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Modeling of Predictive Maintenance Systems for Laser-Welders in Continuous Galvanizing Lines Based on Machine Learning with Welder Control Data

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Abstract: This study aimed to develop a predictive maintenance model using machine learning (ML) techniques to automatically detect equipment failures before line shutdowns due to equipment malfunctions, explicitly focusing on laser welders in the continuous galvanizing lines (CGLs) of a steel plant in Korea. The study selected an auto-encoder (AE) as a base model, which has the strength of applying normal data and a long short-term memory (LSTM) model for application to time series data, such as equipment operation data. Here, a laser welder predictive maintenance model (LW-PMM) based on the LSTM-AE algorithm was developed by combining the technical advantages of both algorithms. Approximately 1500 types of data were collected, and approximately 200 were selected through preprocessing. The training and testing datasets were split at a ratio of 8:2, and the model parameters were optimized using 10-fold cross-validation. The performance evaluation of the LW-PMM resulted in an accuracy rate of 97.3%, a precision rate of 79.8%, a recall rate of 100%, and an F1-score of 88.8%. The precision of 79.8% compared to the 100% recall value indicated that although the model predicted all failures in the equipment as failures, 20.2% of them were duplicate values, which can be interpreted as one of the five failure signals being not an actual failure. As a result of the application to an actual CGL operation site, equipment abnormalities were detected for the first time 27 h before failure, resulting in a reduction of 18 h compared with the existing process. This study is unique because it started as a proof of concept (POC) and was validated in a production setting as a pilot system for the predictive maintenance of laser welders. We expect this study to be expanded and applied to steel production processes, contributing to digital transformation and innovation in the steel industry.

Keywords: steel industry; predictive maintenance; laser-welder; continuous galvanizing line (CGL); machine learning; long short-term memory (LSTM); autoencoder (AE); LSTM-AE; digitalization

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1. Introduction

1.1. Background of Study

The fourth industrial revolution refers to technological innovations that cause significant societal, economic, and cultural shifts. The first through third industrial revolutions established the basis for the mass production of products in factories through mechanization and automation [1].

In a rapidly changing environment, the steel industry, which has the largest facilities among manufacturing industries, is also demanding many changes, such as the establishment of an optimal production process and the prediction of facility service life using smart technologies, such as artificial intelligence (AI) and machine learning (ML). Meanwhile, the steel industry is concerned about deteriorating profits attributed to the economic downturn caused by global inflation and slowing industrial demand [2]. Company P, a prominent Korean steel manufacturer, has been actively introducing smart factories into its manufacturing process since 2016. The foundation for this infrastructure was built by training experts and introducing a standard data analysis platform [2].

Company P, which is the background of this study, is largely divided into iron making, steel making, continuous casting, steel rolling, and galvanizing steel production processes [3]. Iron is a base metal extracted from iron ore, and steel is an iron-based alloy containing carbon, silicon, manganese, and other elements [4].

Iron making is the process of fabricating molten iron by placing iron ore and coking coal into a blast furnace and blowing hot air at a temperature of 1200 °C. Steel making is the process of fabricating crude steel by removing impurities, such as carbon (C), phosphorus (P), and sulfur (S), from the furnace and inserting the molten iron produced in the blast furnace into a converter and blowing pure oxygen into the converter. Continuous casting produces solid semi-finished products, such as slabs and blooms, by passing crude steel into a liquid state through a continuous casting machine. Steel rolling is the process of producing coil-type products and is further divided into hot rolling, cold rolling, and a continuous galvanizing line (CGL). Hot rolling produces hot-rolled coils of appropriate widths and thicknesses (1–22 mm) from slabs fabricated via continuous casting. Cold rolling is the process of producing cold-rolled coils with a thinner width and thickness (0.15–3.0 mm) by cold rolling the hot-rolled coils again [5]. Finally, a CGL is used to produce galvanized iron by plating zinc (Zn) with excellent corrosion resistance on the surface of cold-rolled iron [6]. This process then produces galvanized iron that is alloyed via heat treatment to form an intermetallic compound containing 9–13% Fe rather than 100% Zn in the plating layer. Figure 1 shows the production process of Company P's iron and steel products, from making molten iron to producing galvanized iron, as described above.

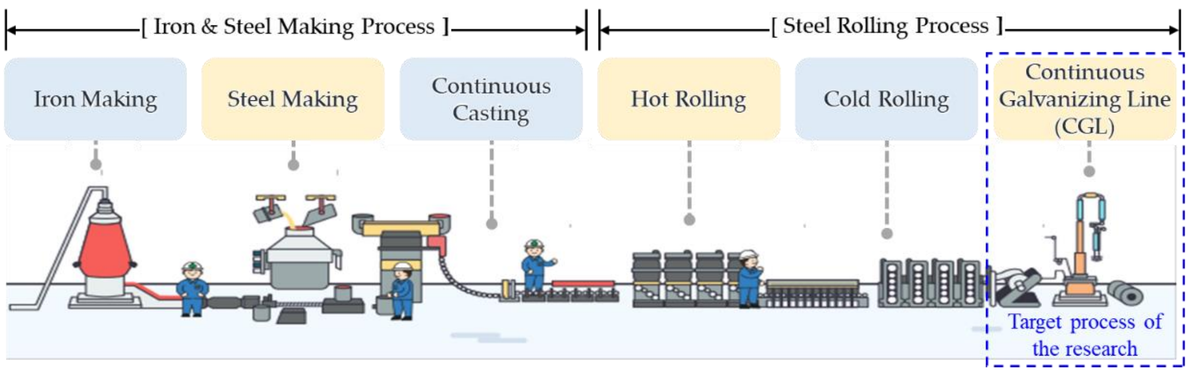

Figure 1. Whole process of iron and steel product making and the target process of this research.

