Domain Knowledge-Based Automatic Voltage Determination System for Welding Machine

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***Abstract*—In the manufacturing industry, quality degradation due to a decrease in skilled operators possessing domain knowledge has become a problem. Digitalization using IoT technology has emerged as a means to tackle this problem. In the resistance welding process, welding quality fluctuates depending on aging of electrodes. Experienced operators adjust the welding voltage to keep the quality constant. As this knowledge is difficult to share, the success rate of voltage changes at the time of quality degradation tends not to be improved. Therefore, we developed an automatic voltage determination system that improves both quality and productivity by improving the success rate, which is one of the main measures. The system learns past sensor data and voltage change logs, determines the voltage according to input real-time sensor data, and sets the voltage for the welding machine. We propose three voltage determination methods: a similarity search method, a voltage prediction method using a regression model that outputs voltage, and a quality prediction and voltage search method that searches for the optimum voltage in a classification model to predict the success or failure of voltage changes. Our evaluation of these methods shows that the success rate improves by up to 12.4 percentage points compared to when the operators performed the process manually. This result demonstrates that we can achieve quality stabilization and productivity improvement by implementing our system in the welding process.**

***Index Terms*—Machine learning, manufacturing quality improvement, factory automation**

I. Introduction

In the manufacturing industry, digitization using Internet of Things (IoT) technology has been increasingly promoted with the aim of improving profitability. Digitization can be applied to a wide range of applications [1] including those for product design process improvement, yield management [2], predictive maintenance [3], root cause analysis [4], manufacturing processes improvement [5], infrastructure improvement, and sales forecasting. An automobile manufacturer recently developed a system that displays the availability of equipment and the manufacturing lead time for each product type by extracting events related to manufacturing status from data related to products, equipment, and operators [6]. Another study has reported a system that analyzes IoT data obtained from manufacturing equipment and maintenance records and provides the appropriate maintenance information to operators, managers, and technicians according to the state when an equipment abnormality occurs [7].

The resistance welding process, which is the target of the present study, is also the focus of research on quality improvement through digitization. Various data related to welding machines are collected and used to establish optimal manufacturing conditions, analyze the causes of defects, and monitor products and equipment during manufacturing. However, since the manufacturing conditions and monitoring items that emerge after analyzing the data and domain knowledge are complicated, operators need to make judgments based on their own knowledge and experience when utilizing them. For example, when the weld quality fluctuates due to aging of electrodes and condition of the product, experienced operators adjust the welding voltage to keep the quality constant. It is particularly difficult to share the knowledge and experience of operators when it comes to quality improvement measures, and as a result the overall success rate of the measures does not improve.

In the current study, we have developed an automatic voltage determination system that improves both quality and productivity by improving the success rate of voltage changes, which is one of the measures taken by the operators when quality deteriorates. Our system learns past sensor data and voltage change logs, determines the voltage on the basis of the input real-time sensor data, and then sets the voltage for the welding machine.

Methods for achieving quality prediction and automatic control of equipment include case-based reasoning methods and machine learning methods. Case-based reasoning was used in fault diagnosis of industrial equipment [8] and flow prediction of sewage treatment plants [9]. A steel industry company developed an intelligent optimization control system for the laminar cooling process [10]. At the same time, the use of machine learning in the manufacturing industry is advancing [11]. One study has reported regression models for the cutting parameter prediction of which parameters have the greatest influence on tool life, quality of surface, and control of machining costs in high-speed turning processes [12]. In the predictive maintenance of

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industrial machines, Auto Regressive Integrated Moving Average (ARIMA) forecasting on the time-series data collected from various sensors has been utilized to predict the possible failures and quality defects, thus improving the overall manufacturing process [13]. In the context of a rolling mill case study, in-line quality prediction systems have been developed to predict the physical quality of intermediate products in interrelated manufacturing processes [14]. Another study has reported a reinforcement learning approach to control the main printing parameters online in printed circuit boards [15]. In addition, a method that combines case-based reasoning and machine learning was reported in a fast-milling process [16].

Other methods include automatic control using mathematical models [17] and a combination of mathematical models and case-based ones used in the steel industry [18].

We propose three voltage determination methods: a similarity search, a voltage prediction method using a regression model that outputs voltage, and a quality prediction and voltage search method that searches for the optimum voltage in a classification model to predict the quality after voltage change. The similarity search method is an application of the case-based reasoning method that associates a case created by dividing the input space of the explanatory variables with the objective variable in the learning phase, and then estimates the objective variable using the information of the case to which the input value belongs and the cases around it in the prediction phase [9]. The voltage prediction method is an application of a machine learning method that implements regression models to predict the withdrawal force of a crimped connection in ultrasonic crimping [19]. The quality prediction and voltage search method, which is our original design, is also an application of a machine learning method. This method generates a quality prediction model (as in [19], [20]) and uses it to search for the optimum voltage.

