State Monitoring System of Robot Welding Gun Based on ART2 Neural Networks

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Abstract: In this paper, we propose an aging state monitoring system for robotic welding gun using ART2 NN (adaptive resonance theory 2 neural network) with uneven vigilance parameters and inspection equipment data. In this method, the inspection equipment data used for diagnosis of robotic welding gun *via* ART2 NN modules. The Graphical User Interface (GUI) program by LabVIEW designed for convenient operation of the monitoring system. We also carried out the computer simulation to confirm the suitability of the proposed monitoring system.

Keywords: Robotic welding gun, inspection data, state monitoring system, ART2 neural network, GUI.

1. INTRODUCTION

AWIS (Auto Welder Inspection System) is welding facility comprehensive diagnosis system that collectively refers to the inspection of facility, data acquisition through server, and monitoring by the manager program. It is a device that automatically inspects the actual welding conditions (Current, Pressure, Straightness, Tip Dressing state) used in the process. It is also applied to increase the productivity and operation rate, reliability in contrast to manual check / inspection item and to shorten analysis time. Until now, the tip dressing check of the welding robot's welding GUN (TIP), after ATD (Auto Tip Dresser) 20 times, the tip replaced. However, in order to improve the efficiency and productivity of the welding process, it is absolutely required to develop a fault diagnosis system that automatically predicts the state of the welding gun of the welding robot or diagnoses the fault so that the replacement timing and repair can be performed appropriately.

So far, many studies have been done to solve the system fault detection, isolation, and compensation problems. Fault detection and isolation (FDI) methods can be divided into model-based methods and model-free (or nonparametric) approaches [1]. In recent years, neural network (NN) models have been studied to address FDI problems [2-7]. Some advantages in employing a NN model for fault diagnosis applications include the fact that the system can be efficiently approximated by nonlinear functions and adaptive learning and parallel processing can update the system parameters. It has been noted that the NN models have a suitable structure that can generally represent unknown nonlinear functions. Therefore, NNs can be used as a powerful tool for handling nonlinear problems. However, these methods find difficulty to isolate new faults.

In order to overcome this problem, Srinivasan *et al.* [8] proposed an FDI algorithm using the Hopfield and ART1 NN protocols. In this method, the algorithm is divided into three main parts: an estimation of the system parameters, fault detection, and fault isolation using the ART1 NN. However, the ART1 NN is utilized to classify binary patterns only. Therefore, the ART2 NN, which uses adaptive resonance theory 2, is more suitable for fault isolation classification because the estimated parameters employ analog patterns.

In this study, we developed a fault diagnosis algorithm using ART2 NN that can predict the degree of aging or failure of welded GUN of welding robots based on current and pressurized data measured by AWIS welding equipment inspection system as shown in Figure **1** and Figure **2**. We also made the fault diagnosis software for robot welding gun monitoring. The Graphical User Interface (GUI) program by LabVIEW has also been designed for more intuitive and convenient operation of the system.

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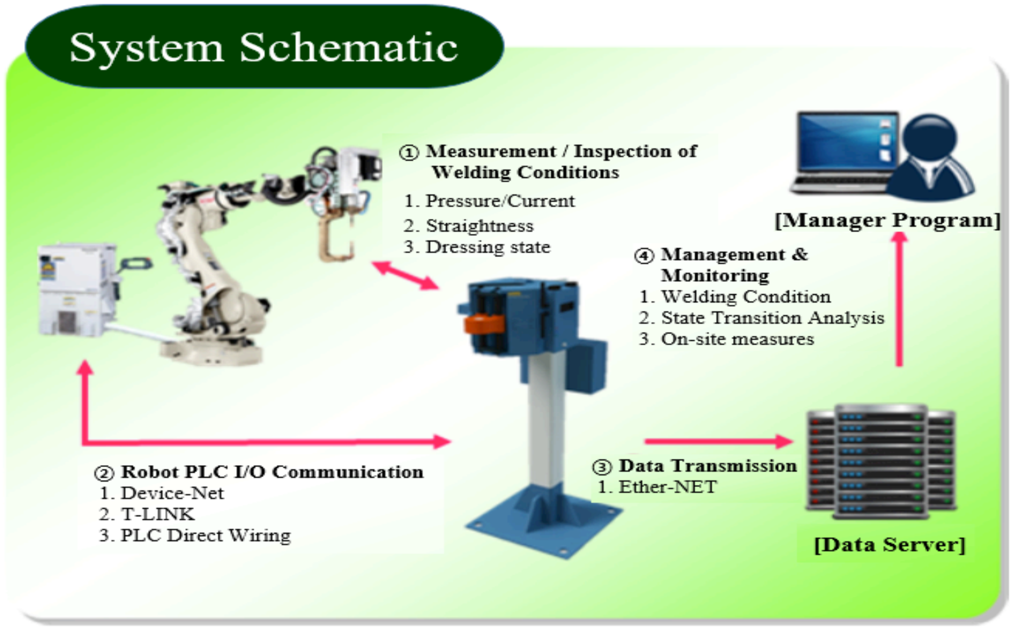