In particular, galvanized iron, which requires the most processing in steelwork production, must have a sleek surface, as well as excellent weldability and workability. It is primarily used in the inner and outer panels of automobiles and home appliances that require corrosion resistance. Company P ensures the weldability by adjusting the components of the steel making process for the galvanized iron as an automotive steel strip.

Strip tears are a phenomenon in which a part or the whole strip is torn during production and are possibly the most fatal loss factor in a CGL, which generates products continuously. For the cause of such strip tears, welding defects at the connection point of leading and trailing strips account for the largest portion at 57%, followed by strip material defects at 38% and process defects at 4%. If strip tears occur, the facility engineer must manually weld the leading and trailing parts using a portable welding machine to reconnect them. In addition, if strip tears occur in the welded part, the welder's performance must be checked, and a failure action should be taken when an abnormality is found. Therefore, more time is required before resuming regular operations because it is necessary to check for any damage to the surrounding operating environment and adjust the operating conditions. For this reason, if the CGL cannot generate products continuously, an economic loss of approximately USD 400 K (approximately KRW 400 million) per year will occur; therefore, strip tears must be prevented.

The leading and trailing strips are connected using a CGL laser welder, and for the continuous production of the CGL, a welder must be installed. In the early days, the seam welder—a method of welding by overlapping both ends of the strip, sending a high current in an electrode-pressurized state, and melting the strip with the resistance heat generated in the current concentration part—was widely used because of its relatively simple structure and ease of management. However, with the recent increase in high-strength steel production, it has been replaced by laser welders with high thermal efficiency. It can generate a high laser power and minimize welding deformation by adjusting the laser power and velocity.

As listed in Table 1, the laser welder consists of mechanical parts, such as a header, carriage, and shear; electrical and control facilities, such as a quality control data system (QCDS) and heater; and a laser system, such as a laser resonator and high-frequency generator. The header is a consumable product, and Company P is currently performing maintenance through regular replacement. However, the laser resonator and high-frequency generator form a single facility provided by the supplier. The device itself is black-boxed; therefore, it takes a long time to repair or replace it in case of failure.

Table 1. Composition of a CGL laser welder by facility category.

Category	Facility	Main Functions
Mechanical	Header	Laser focusing and laser beam power control
	Carriage	Fixed to weld leading and trailing strips
	Shear	Cutting the leading strip tail part and the trailing strip top part
Electrical/Control	QCDS	Welding quality determined by analyzing the gap between strips, welding spark, bead amount, and laser output
	Heater	Strip heating before welding
Laser System	Resonator	Laser resonation by mixing gas (N_2, CO_2, He, etc.)
	High-frequency generator	High voltage generation for laser gas activation

Laser welder failure refers to a situation in which a strip cannot be welded normally because the required function is degraded or does not function. As the primary data for this study, the authors compared and analyzed the total strip tears and welder failures in the CGL, where welders were installed within a period of 21 months from January 2021 to September 2022 at Company P. There were 19 cases of strip tears, a representative phenomenon caused by welder failure, which took approximately 90 h to resolve. Among all CGL failures, 52 welder failures, the main cause of strip tears, occurred during the same period, and it took approximately 71 h to act against them [7].

1.2. Problem Statement and Research Objectives

The reason for the continued occurrence of laser welder failures is that the devices constituting the facility are diverse, and all devices require precise control. As a result, even a minor anomaly in the facilities becomes a factor that significantly deteriorates the welding quality. While other facilities show relatively clear abnormal signs before failure, such as vibrations or noise, the laser welder displays almost no abnormal signs indicating failure. Therefore, various IoT sensors have been attached to facilities to monitor conditions and detect abnormal signs. However, these measures are yet to reach the level of prevention by detecting anomalies in advance. Despite the significant advances in facility management technologies, laser welder failures continue to occur for several reasons. Company P is experiencing an economic loss of more than 400 K (KRW 400 million) per year owing to the failure of the CGL laser welder and the failure to produce normal products. In addition, the workload of the engineer in charge of field safety measures, facility repair, and production schedule adjustments also increases in the event of a failure. Facility management in the manufacturing industry should include preventive maintenance to detect anomalies and signs before failures, rather than breakdown maintenance after the failures. With the spread of smart factories, there is a need for technology development that actively utilizes AI technology to detect anomalies and prevent failures of core facilities in the steel industry, such as laser welders.

This study aims to develop a predictive maintenance model by applying machine learning (ML) techniques to automatically detect facility failures before line stoppage. To this end, a model was developed and trained using the operating sensor data of a CGL laser welder at Company P's steel making plant in Korea. An auto-encoder (AE) was selected as the basic algorithm because of the large deviation between the normal and abnormal data of the laser welder operation. A long short-term memory (LSTM) algorithm was also applied due to the time series characteristics of the data. This study developed a laser welder predictive maintenance model (LW-PMM) based on LSTM-AE, integrating the technical advantages of the two algorithms.

