholds using ROC curves

The predictive performance during the approximately one-year trial period was 66% precision rate and 30% false positive rate. Our goal was to achieve a precision rate of 80% or higher and a false positive rate of 30% or lower. Although the precision rate fell slightly short of our goal, we were able to raise the values quite close to our target. We would like to further improve the precision rate and false positive rate in the future.

3.2. Validation of Variable Selection

For each health index variable group, we confirmed whether the appropriate explanatory variables were selected and whether deviations from the training data were consistent with the occurrence of product defects.

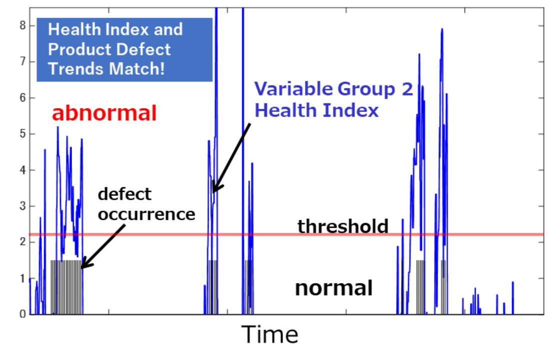
Figure 10 shows the health index structure of variable groups 2 and 9. Variable Group 2 consists of the measured control values of Part 2, and Variable Group 9 consists of the measured control values of Parts 1 through 4. Variable group 9 expresses the balance of the measured control values of Part1 to 4.

		glass flow		glass flow		glass flow	
glass process flow	Part1	⇒	Part2	⇒	Part3	⇒	Part4
Variables to manage at every part	Measured Control Value		Measured Control Value		Measured Control Value		Measured Control Value
	External Measurements		External Measurements		External Measurements		
	Control Setpoint		Control Setpoint		Control Setpoint		Control Setpoint
	Internal Measurements		Internal Measurements		Internal Measurements		

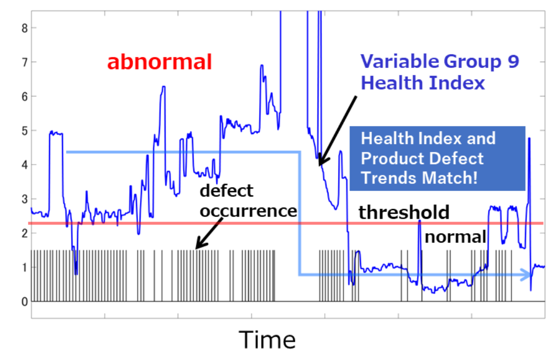
variable group	Measured Control Value @part1	Measured Control Value @part2	Measured Control Value @part3	Measured Control Value @part4	External Measurements @part1	External Measurements @part2	External Measurements @part3	Control Setpoint @part1	Control Setpoint @part2	Control Setpoint @part3	Control Setpoint @part4	Internal Measurements @part1	Internal Measurements @part2	Internal Measurements @part3
1	○													
2		○												
3			○											
4				○										
5					○									
6						○								
7		balance among Part1～4					○							
8								○	○	○	○			
9	○	○	○	○										
10												○	○	○

Figure 10 Health index configuration for variable groups 2 and 9

Figure 11 shows the health index actual performance graphs for variable groups 2 and 9 as an example. There is a good agreement between the time of product defect occurrence and the actual results of health index. Thus, it was found that not only an increase in the health index of a single part, as in variable group 2, but also a change in the relationship between variables of multiple parts, as in variable group 9, can cause the health index to increase, and also, product defects occur actually. Figure 10 shows the health index structure of variable groups 2 and 9.



		glass flow		glass flow		glass flow	
glass process flow	Part1	⇒	Part2	⇒	Part3	⇒	Part4
Variable Group	Measured Control Value		Measured Control Value		Measured Control Value		Measured Control Value
2			○				



		glass flow		glass flow		glass flow	
glass process flow	Part1	⇒	Part2	⇒	Part3	⇒	Part4
Variable Group	Measured Control Value		Measured Control Value		Measured Control Value		Measured Control Value
9	○		○		○		○

Figure 11: Health index results for variable groups 2 and 9

3.3. Evaluation of the contribution of each variable

When the Overall Health Index exceeds the threshold, it is determined that an abnormality has occurred in the manufacturing process, and furthermore, manufacturing actions are taken to check which variable group is abnormal and to ensure that the part and physical quantity of that variable group is normal. In addition, within the variable group that shows abnormality, we referred to which variable worsened the health index the most by looking at the contribution ratio.

Figure 12 shows the percentage contribution of each variable in the Health Index of Variable Group 9. This health index was calculated for Part1-4 variables. The contribution rate of Part 4 in the abnormality at this time was relatively low compared to the other Parts 1-3, indicating that it was the manufacturing actions of Parts 1-3 that improved the health index. By examining the contribution rate in this way, we can learn the direction of manufacturing actions for improvement.

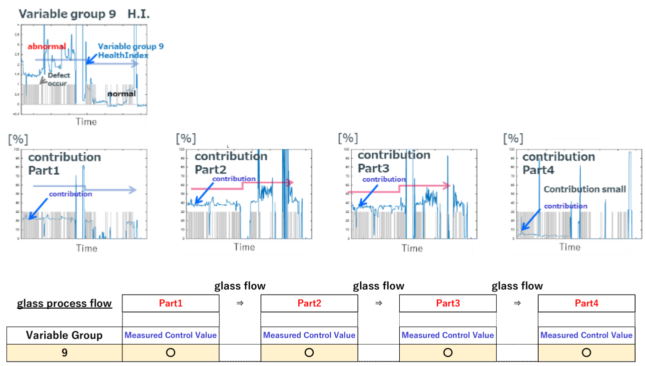


Figure 12 Variable Group 9 Health Index Contribution of each variable

4. Conclusion

As an abnormality detection method for improving the yield rate of glass manufacturing, we have implemented the abnormality sign detection method that foreshadows abnormality from a variety of variables by setting up a group of variables. We have confirmed that this method is effective as a method for detecting signs of abnormality in large facilities such as glass manufacturing where there are many sensing values. We would like to utilize this system for other product defects and equipment maintenance in the future.

References

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Haruo Yonemori

Haruo Yonemori received B.E degree in Mechanical Engineering from Keio University. He has been working for AGC Inc. after graduation from university and now engaged in process improvement with data analysis and computer simulation at Yokohama Technical Center of AGC Inc.

Kenihchi Arai

Kenichi Arai received B.E and M.E degrees in applied Chemistry from Tokyo University. He has been working for AGC Inc. after graduation from university and now engaged in improvement of Glass manufacturing job with AGC Inc.

Hironobu Yamamichi

Hironobu Yamamichi received B.E and M.E in Applied Chemistry and Chemical Engineering degree from Waseda University. After graduation, he has been working for AGC Inc. in production, process development and technology planning filed at in-house Glass company and Yokohama Technical Center of AGC Inc.

Ichiro Sakata

Ichiro Sakata received B.E and M.E degrees in applied Chemistry from Tokyo University of Science. He has been working for AGC Inc. after graduation from university and now engaged in improvement of Glass manufacturing job with IT technology at Yokohama Technical Center of AGC Inc.

Makoto Imamura

Makoto Imamura received B.S. and M.E. degrees in Applied Mathematics and Physics from Kyoto University and a Ph.D. in Information Science and Technology from Osaka University. After working for Mitsubishi Electric Corp., he became a full professor at Tokai University in April 2016. His research interests include time series analysis, data mining, and PHM. He is a member of IEEE and ACM.