A Study on the Production Management System for Analyzing Operator Errors and Manufacturing Data in the Assembly Process

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***Abstract*—**This study adopts augmented reality, data analysis, and co-robot integration to develop and implement system integration technology for productivity improvement and quality management. The proposed system can help companies reduce work errors based on work information augmentation technology optimized for a field-work environment, manage work quality with alarms on assembly torque anomalies compared with upper and lower thresholds with actual torque data collection and presentation, and manage accumulated productivity by work stage and monthly unit time. With regular production process optimization for productivity increase and defect minimization, the system optimizes the manufacturing process for high-difficulty core components and improves productivity.

Keywords— smart factory; automation; relay selection; virtual reality; co-robot

I. Introduction

Recently, the sales of eco-friendly vehicles such as pure electric cars, hybrid cars, and hydrogen fuel cell electric cars have rapidly increased. Although automotive OEMs are currently operating low-volume production systems for hybrid cars, they are required to develop novel technologies that maximize the efficiency of workers and automation robots to achieve mass production of key components and improve product quality in preparation for future demands [1]. In smart manufacturing processes where data are generated in real time, a continuous data analysis helps validate data from production processes for any anomalies and improve the performance of the manufacturing process via prompt feedback. Machine learning-based big data analytics in manufacturing enables companies to analyze their manufacturing processes, identify the causes of defects, predict productivity, and potential equipment failures, which contributes to productivity management and defect reduction with minimum investment. Therefore, to analyze and identify errors in the work data of the production line for high-difficulty core components, advanced systems are required to proactively manage production quantity, defect rate, and inventory, by identifying incidents or process delays in the production processes. Such systems collect and analyze data on work errors from each production stage and worker to identify data-driven scenarios for improvement and prevention of work errors [2]-[5]. Here, a scenario is developed to collect and analyze the human worker data from a manufacturing facility called workbench and the process data from co-robots. The scenario lays the foundation for implementing systems for early detection and management of work errors (i.e., human errors from handling various parts and work stages) that cause product defects. This study focuses on implementing analytics systems that collect data from workers and co-robots in the industry processes and analyze them to prevent worker errors.

The remainder of this paper is structured as follows. Chapter II presents the proposed workbench data analysis and production management system. Chapter III presents experiments results, and Chapter VI summarizes this paper.

II. Proposed Workbench Data Analysis and Production Management System

This study analyzes the process flow covering the laser welding and vision in the engine assembly process of eco-friendly cars. As these processes are managed by an integrated system, metric data and abnormality thresholds from each of the process stages are compared for separate data collection and analysis for anomalies. The data generated from co-robots and PLCs associated with the automatic assembly process are integrated with a manufacturing execution system (MES) to implement the developed scenario. A learning system is designed to analyze worker's safety and anomalies in the assembly process. The Open Platform Communications Unified Architecture (OPC UA) as an industrial standard interface was used to integrate the data between processes. The smart workbench comprises a fastener, co-robot, and touch panel, and is connected to the production management system, providing work guidance and results via augmented reality (AR) or virtual reality (VR) glasses. To improve productivity, the assembly process is subdivided into several stages, and workers are provided with visual information from each stage, such as actual part locations, nut runner tightening information, and alarms when they put their hands in a wrong parts bin. Visualization of the production process via AR glasses is developed to intuitively present information based on the analysis of the historical process data to indicate any production stage where product defects or process delays are expected.

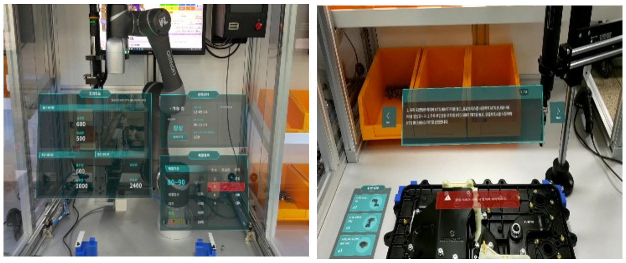

Fig. 1. Data management of the work process and visual alarms of defect alarm via AR

Considering the different stages of the process, similar tasks are categorized into stages to ensure consistency in assembly. For assembly processes which require identical bolts, the system is designed to utilize an automatic feeder, which enables workers and co-robots to pick up bolts and perform the assembly with the minimum amount of movement to minimize loss time in their collaboration. After each stage is completed, the transfer button and safety sensor are utilized to ensure safe operations of the robot and worker.

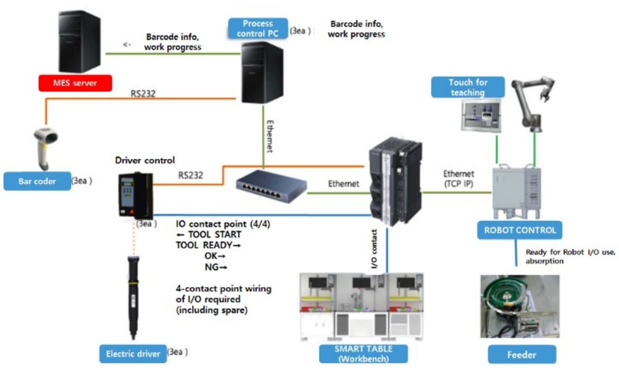

Fig. 2. Overall architecture of automatic assembly and equipment networking plan

When the worker initiates the assembly process by reading the barcode of a work item with the barcode reader at the workbench, the co-robot moves the work item to Stage 1 workbench and then to the next Stage 2 workbench after task completion. To integrate with various processes, the status data from the equipment and defect occurrence data from the MES are compared to verify the facility status.