This study differs from the previous studies. Equipment failure cases are very diverse, but abnormal data are insufficient; therefore, in the case of a training model, when a new facility failure case appears, it may not be detected. This study differs from previous studies in this regard. The model developed in this study predicts failures by detecting anomalies in situations with a significant lack of abnormal data compared with normal data. The target facility of this study, a CGL laser welder, is used only in steel plants; therefore, few studies have applied AI to the same type of facility. To overcome these limitations, its performance was compared with those of existing facilities currently operating at the actual site, although the LW-PMM is a model at the PoC level. It is also different from other studies by showing the economic benefits of the developed technology through an economic analysis of the model developed in this study.

1.3. Literature Review

The prior research first summarized the ML studies regarding maintenance, repair, and operation (MRO). In addition, the deep learning applications of predictive maintenance and anomaly detection models in the steel industry were reviewed.

1.3.1. ML Application for Maintenance, Repair, and Operation (MRO)

Studies have been conducted in facility maintenance, repair, and operation (MRO) using ML to detect anomalies by applying various ML algorithms. Liu et al. performed research to predict the quality of molten metals by developing a support vector machine (SVM)-based anomaly detection model using 14 types of data such as temperature and composition data that can be measured during blast furnace operation [8]. Yan and Zhou, using text data from aircraft maintenance history management, confirmed that it was possible to build a predictive maintenance system based on random forest (RF) and term frequency–inverse document frequency (TF-IDF) methods [9]. Quiroz et al. developed a model to predict the motor and rotor bar failures using a random forest based on the current signal generated during a line start permanent magnet synchronous motor (LS-PMSM) [10]. Gohel et al. proposed a predictive maintenance framework that applied SVM and logistic regression algorithms based on the data of intelligent drivers, controllers, and monitors of nuclear power plants to perform predictive maintenance of nuclear power plants with few failure samples [11]. Go et al. developed a prediction model of rolling bearing water corrosion based on the SVM algorithm by using vibration data obtained from the rolling bearing acceleration sensor to diagnose the failure of the rotating body [12]. Choi et al. developed a support vector regression (SVR)-based tap temperature prediction model (TTPM) using EAF operation data to automatically set the amount of power input by predicting tap temperatures in real time in the electric arc furnace (EAF) process of an integrated steelworks [13]. These studies aimed to control this process more precisely and improve productivity by minimizing deviations or errors that occur while engineers control the process.

1.3.2. Predictive Maintenance Applying Deep Learning Technology

Biswa and Sabareesh developed an ANN-based condition monitoring system for wind turbines using vibration signals from bearings, gearboxes, and shafts that imitated the operating conditions of actual wind turbines [14]. De Benedetti et al. developed an ANN-based PV systems failure detection model using solar irradiance and PV panel temperature data of photovoltaic (PV) systems [15]. This model detected an anomaly through the difference between the predicted value of AC power production and the actual measured value, and showed a positive predictive detection rate of over 90%. Zhang et al. conducted a comprehensive survey of data-driven methods for predictive maintenance using public datasets such as intelligent maintenance systems (IMS). Especially, specific industrial applications were classified based on six algorithms from ML and deep learning [16]. Sampaio et al. developed a failure prediction system using various ML techniques, such as ANN, regression tree (RT), random forest (RF), and SVM, using vibration data measured in a motor operation simulation system. Compared to the root mean square error (RMSE), ANN demonstrated superior performance in periodic fluctuations, such as vibration [17]. Renström et al. proposed an AE-based wind turbine condition monitoring and failure detection system using supervisory control and data acquisition (SCADA) data to detect wind turbine faults and anomalies [18]. However, this system has a limitation if the model does not detect an anomaly; it selects a model with high recall even at the cost of precision. Van et al. secured operational data from an IoT sensor for laser transmission welding equipment. They developed a web-based real-time abnormal monitoring framework applying a supervised learning-based ML algorithm [19]. Zhao et al. analyzed and optimized a multivariate statistical process control (MSPC) model for missing alarms or delay prediction in the anomaly detection of the traditional blast furnace iron making process to develop a TOSIS and gray (GT-MSPC)-based model [20]. Yang et al. proposed a new method based on SAE-LSTM and the sliding window method by combining A sparse auto-encoder (SAE) and LSTM for the early alarming of overheating defects of stator winding of water-cooled turbo generators [21]. However, this study was conducted on only one turbo generator of a single type, and the limitation was that the performance for other types of turbo generators could not be confirmed. Esmaeili et al. developed predictive models based on unidirectional LSTM (U-LSTM) and bidirectional LSTM (Bi-LSTM) auto-encoders (AEs) to automatically detect anomaly data recorded from electro-chemical aptasensors [22]. However, their study had limitations in preprocessing due to the lack of sufficient normal data. Compared to other integrated models, their model also has a limitation in that the effect of the conventional autoencoder model is not applicable. The developed model showed a higher anomaly detection rate than the manual observation method, and it was found to activate an sound alarm 16.4861 min earlier than the manual detection. However, this model has limitations in being applied only to the blast furnace production process and not to other industrial fields.