After evaluating the three methods, we found that the quality prediction and voltage search method had the highest performance. This result demonstrates that it is possible to achieve quality stabilization by implementing the automatic voltage change in the welding process.

In Section II, we briefly describe the background and current challenges. Our automatic voltage determination system is explained in Section III. In Section IV, we report the evaluation results of the voltage change methods. We conclude in Section V with a brief summary and mention of future work.

II. Background and Challenges

A. Background

Quality degradation due to a decrease in skilled operators possessing domain knowledge has become a problem in the manufacturing industry. Digitalization using IoT technology has recently emerged to tackle this problem, where the aim is to reduce the reliance on individual domain knowledge by collecting, analyzing, and visualizing data from products and devices. The target process of this research uses an automatic welding machine. When the quality deteriorates, the operators need to decide which countermeasures to implement on the basis of their own knowledge and experience. In this paper, we report our efforts to improve quality by automating the implementation of countermeasures in this process.

Yield is typically used as a quality evaluation KPI, as its reduction effect is directly linked to cost reduction, but it is not possible to measure short-term quality without defects. Therefore, we utilize a process capability index, which represents the ability to produce a product within a defined standard, as a short-term quality KPI that includes a defect period. There are many different types of capability indices, but we use Cpk to estimate what the process can produce, considering that the process mean may not be centered between the specification limits. (1) shows the formula for calculating Cpk where the upper and lower specification limits are USL and LSL, and the mean and standard deviation of the measured values are μ and σ.

$$\mathrm{Cpk} = \min\left[\frac{\mathrm{USL}-\mu}{3\sigma},\ \frac{\mu-\mathrm{LSL}}{3\sigma}\right] \tag{1}$$

B. Challenges

The judgment of which countermeasures to implement when quality deteriorates tends to vary, and because the judgment depends on the operator’s domain knowledge, the quality does not always necessarily improve. Failure of countermeasures reduces not only quality but also productivity, as equipment downtime increases when the number of countermeasures increases. In this research, we propose a system that automates voltage changes as a countermeasure against quality deterioration. There are three reasons for focusing on the voltage change: (i) it has the highest number of implementations, (ii) full automation is possible because parts replacement is not required, and (iii) difficulty is high because it is necessary to determine the changed voltage value as well as the implementation decision. At present, the success rate of voltage changes is only 74.4%. We interviewed several operators to investigate why this is so and found that they sometimes took measures they were not sure would succeed, or did not take measures even when the quality deteriorated.

Our system makes it possible to change the voltage without relying on the knowledge and experience of the operators, and it can achieve a higher success rate than the operators can. There are three requirements when it comes to the voltage change determination method:

1) High success rate
2) High availability under various conditions
3) Highly acceptability in the field

III. Proposed Automatic Voltage Determination System

A. System Architecture and Preprocessing

Fig. 1 shows an overview of the automatic voltage determination system. The system obtains the sensor data from the welding machine, determines the voltage value that will improve the quality, and sets the voltage value. Operators can view the sensor data and work recommendation on a tablet and record the action logs. The system learns past sensor data and voltage change logs to determine the voltage. The obtained sensor data consists of one record for each weld shot, including voltage, current, pressure, and thickness before and after welding.

The preparation process of the training data is as follows. First, the voltage change time is obtained from the voltage change log. Then, the sensor data of 20 records before and 20 records after the voltage change (about two minutes) is extracted. Finally, the feature values shown in Table I are created from the extracted sensor data.

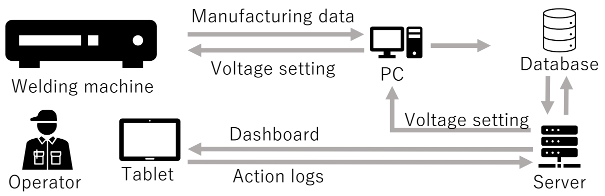

Fig. 1. Overview of automatic voltage determination system.