Figure 1: AWIS Schematic.

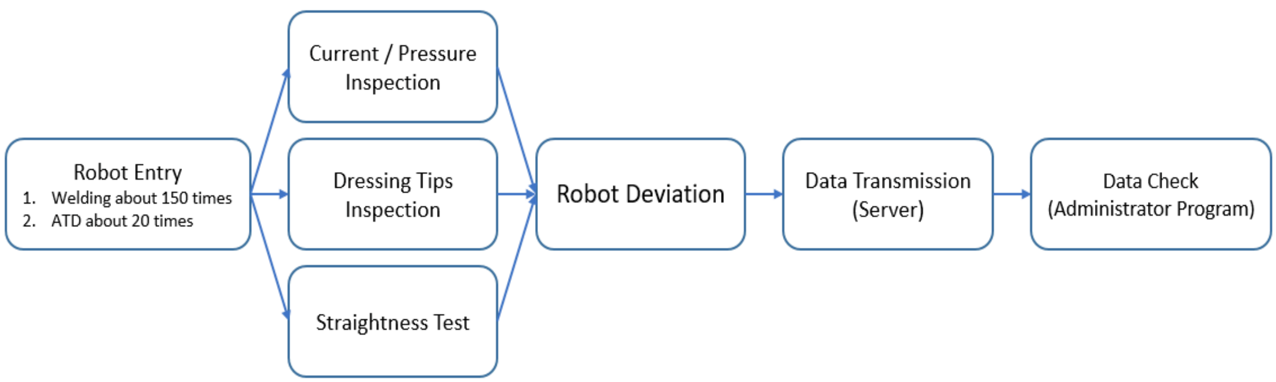


Figure 2: AWIS Operation Process.

The remainder of this paper is organized as follows: in the next section, we present the monitoring system using the ART2 NN. In Section 3, the simulation results are discussed to demonstrate the performance of the proposed state monitoring method. The last section provides concluding remarks.

2. PROPOSED ROBOT WELDING GUN MONITORING METHOD

2.1. Monitoring System Based on ART2 Neural Network

The proposed robot welding gun aging monitoring system as shown in Figure **3**, the current flow and current flow time measured by the welding inspection device are used as inputs to the ART2 NN to implement the welding robot welding gun-aging diagnosis. That is, the current flow and the current flow time are used for input of ART2 NN modules 1 and 2, respectively. Moreover, the state of the welding gun will be divided into three states of normal, attention and warning. For this purpose, the standards for judging the degree of inspection and aging of robot welding guns are shown Table **1**.

2.2. ART2 Neural Network

In this research, we use the ART2 NN with various boundary arguments [9] to compensate the