1.3.3. Anomaly Detection Models in the Steel Industry

A study on the automation of anomaly detection applying ML techniques in the steel industry is as follows. Kothari applied the U-Net architecture algorithm to train a model to classify normal and abnormal conditions based on welding quality and X-ray photography results of welds [23]. He developed a system for detecting welding quality and showed an unsafe welding detection rate of 94.3%. Bacioiu et al. suggested a welding quality detection model based on CNN and fully connected neural networks (FCN) using high dynamic range (HDR) sensor data after conducting tungsten inert gas welding on stainless steel 304 plates [24]. Du et al. proposed a model to evaluate the welding quality of friction stir-welded joints of three aluminum alloys based on a decision tree and Bayesian neural network (BNN) using welding variables and material property data [25]. Zhang et al. proposed a condition monitoring system for laser welding based on deep belief network (DBN) by utilizing various visual sensor data generated during the high-power disc laser welding process [26]. Fu et al. proposed an end-to-end SqueezeNet-based model that applied CNN to classify the defect classification of the steel surface [27]. This study used the publicly available Northeastern University (NEU) steel surface defects dataset. The proposed lightweight model is expected to enable online steel production inspection tasks. Zhao et al. proposed a faster R-CNN model integrating faster R-CNN network structure reconstruction and a network with multiscale fusion to detect steel surface defects using six types of steel surface defect image data [28]. This proposed method has better detection performance, and the precision is 0.752, which is 0.128 higher than the original algorithm. Wang et al. developed a model for recognizing edge defects of hot-rolled coil based on LeNet-5, AlexNet, and VggNet-16 using a CNN as a core, applying a dataset of edge defect images of hot-rolled strips [29]. The accuracy of the AlexNet-based recognition model was 93.5%, and a single defect image's average recognition time was 0.0035 s. Wang et al. proposed a model that detects abnormalities in welding quality by applying the LSTM algorithm of a deep neural network to monitor the welding quality results of ultrasonic welding (USW) [30]. De Paepe et al. developed an incremental grey box welding current prediction model by combining knowledge-based techniques and existing statistical models based on industrial welding data to detect welding defects in the steel production process [31]. The strengths and limitations of this model stem from its dependence on physical knowledge. In this study, satisfactory results were obtained using universally known physical rules. Their difficulty is that the physics knowledge for other cases is incomplete or not easily available to experts. Meyer and Mahalec developed an anomaly detection model for detecting welding defects using a single-class neural network autoencoder and a principal component analysis (PCA) algorithm based on standard process data for resistive seam welding [32].

On the other hand, the method proposed in this paper has the advantage of working well with a relatively small amount of data. Most of the previous studies on anomaly detection were performed to monitor or detect welding defects of strips, and such studies have focused on post-repair maintenance (in other words, traditional preventive) rather than on preventive maintenance MRO, as is the focus of this paper research. In addition, the data used in previous research on welding defects of steel strips were unstructured image pictural data. On the other hand, the operating data of the laser welder applied in our study are structured data, and furthermore there is a difference between the anomaly detection model of the welding and the characteristics of the data. As a result of reviewing previous studies, ML is used in several innovative ways to improve production efficiency. In particular, studies on facility failure prediction, which were attempted in only a few industries, have been researched using ML technology to develop IoT sensors based on a large amount of data. However, with the exception of a few studies, a significant number of studies have been implemented to validate a model's accuracy and availability, as opposed to applying operational data from production sites to develop a commercially usable system. In addition, various studies have proposed models that determine mainly the welding quality, upon which the welding results are based. Previous studies on monitoring the operation and controlling status of welding devices, which is the fundamental cause of deteriorating welding quality and detecting anomalies, are scarce.

In summary, this paper presents an ML-based facility anomaly detection model using the operation data of a laser welder from an actual production site, which is essential for enabling continuous production in a CGL. Therefore, it is expected that this model can minimize or prevent the failure of the laser welder operation, which is the fundamental cause of degradation in the welding quality. Table 2 shows the recent studies on predictive maintenance and anomaly detection for this study.

Table 2. A summary of the recent studies for predictive maintenance and anomaly detection.

Category	Proposed Methods	Data or Signals	Research Goal	References	Year
Machine Learning based approaches	Support Vector Machine (SVM)	Blast furnace operation data such as temperature	Anomaly detection in the quality of molten metal	Liu et al. [8]	2011
	Random Forest (RF), Term Frequency–Inverse Document Frequency (TF-IDF)	Text data from aircraft maintenance history management	Detection and predictive maintenance of aircraft anomalies	Yan and Zhou [9]	2017
	Random Forest (RF)	Current signal generated during a line start permanent magnet synchronous motor (LS-PMSM)	Prediction of motor and rotor bar failures	Quiroz et al. [10]	2018
	Support Vector Machine (SVM), Logistic Regression	Data of intelligent drivers, controllers, and monitors of nuclear power plants	Predictive maintenance of nuclear facilities	Gohel et al. [11]	2020
	Support Vector Machine (SVM)	Vibration data obtained from the rolling bearing acceleration sensor	Prediction of moisture-induced corrosion in rolling bearings	Go et al. [12]	2021
	Support Vector Regression (SVR)	Operation data of an electric arc furnace (EAF)	Real-time prediction of tap temperature and automatic setting of power input for EAF	Choi et al. [13]	2023
Deep Learning based approaches	Artificial Neural Network (ANN)	Vibration signals from bearings, gearboxes, and shafts that imitated the operating conditions of actual wind turbines	Detection of gear-related faults such as cracks or bearing inner race cracks	Biswa and Sabareesh [14]	2015
	Artificial Neural Network (ANN)	Solar irradiance and PV panel temperature data of photovoltaic (PV) systems	Anomaly detection in photovoltaic (PV) systems	De et al. [15]	2018
	Artificial Neural Network (ANN), Deep Neural Network (DNN), Auto-encoder (AE)	Public datasets such as intelligent maintenance systems (IMS)	Classification of specific industrial applications	Zhang et al. [16]	2019
	Artificial Neural Network (ANN), Regression Tree (RT), Random Forest (RF), Support Vector Machine (SVM)	Vibration data measured in a motor operation simulation system	Predictive maintenance for motors	Sampaio et al. [17]	2019
	Auto-encoder (AE)	Supervisory control and data acquisition (SCADA) data	Detection of wind turbine faults and anomalous behavior	Renstrom et al. [18]	2020