When the work item is loaded onto jigs by the co-robot, information on the location of the item is displayed on AR glasses based on the work order and process. When the lamp attached to the assembly parts bin lights on, the worker takes the parts from the bin and performs the assembly work based on the torque information entered in the smart tool. If a work error occurs, an alarm signal is generated.

TABLE I. DEFINITION OF ERROR TYPES IN ASSEMBLY PROCESS

Error Type	**Description of Errors from Workers or Assembly Machine**
1	Duplicate assembly
2	Missing bolt or washer
3	Cross-threaded assembly
4	Defective machined parts and assemblies during assembly
5	Issue with torque and bolt rotation angle
6	Work stage sequence disregarded
7	Wear of cross head of fastening screw
8	No object for assembly

If the process order is not followed, a warning is displayed and it is impossible to proceed to the next step. For each work process, work instructions and work status information are visualized for the workers with intuitive and easy-to-understand UI.

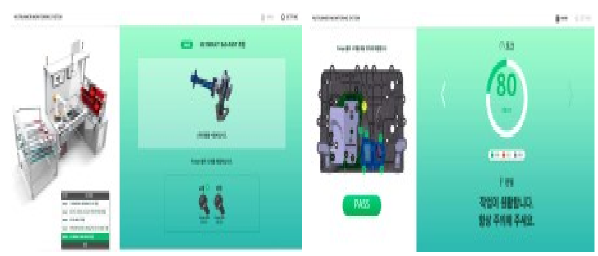

Fig. 3. UI design according to work scenario

Information on the assembly items and assembly parts is provided for each step of the item to be assembled, and the work error occurrence is determined based on the information on the assigned torque value and location for each work item when the nut runner performs the assembly tasks. To collect information on the types of errors made by workers, the historical work data of workers are stored in a database for each process via PLC communication. In the database, data types are categorized, and the success or failure of the work result is determined using the dynamic time warping (DTW) method. The DTW method is an algorithm adopted to measure the similarity between two time series with different speeds. It calculates the distance between each element in the two time series, considering possible differences in their timing, to determine the shortest distance between them. This allows the DTW method to determine the degree of similarity between time series. The productivity gain after the improvement can be measured by the difference in work time due to the removal of redundant operations (t_3–t_4), and the production volume per hour after the improvement can be calculated as $(3600/t_4)\times 2$.

III. EXPERIMENTS

The process data generated during the assembly process were validated by linking with the MES of the experiment company. Data integrity check was conducted by comparing the number of process data generated by the smart workbench and that of the actual process data processed in the MES.

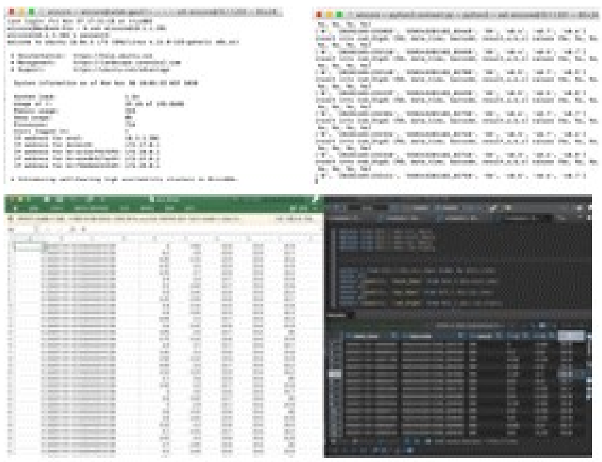

Fig. 4. Result of data integrity check between production management system and assembly workbench

In the existing process, it required 10 min per unit for one person to complete, while it required 4 mins and 10 s per unit when three workers worked together. After applying the developed system to the actual production process, the hourly productivity increased by 27%, from 5.5 units to 8 units based on the quantity of products produced per unit time. By applying the automatic assembly and fastening equipment, the error rate due to process anomalies based on torque values decreased, and the repetitive error rate of the assembly bolt position also decreased by more than 83%, from ±0.3mm to ±0.05mm.

IV. CONCLUSION

In the assembly process, workers and co-robots were assigned specific roles. To improve the overall efficiency, part arrangements were modified to minimize movement distance, and feeder/shooter type fastening machines were utilized to reduce the tack time for co-robot fastening.

For skilled workers, errors from loose or excessive fastening that caused wear and tear were more critical than human errors such as duplicate or cross-threaded fastening. The assembly torque values in the assembly machine or co-robot were detected in real time to minimize fastening errors, eventually improving productivity. Data from the automatic assembly were stored in the production management system, allowing for the construction of a data learning infrastructure that enabled diverse analyses and integration with other processes. This also laid the foundation for collecting and saving process data, which will enable companies to develop additional scenarios in the future via data integration. Furthermore, work process optimization was achieved by considering worker movement paths, co-robot operation ranges, and assembly error frequencies.

ACKNOWLEDGMENT

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