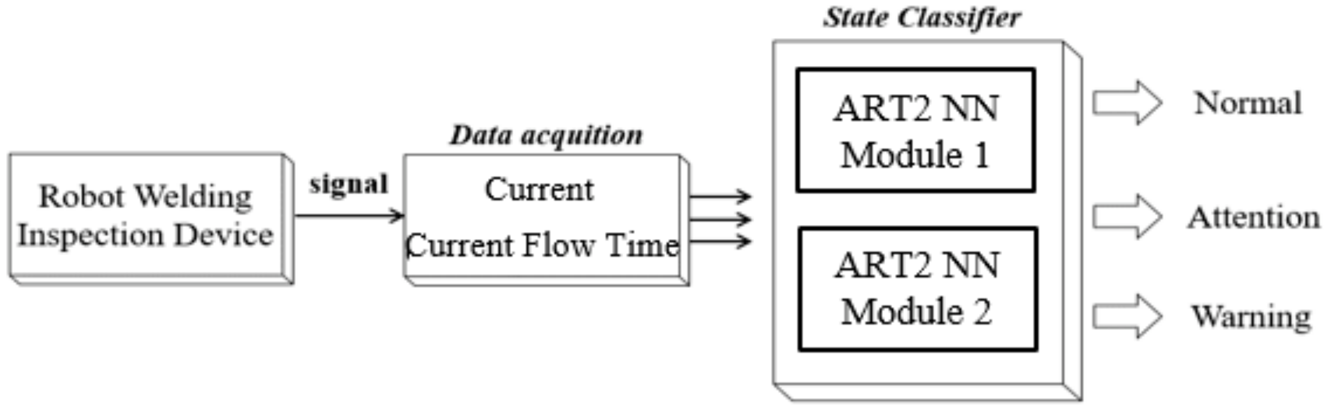


Figure 3: The proposed robot welding gun monitoring system.

Table 1: Robot Welding Gun Standard Specification for Inspection

Management Range and Reference Value of customer					
Item	**Attention**	**Warning**	**A Company**	**B Company**	**C Company**
Current (A)	± 3%	± 5%	9,000	8,000	9,000
Current Flow Time (ms)	± 4%	± 8%	250	250	250

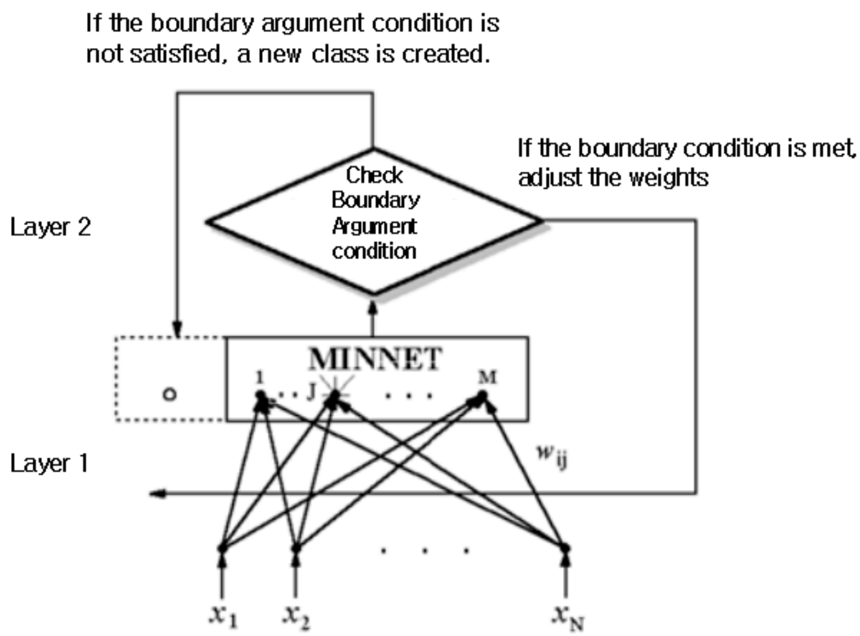


Figure 4: Structure of the ART2 NN.

disadvantages of the conventional ART2 NN [10] as shown in Figure **4.**

When the first input pattern is transferred to the ART2 NN, the input pattern is classified as the first class and the input pattern is stored as the weight between the first output node and the input nodes. When a new input pattern is transmitted to the neural network, the distance between the input pattern and each output node is calculated as follows:

$$d_j = \| W_j - X \|_\infty^E \triangleq \max_i \left| \frac{1}{\varepsilon_i}(w_{ij} - x_i) \right|, \quad j = 1, 2, \cdots, M \tag{1}$$

where w_j and w_{ij} is the weight vector for the j[th] output node, and the weight between the i[th] input node and the j[th] output node, X and x_i respectively, are the N input vector and the i[th] input, and $\|\bullet\|_{\infty}^{B}$ is the weighted infinite norm, ε_i is the boundary argument for the input pattern of i[th] input.

The similarity of the input pattern with the output node with the minimum distance calculated by Eq. (1) is determined through the following boundary argument condition test,

Boundary test condition: $\|W_J - X\|_{\infty}^{E} \quad < \quad 1$ (2)

If the input pattern passes the boundary argument test, it learns the same class as follows:

$$W_J^{new} = \frac{X + W_J^{old}\,[class_J^{old}]}{[class_J^{old}] + 1} \tag{3}$$

where $[class_i]$ is the number of the patterns in class i. On the other hand, if class J fails the boundary argument test, a new class is created with weight $W_{M+1} = X$.