Table 2. *Cont.*

Category	Proposed Methods	Data or Signals	Research Goal	References	Year
	Supervised Learning	Operational data from an IoT sensor to laser transmission welding equipment	Real-time anomalous condition monitoring of laser transmission welding machines	Van et al. [19]	2022
	Multivariate Statistical Process Control (MSPC), Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS), GT-MSPC	Field data collected from a blast furnace ironmaking production process	Anomaly detection and early warning in blast furnace ironmaking processes	Zhao et al. [20]	2022
	Sparse Auto-encoder (SAE) and Long Short-Term Memory (LSTM)	Operation data of a water-cooled turbo-generator stator winding collected by a distributed control system (DCS)	Early warning for overheating faults in stator windings of water-cooled turbo generators	Yang et al. [21]	2023
	Unidirectional LSTM (U-LSTM), Bidirectional LSTM (Bi-LSTM), Auto-encoder (AE)	Anomaly data recorded from electro-chemical aptasensors	Anomaly detection for sensor signals	Esmaeili et al. [22]	2023
Anomaly Detection in the Steel Industry	U-Net Architecture Algorithm	Welding quality and X-ray photography results of welds	Quality discrimination and defect detection of welded joints	Kothari. [23]	2018
	Convolutional Neural Networks (CNN), Fully-connected Neural Networks (FCN)	High dynamic range (HDR) sensor data from tungsten inert gas welding on stainless steel 304 plates	Evaluation of welding quality	Bacioiu et al. [24]	2019
	Decision tree, Bayesian Neural Network (BNN)	Welding variables and material properties data	Evaluation of welding quality for friction stir welded joints	Du et al. [25]	2019
	Deep Belief Network (DBN)	Various visual sensor data generated during the high-power disc laser welding process	Real-time condition monitoring of laser welding	Zhang et al. [26]	2019
	Convolutional Neural Networks (CNN)	Publicly available northeastern university (NEU) steel surface defect dataset	Defect recognition and grade classification of steel surface	Fu et al. [27]	2019
	Faster R-CNN	Six types of steel surface defect image data	Detection of defects on steel surface	Zhao et al. [28]	2021
	Convolutional Neural Networks (CNN), LeNet-5, AlexNet, and VggNet-16	Edge defect images of hot-rolled strips	Recognition of edge defects in steel plates	Wang et al. [29]	2021

Table 2. *Cont.*

Category	Proposed Methods	Data or Signals	Research Goal	References	Year
	Deep Neural Network (DNN)	Time series signal data of ultrasonic welding (USW)	Anomaly detection in ultrasonic welding (USW) quality	Wang et al. [30]	2021
	Combination of statistical models and knowledge-based techniques	Industrial welding data from the steel production process	Prediction of welding current in incremental grey box models	De et al. [31]	2022
	Auto-encoder (AE), Principal Component Analysis (PCA)	Resistive seam welding data	Monitoring and detection of welding defects	Meyer and Mahalec [32]	2022

1.4. Research Framework and Overall Process

The overall model development process is shown in Figure 2. Section 2 describes the collection of operation data for the laser welder to be used in developing the failure prediction model. The authors excluded data not directly related to the failure of the laser welder and preprocessed it to select missing values and outliers. In Section 3, the authors review algorithms suitable for the operation data of laser welders. After selecting and training the LSTM-AE model that combines the AE and LSTM algorithms, the laser welder predictive maintenance model (LW-PMM), a failure prediction model of the laser welder, was finally developed. The performance of the LW-PMM model is evaluated using a confusion matrix in Section 4. In addition, the authors verified the model's anomaly detection performance by using the operation data of the actual CGL site in Company P. Section 5 reviews the economic effects of the LW-PMM by applying the concept of opportunity cost.