TABLE I: LIST OF FEATURES

Symbol	Parameter	Section	Aggregation method
$\bar{V}_b$	Voltage	Before	Average
$\bar{T}$	Thickness	Before	Average
T_{SD}	Thickness	Before	Standard deviation
C_b	Cpk of thickness	Before	Formula (1)
$\bar{V}_a$	Voltage	After	Average
C_a	Cpk of thickness	After	Formula (1)
$\bar{V}_D$	Voltage	Diff	$\bar{V}_a - \bar{V}_b$
C_D	Cpk	Diff	C_a–C_b
L	Label	–	if C_D>0 then 1 else 0

B. Similarity Search Method

Fig. 2 shows the process flow of the similarity search method (SSM) that searches the training data each time without creating a model to determine the voltage.

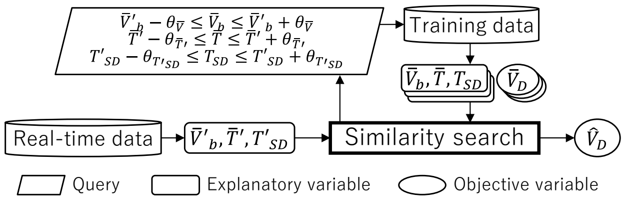

Fig. 2. Workflow of similarity search method.

First, this method calculates the feature values $\bar{V}'$, $\bar{T}'$, T'_{SD} corresponding to the train data $\bar{V}_b$, $\bar{T}$, T_{SD} from the sensor data of the last 20 records, and then extracts the train data $\bar{V}_b$, $\bar{T}$, T_{SD} similar to the last feature values $\bar{V}'_b$, $\bar{T}'$, T'_{SD}. The conditions of similar search are $\bar{V}'_b \pm \theta_{\bar{V}'}$, $\bar{T}' \pm \theta_{\bar{T}'}$, and $T'_{SD} \pm \theta_{T'_{SD}}$, where the thresholds of $\bar{V}'_b$, $\bar{T}'$, T'_{SD} are $\theta_{\bar{V}'}$, $\theta_{\bar{T}'}$, $\theta_{T'_{SD}}$, respectively. If there is no similar data, the method assumes that voltage change is necessary and does not output anything. Next, the method calculates the success rate S of the voltage change, which is the percentage of cases where the process capability increased for every V of all cases from the extraction result. The method calculates, for each $\bar{V}_D$, the success rate of the voltage change, which is the ratio of cases in which Cpk has increased (L=1) to the total cases from the extraction results. We defined the success rate as 51% if the result count of similar search is less than 2, due to low reliability. Finally, $\bar{V}_D$ with the highest success rate and 50% or more is determined as the voltage change value $\hat{V}_D$.

The thresholds of similar search $\theta_{\bar{V}'}$, $\theta_{\bar{T}'}$, $\theta_{T'_{SD}}$ are optimized using Optuna [21]. In the optimization, 2-fold cross-validation is performed, and the score to maximize is shown in (2), which is calculated from the success rate S, output rate O, and weight β (in this report, β=0.5).

$$\text{Score} = \frac{\left(1+\beta^2\right)SO}{\beta^2 S + O} \tag{2}$$

Since the system output voltage and the voltage change log are often related to different cases, the success rate is considered the same case if the difference between these voltages is within 0.02. The output rate is the ratio of outputting voltages in the case of low quality (Cpk<1.1).

C. Voltage Prediction Method

Fig. 3 shows the process flow of the voltage prediction method (VPM) using a regression model that outputs voltage. In the training phase, this method extracts the data that is L=1 from the train data and then uses a tree-based regression algorithm such as Random Forest [22] (VPM-RF) or XGBoost [23] (VPM-XG) to create a regression model with $\bar{V}_D$ as the explanatory variable and $\bar{V}_b$, $\bar{T}$, T_{SD} as the objective variables. The hyper-parameters of each model are optimized using Optuna to minimize the mean squared error with 2-fold cross-validation.

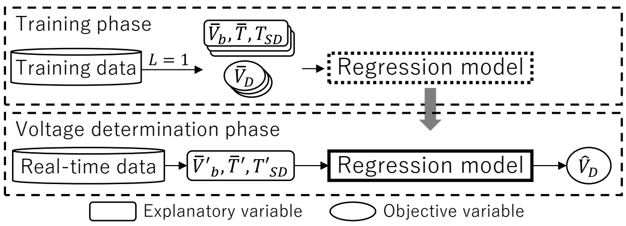

Fig. 3. Workflow of voltage prediction method.

In the voltage determination phase, the method inputs the feature values $\bar{V}'_b$, $\bar{T}'$, T'_{SD} created from the sensor data of the last 20 records into the model and determines the output $\hat{V}_D$ as the voltage change value. Note that $\hat{V}_D$=1 is treated as no voltage change, and the method outputs nothing.