2.3. GUI Program of the State Monitoring System

A GUI (graphical user interface) program of the proposed monitoring system for robot welding gun is shown in Figure **5**, and is achieved by the GUI program of Lab View. The Lab View connects the multiple functions by wire. Compared to the other languages, the designed image based on the graphical programming language is more intuitional and the programming is faster.

3. Simulation Results

In order to verify the performance of the proposed robot welding gun-monitoring system, computer simulation was performed using experiment data. The data were obtained from the comprehensive diagnosis system for robot welding equipment operated by Ajin Industry Co., Ltd. as shown in Figure **6** and the condition of the welding gun was tested using the current, the pressing force, and the current flow time as the inputs of the ART2 NN module 1, 2 and 3, respectively. The input of three ART2 NN modules are all five, and the boundary factors of ART2 NN module 1 and module 2 for diagnosis are set to $\varepsilon = [320 \quad 320 \quad 320 \quad 320 \quad 320 \quad 320 \quad 320 \quad 320 \quad 320 \quad 320]$

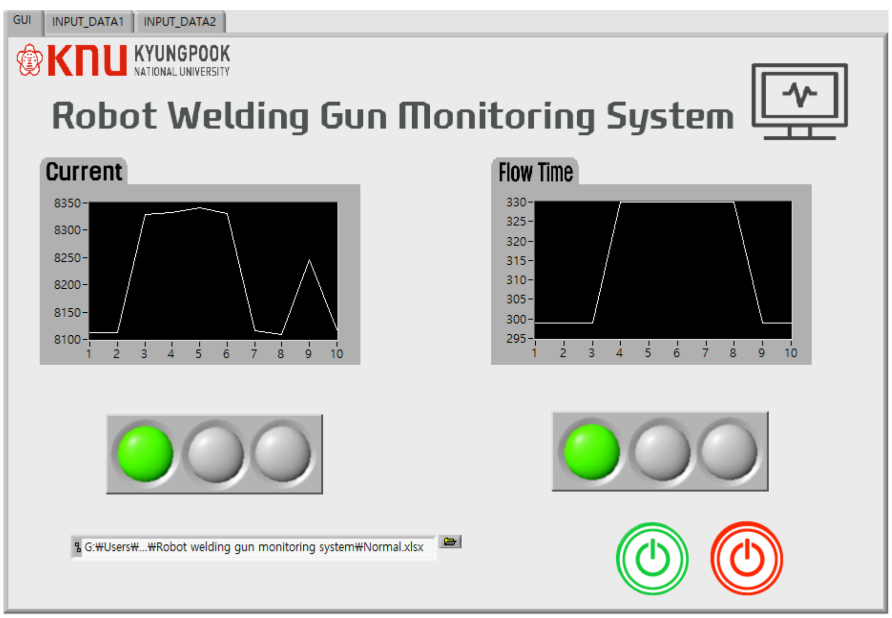


Figure 5: GUI program for robot welding gun monitoring.