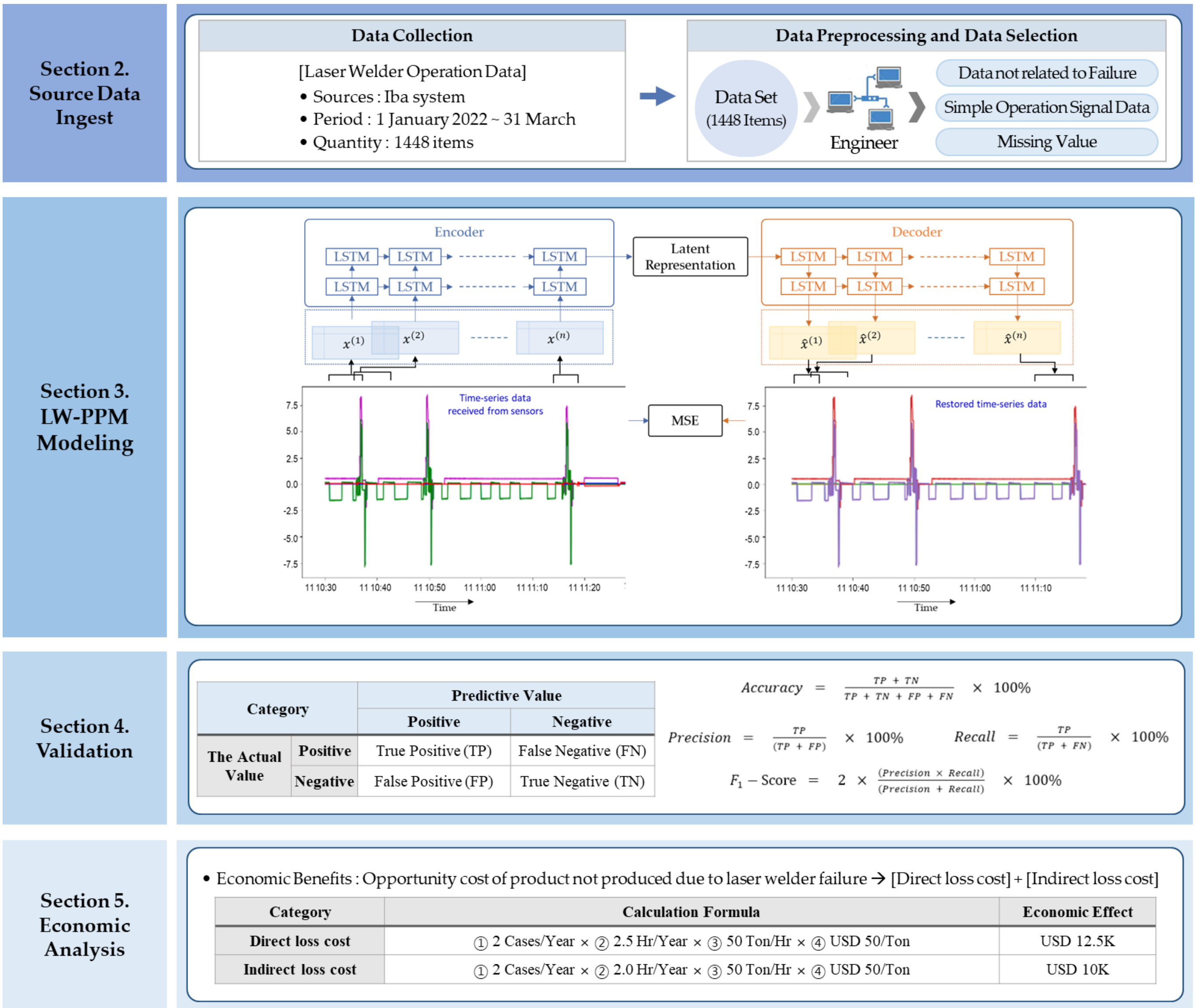

Figure 2. Research framework.

2. Data Collection and Data Preprocessing

2.1. Data Collection

For this study, the laser welder operating data of "A" CGL at Company P was first collected. Operation-related data were collected in real-time using the data storage and analysis system of ibaAG in Germany. The saved data were imported into Excel and Python before conversion to a .csv file for analysis.

This study utilized the laser welder operation data for three months, from 1 January 2021 to 31 March 2021. The data consisted of 1448 items of measurement data in seconds, such as the operation status of the device comprising the laser welder position and speed and signals from the sensors attached to the front and back of the laser welder. There were 266 items of continuous analog data and 1222 items of digital data representing repetitive operation signals, such as the operation and stopping of the device. The collected data are categorized by type in Table 3 as mechanical, electrical or control, utility, and other devices, along with the numbers and types of devices.

Table 3. Data collected from the laser welder system by category.

Category	Define	Quantity (Analogue/Digital)	Types
Mechanical	Driving devices	539 (125/414)	Position, Speed, Torque, etc.
	Welding devices	254 (32/222)	Welding Time, Temperature, etc.
	Cutting devices	135 (24/111)	Cutting Time, Position, Centering, etc.
Electrical/Control	Laser system	108 (20/88)	Laser, Chiller, Resonator, etc.
	Sensor, Signal	265 (0/265)	Camera, Strip Position detector, etc.
Utility and Other Devises		147 (25/122)	Pump Start/Stop, Filter, etc.

2.2. Data Preprocessing and Data Selection

The collected data consisted of 1448 items in seconds. Because the performance of the analysis server was insufficient to analyze all the data, additional data preprocessing was necessary to select the operation data that could affect the failure of the actual laser welder. Data preprocessing significantly affects the performance of the implemented model and removes unnecessary or outlier data to suit the purpose and method of analysis [33]. In this study, data were analyzed and selected during preprocessing by utilizing the domain knowledge of facility engineers and basic Python libraries such as pandas, numpy, scikit-learn, and matplotlib. Preprocessing was performed on all the collected data to remove unnecessary or abnormal data from the analysis, as shown in Figure 3.