D. Quality Prediction and Voltage Search Method

Fig. 4 shows the process flow of the quality prediction and voltage search method (QPM) that searches for the optimum voltage in a classification model to predict quality after voltage change. In the training phase, this method uses Random Forest (QPM-RF) or XGBoost (QPM-XG) to create a classification model with $\bar{T}$, T_{SD}, $\bar{V}_D$ as the explanatory variables and L as the objective variable. The hyperparameters are optimized using Optuna with 2-fold cross validation. Since the model needs to be able to predict the quality due to the differences in V, the importance of V is added to the score in addition to the accuracy rate. Specifically, the score to maximize is $A+I_V/10$, where the accuracy is A and the importance of $\bar{V}_D$ is I_V.

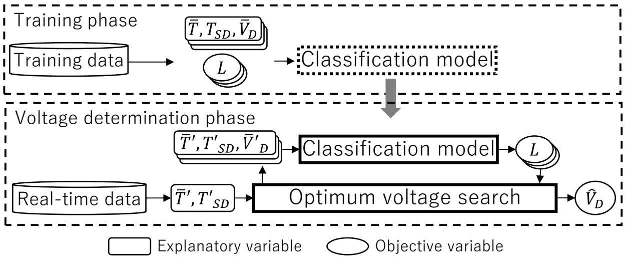

Fig. 4. Workflow of quality prediction and voltage search method.

In the voltage determination phase, the method first inputs the feature values $\bar{T}'$, $\bar{T}'_{SD}$ created from the sensor data of the last 20 records to the optimum voltage search process, which is shown in (3).

$$\hat{V}_D = \min \left| \underset{-0.02 \le v \le 0.02}{\arg\max} f\left(\bar{T}, T_{SD}, v\right) \right| \tag{3}$$

The classification model f outputs a classification probability regarding whether the quality can be improved by changing the voltage. f receives values in the range of –0.02 to 0.02 every 0.01 as a voltage candidate $\bar{V}'_D$ and then determines a voltage change value $\hat{V}_D$ with the smallest absolute value among the $\bar{V}'_D$ having the highest classification probability. Note that $\hat{V}_D$ =0 is treated as no voltage change, and the method outputs nothing. The reason for selecting $\hat{V}_D$ =0 with the smallest absolute value is that it is better to minimize the changes to the welding machine if the same quality improvement effect can be obtained.

IV. Evaluation

A. Evaluation Conditions

We evaluated our voltage change method using the actual sensor data and voltage change log collected from a welding machine in an automobile parts factory.

Table II shows an overview of the evaluation data created by the method described in Section III-A. This data covers a period of about four years, during which 3750 cases of voltage change were executed and 2791 of them improved the quality. The success rate before introducing our system was 74.4%. We divided this evaluation data into 2000 cases for training and 1750 cases for test while maintaining the success rate. Furthermore, in order to evaluate the relationship between the number of train data and the performance, we created 16 patterns of train data by changing the data number from 500 to 2000 in increments of 100.

TABLE II: Evaluation Conditions

Content	Description
Data period	4 years (2016–2019)
No. of records (train/test)	3750 (2000/1750)
No. of success cases (train/test)	2791 (1489/1302)
Success rate	74.4%

Three evaluation scores are used: success rate, coverage rate, and output rate. The higher these scores, the better. The success rate is the ratio of cases where Cpk is improved when the difference between the system output and the voltage change log is within ±0.02.

Although the success rate can tell us the accuracy of the voltage determination method, it can be high even if the system outputs nothing, so the success rate alone is not sufficient for our evaluation. Coverage rate and output rate are therefore used as indices for evaluating the rate at which the system can determine the voltage.

The coverage rate is the ratio of the successful cases extracted when the success rate is calculated to the total successful cases of the test data, and it represents how much the successful cases by the operators are covered.

The output rate is the rate of outputting some voltage when the quality is low (C_b<1.1).

The drawback of the coverage rate is that it is not possible to evaluate when the output voltage is different from that of the operators. In contrast, the drawback of the output rate is that the result of voltage change due to the output voltage cannot be evaluated. In this evaluation, both scores are used to make up for each defect.

B. Evaluation Results

Fig. 5 shows the success rate, coverage rate, and output rate scores for 18 patterns of train data. Compared to the operators' result (77.4%), the success rate for SSM, VPM-RF, and VPM-XG only improved by a few percentage points, but the success rate for QPM-RF and QPM-XG improved by about 10 percentage points. Moreover, Random Forest had a better success rate than XGBoost in both VPM and QPM. The coverage rates of QPM-RF and QPM-XG were about twice those of SSM, VPM-RF, and VPM-XG. The output rates of SSM, QPM-RF, and QPM-XG were around 96–99%, and the output rates of VPM-RF and VPM-XG were almost always 100% except for outliers.