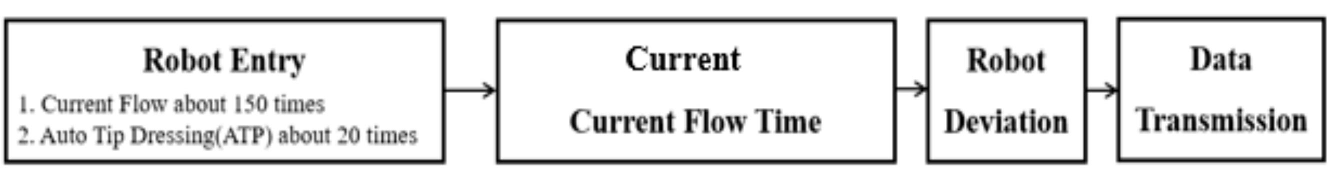
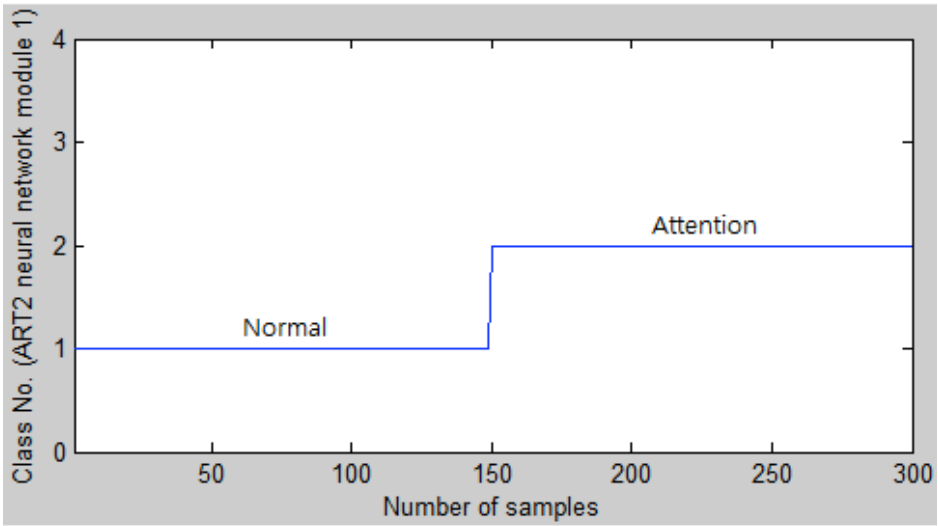


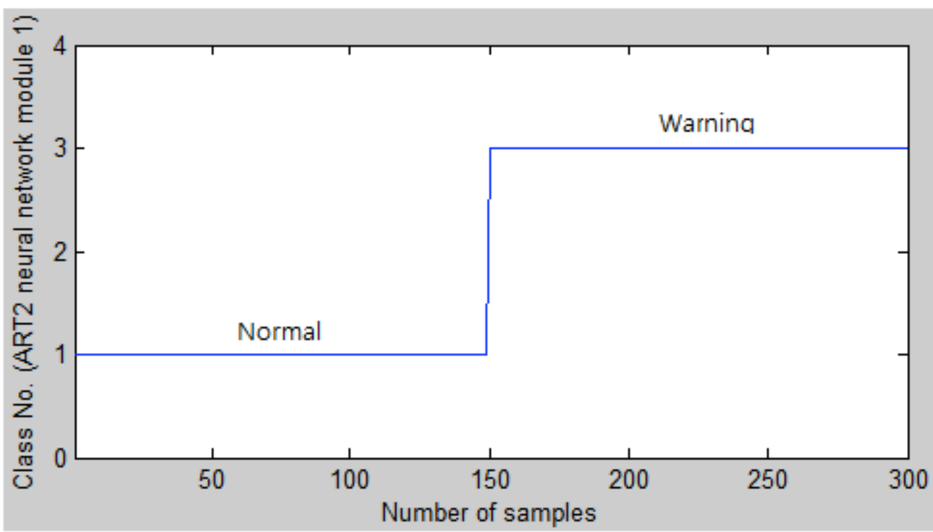
Figure 6: Obtain data for monitoring of welding guns.

Table 2: Current Flow Measurements

Welding Gun State	Current(A)
Normal	8112 8113 8329 8332 8342 8330 8116 8109 8247 8117
Attention	8610 8612 8750 8740 8735 8755 8613 8611 8735 8655
Warning	9020 9022 9150 9140 9133 9148 9011 9007 9132 9077



(a) Attention State



(b) Warning State

Figure 7: Monitoring result of welding gun condition according to current amount.