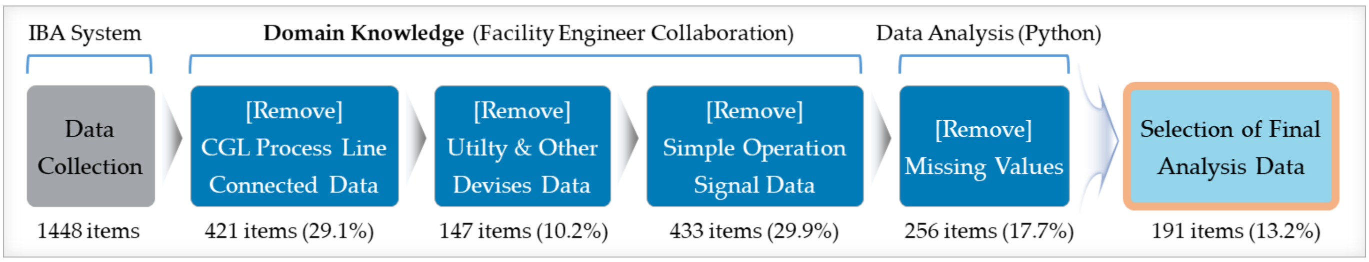

Figure 3. Data preprocessing and data selection processes.

Data preprocessing was performed in a two-step sequence, in which data not necessary for realizing the laser welder failure prediction model were removed. Similarly, missing values and outliers were analyzed and removed. Data removal was performed in collaboration with a facility engineer with more than ten years of experience and sufficient domain knowledge of laser welders based on extensive experience and know-how. As described above, the operating data of the laser welder collected in "A" CGL included 1448 items. From the perspective of facility operation, data can be classified into two types. Line-connected data allows the entire CGL and laser welding process, which is a single facility, to operate organically, and exclusive data are generated from the laser welder system facilities.

The measurable data from the device directly related to the regular operation of the laser welder were selected as input values for the LW-PMM. However, line-linked data, such as the CGL process line-connected data, which send and receive signals between facilities so that the production process can be conducted smoothly; items related to utility and roll operation auxiliary facilities that are not directly related to laser welder failures; and missing model implementation value items that may cause distortion were removed through preprocessing.

Line-connected data contain information related to the overall operation of the CGL, including operational data on the production speed and tension, and product information, such as on the width and thickness of the strip being produced. The laser welder was operated based on these data; however, because the data were not directly related to the failure of the actual laser welder, the corresponding 421 items were excluded from the analysis. In addition, in the laser welder system, 147 items related to supplying utility to the laser welder and driving the surrounding rolls were excluded from the data analysis because they were not directly related to the failure of the laser welder. Finally, 1001 items were preferentially excluded from the analysis by additionally screening 433 items unrelated to the failure of the welder among the digital data, which consisted of the operation signal of the laser welder and the front and back facilities for the welding sequence inside the laser welder system.

Next, when implementing the laser welder failure prediction model, the missing values and outliers, which were the main causes of significant distortion and deterioration in accuracy, were identified. As a result of analyzing the data using the Python library's analysis tool, there were many items for which data were not normally collected. Consequently, 256 data items that were not normally collected owing to sensor failure or cable disconnection were excluded from the analysis.

An outlier refers to an excessively large or small value outside the normal range of collected data. The most common method of removing outliers is to use an interquartile range (IQR). The IQR is the difference (Q3 − Q1) between the Q3 value representing the upper 75% of the quartile and the Q1 value representing the lower 25% of the quartile. The range of values between the minimum Q1 − 1.5 × IQR and the maximum Q3 + 1.5 × IQR constituted normal data, and values outside this range were considered outliers and removed or replaced with the average value of normal data [34]. In this study, the data analysis was performed by including outliers without removing them because the possibility that these outliers could be related to actual failures cannot be ruled out.

Therefore, through three stages of preprocessing, 191 data items were selected for modeling, excluding 1001 items deemed unnecessary for the analysis and 256 items with missing values.

3. Modeling and Training for the CGL Laser Welder

It is necessary to select an algorithm suitable for the operating characteristics of the facility to develop a failure prediction model. This section explains the ML algorithm and its training for developing a failure prediction model for laser welders.

3.1. Classification of ML Techniques for Anomaly Detection

The work rate (time required for production) of CGLs in which laser welders are used exceeds 98%, and unplanned downtime owing to breakdowns occurs only when there is a problem with the planned repair time. As a result, obtaining abnormal data from a laser welder can take longer than expected. In addition, the abnormal data collected in this manner constitute a minor portion of the total operation data. Therefore, a significant deviation occurs between normal and abnormal data. The basic concept of anomaly detection is to distinguish between normal and abnormal data. Anomaly detection is classified into supervised, semi-supervised, and unsupervised depending on whether abnormal data are used when training the model and whether labeling is performed to distinguish normal from abnormal data [35].