Table III lists the cases where the success rate was highest in each method among the results shown in Fig. 5. Compared to the operators' result (77.4%), the success rate improved by 5.1 percentage points for SSM, 5.9 percentage points for VPM-RF, and 12.4 percentage points for QPM-RF. In these cases, the coverage rate of QPM-RF was about twice that of SSM and VPM-RF, and the output rates were all similar.

TABLE III: Results for Cases with the Highest Success Rate

Method	Success rate	Coverage rate	Output rate
QPM-RF	86.8%	27.8%	100%
QPM-XG	85.3%	28.4%	100%
VPM-RF	80.3%	60.0%	95.9%
VPM-XG	79.9%	60.0%	97.9%
SSM	79.5%	29.8%	97.5%

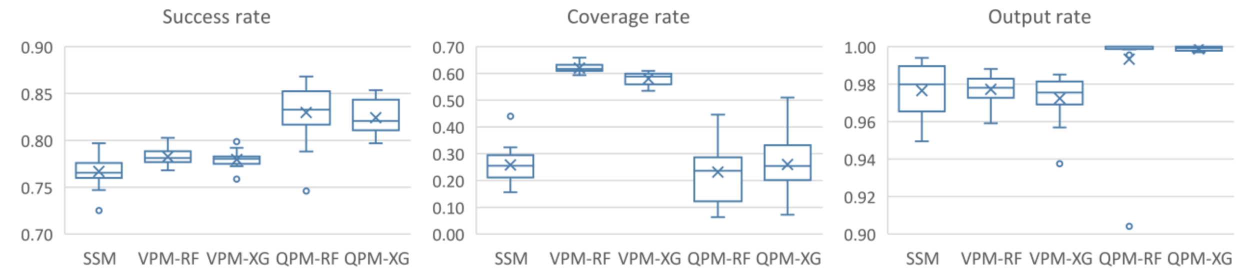

Fig. 5. Score for each method.

C. Discussion

SSM had a low success rate, coverage rate, and output rate, but it is highly explainable in the field because it outputs the past voltage changes of the operators.

VPM had a high coverage rate and could make voltage decisions that were similar to successful cases by operators. This suggests that VPM can determine the voltage without considering the failure cases, as the training data contains only success cases.

On the other hand, it seems that QPM improved the success rate by making different voltage determinations than operators, as indicated by its high success rate and output rate, and low coverage rate. One reason for this may be that QPM uses the train data only for quality prediction, not for optimal voltage search. However, this evaluation only clarified that the success rate is high when the voltage is close to the operators' result, while in reality, there are many voltages different from the operators'. Therefore, additional evaluations in the field are required to determine whether the success rate can be improved when the system makes a different voltage decision from the operators.

From the above results, we conclude that QPM-RF should be used to achieve a higher success rate, and VPM-RF should be used to achieve automated voltage change that is close to the operators'. However, a highly explanatory SSM was adopted at the actual site we examined because operators valued reliability over improving the success rate. In the future, in order to apply QPM and VPM, which have a high success rate improvement effect, it will be necessary to improve their explainability.

V. Conclusion

In this research, we developed an automatic voltage determination system to improve both quality and productivity by improving the success rate. The system learns past sensor data and voltage change logs, determines the voltage as input real-time sensor data, and sets the voltage value for the welding machine. We proposed three voltage determination methods: a similarity search method (SSM), a voltage prediction method (VPM) using a regression model that outputs voltage, and a quality prediction and voltage search method (QPM) that searches for the optimum voltage in a classification model to predict the success or failure of the voltage changes. Evaluation results showed that the success rate was improved by 5.1 percentage points for SSM, 5.9 percentage points for VPM, and 12.4 percentage points for QPM compared to the operators' result. Therefore, QPM should be used to achieve a higher success rate, and VPM should be used to achieve automated voltage change that is close to the operators' voltage change. These results demonstrate that it is possible to achieve quality stabilization by implementing the automatic voltage change in the welding process.

However, a highly explanatory SSM was adopted at the actual site because the reliability of the system was emphasized by the operators there. For future work, we will improve the explainability of the system so that it can achieve high acceptability. After that, we will deploy this system to other processes and factories.

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

Masakazu Takahashi conducted the research, evaluated the methods, and wrote the paper; Takuro Yasui analyzed the data and developed the system; and Keiro Muro supervised the research and reviewed the paper; all authors had approved the final version.

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