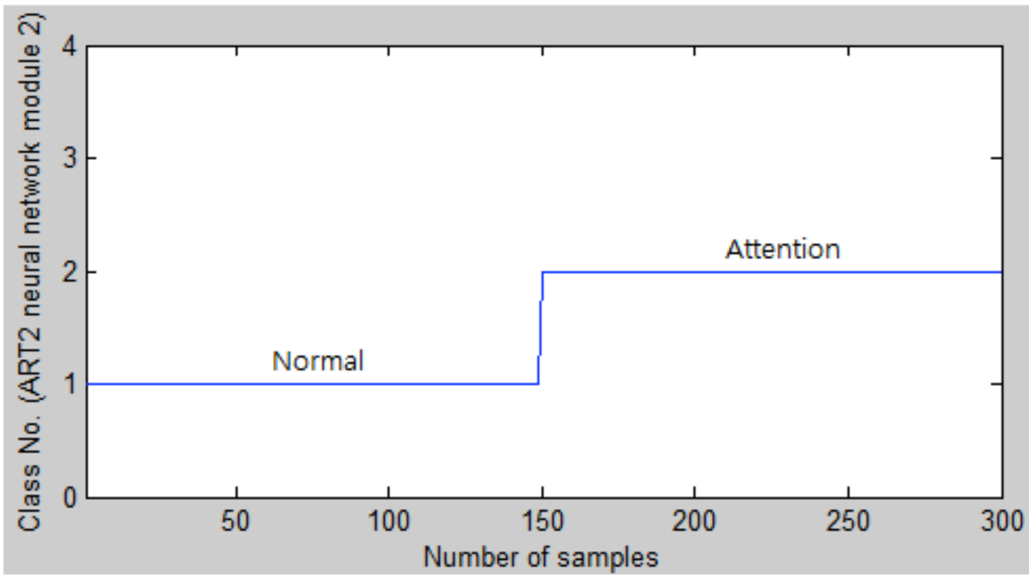
and $\varepsilon = [15 \quad 15 \quad 15 \quad 15 \quad 15 \quad 15 \quad 15 \quad 15 \quad 15 \quad 15]$, respectively.

Figure **7** shows the simulated results when the current was changed to the level of attention and warning at the 150th instant as shown in Table **2**. When the state changes from steady state to attentional state, the ART2 NN correctly classified as the class 2 state. In addition, in the case of the warning state, it shows that the ART2 NN successfully classifies as the class 3 warning state as shown in Figure **7**(**b**).

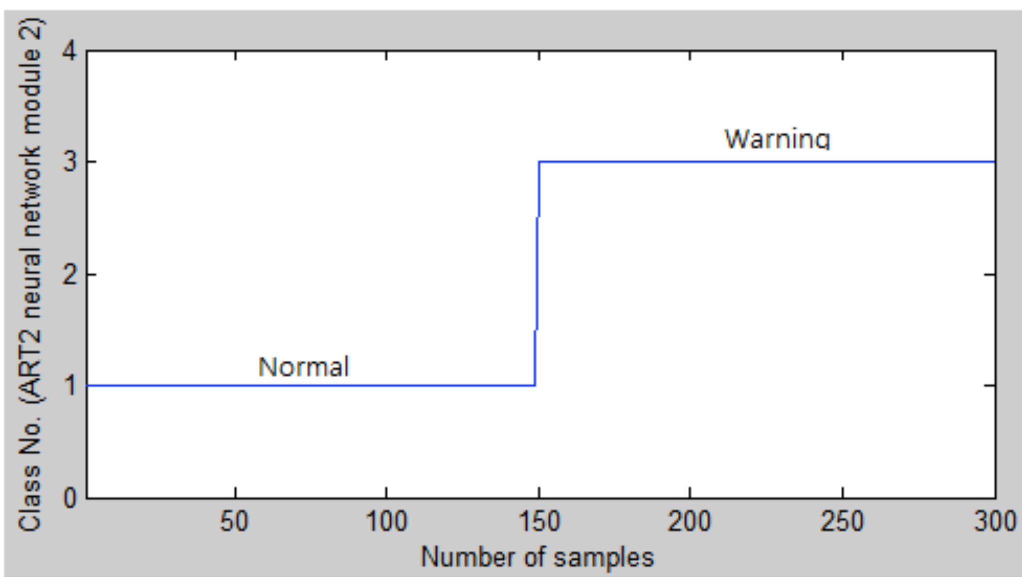
As shown in Figure **8**(**a**) and (**b**), when the current flow time is as shown in Table **3**, the ART2 NN based monitoring system proposed in this study accurately classifies the states of normal, attention and warning.

Table 3: Current Flow Time Measurements

Welding Gun State	Current Flow Time (ms)
Normal	299 299 299 330 330 330 330 330 299 299
Attention	317 318 318 318 318 318 318 318 318 318
Warning	335 336 337 335 335 335 335 335 335 335



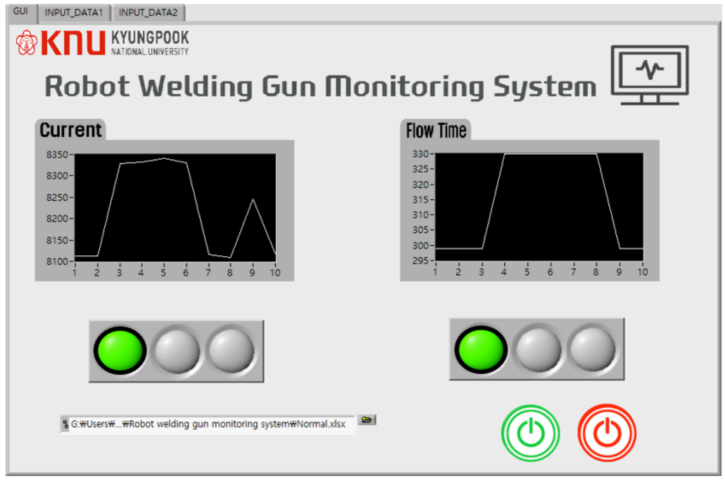
(a) Attention State



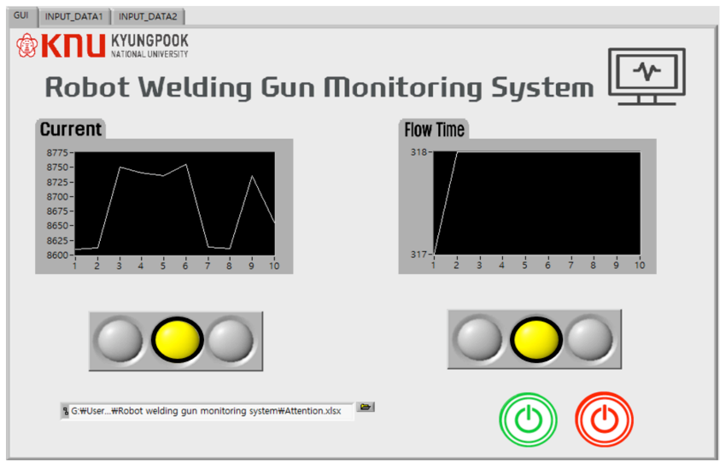
(b) Warning State

Figure 8: Monitoring result of welding gun condition according to current flow time.

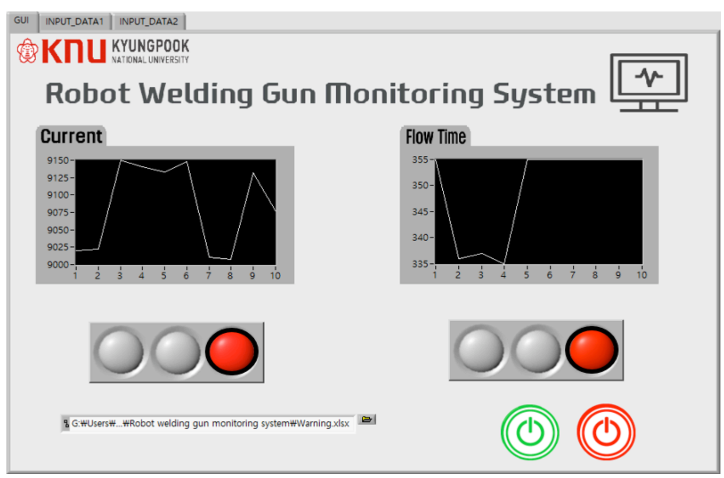
We also made the GUI (graphical user interface) program for robot welding gun monitoring based on Matlab and Lab View as shown in Figure **9**. Thereafter, a GUI program was applied to determine the state of the robot welding gun. If the system status is normal, the normal button indicator lights as shown in Figure **9** (**a**). In addition, if the status of the system is caution or warning, the caution or warning button indicator lights up respectively.



(a) Normal State



(b) Attention State



(c) Warning State

Figure 9: GUI program for robot welding gun monitoring.

CONCLUSION

In this paper, we proposed a diagnosis system for aging monitoring of robot welding guns using the ART2 neural networks. The proposed state monitoring system performed to diagnose the aging of the robot welder using three types of data such as current and current flow time that were measured by the welding equipment inspection system. The proposed state monitoring system consists of two ART2 neural network modules to determine the state of the welding gun. In this study, we also made the GUI program based on Matlab and Lab View for robot welding gun monitoring. From the simulation results, we know that the ART2 neural networks based state monitoring system has been successfully diagnosed the condition of the robot welding gun.

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