Supervised anomaly detection model is applied when sufficiently normal and abnormal data are present in a given training dataset, and distinct labels exist for both. This method has high accuracy compared to other methods because it has been trained by securing sufficient normal and abnormal data and shows higher performance as the amount of abnormal data increases. However, the frequency of abnormal data at general industrial sites is significantly lower than that of normal data. Therefore, considerable time and money are required to secure abnormal data, and the class imbalance problem between normal and abnormal data must be solved. Semi-supervised anomaly detection is used when the training dataset has a significant imbalance between normal and abnormal data. This method was developed to overcome the disadvantage of supervised anomaly detection, which requires better learning accuracy when the imbalance between data is significant. When the imbalance between the data was severe, a discriminative boundary surrounding the normal data was set, and all data outside the boundary were considered abnormal and assigned a maximum. This method can be applied even when there is a significant imbalance between the data. However, even in this case, a label that distinguishes normal data from numerous other data points is required. In addition, compared to supervised anomaly detection, it is relatively less accurate; therefore, its usability is low.

Unsupervised anomaly detection was devised to eliminate the inconvenience of securing labels for normal and abnormal data in semi-supervised anomaly detection. This learning method assumes that most of the data are normal without securing labels. A representative method is required to detect abnormal data by applying dimension reduction and restoration using a principal component analysis (PCA) to the given data. Recently, AE-based neural networks have become the most commonly used [36]. Table 4 classifies the anomaly detection methods described above into three types according to the learning method and briefly explains the characteristics of the normal and abnormal data used to determine whether normal data labeling is necessary for accuracy.

Table 4. Classification of anomaly detection data.

Category	Normal Data	Abnormal Data	Labels	Accuracy
Supervised Anomaly Detection	Use	Unused	Need	Excellent
Semi-supervised Anomaly Detection	Use	Unused	Need	Lowness
Unsupervised Anomaly Detection	Use	Unused	Unnecessary	Moderation

3.2. Model Selection for the CGL Laser Welder

Considering situations in which laser welders fail, in many cases, failures are not caused by instantaneous facility failures but rather by small facility failures accumulating and exceeding the allowable range. For failure prediction, it is necessary to predict the possibility of future failures by analyzing the sequence data collected from the laser welder. RNN and LSTM methods, which are variants of RNN, are commonly used for sequence data analysis. LSTM has more advantages than an RNN; however, it is necessary to select an appropriate algorithm according to the problem type. The characteristics of the RNN and LSTM were compared to select an algorithm suitable for analyzing the characteristics of the laser welder operation data.

An RNN is a type of artificial neural network that forms a directed cycle by sending the result value from the activation function to the hidden state in the output direction and sending it to the next computational input value of the hidden state. RNNs that sequentially receive previous output values as inputs do not structurally remember information far from the output and are designed to reflect more recent information in the prediction. The disadvantage is that a vanishing gradient problem occurs such that the learning ability deteriorates significantly as the distance between the relevant data and currently used data increases [37]. The LSTM was devised to overcome these disadvantages. The LSTM is designed to continuously use important past data for analysis by adding a cell state to the hidden state of an RNN.

In this study, because the deviation between normal and abnormal data for laser welder operation data is significant, the AE, the most commonly used unsupervised anomaly detection method with strength in implementing a model using only normal data, was selected as the basic algorithm. Furthermore, because laser welder failure detection must be able to handle time series data with prior and post-relationships, an LSTM algorithm was used for the analysis by correlating past data with additional selected data. Using the LSTM-AE, which combines the strengths of the two algorithms, the LW-PMM model was created to predict laser welder failure.

3.3. LW-PMM Modeling

The most prominent feature of the selected LSTM-AE-based LW-PMM model is that it uses an unsupervised learning-based AE as the basic algorithm for failure prediction. The AE aims to output the same data as the input data when the input data are encoded and decoded again. Techniques for anomaly detection based on AE use this learning goal, such that an AE trained only with normal data outputs the same input value if normal data are input. However, if abnormal data that have not been previously learned are used as inputs, the restored output value differs from the input value.

The LSTM-AE is a combination of the LSTM and AE and has a structure in which the network cells of the AE are replaced with LSTM cells to consider the temporal characteristics of the time series data. For anomaly detection, the concept of reconstruction error, which judges anomalies when the input data are over a threshold, is used, whereby the input data are output again through the encoder and decoder.

The detailed functions of the LSTM-AE algorithm used in the LW-PMM model in this study are as follows:

- Encoder: The encoder of the LSTM-AE algorithm refers to the part that receives and processes the sensor data from the laser welder as the input. Since the sensor measurements are time series data, an encoder based on recurrent neural networks such as LSTM is suitable. During training, the encoder learns the patterns and structures of the input time series data and projects them onto a latent space as vector representations. By utilizing the encoder, information from the input data is extracted while preserving the key features of the original data, enabling more efficient data processing and analysis through dimensionality reduction.
- Latent space: The time series data of the laser welder, represented as vectors through the encoder, can be projected onto a latent space. The latent space refers to a vector space that encompasses the vectors generated by the encoder.
- Decoder: The decoder is used to restore the compressed time series data to their original form by utilizing the encoder. The decoder takes the time series data represented as vectors through the latent space and converts them back into the original data. During training, the LSTM-AE model sets the goal of correctly restoring the input data as the training objective.
- Loss function: The loss function measures the difference between the actual time series data and the data restored by the decoder of the LSTM-AE model. The training objective set during the training process is to minimize this loss function. This study used the mean squared error (MSE) as the loss function. The MSE is a commonly used loss function for analyzing time series data, such as sensor data from a laser welder,

which calculates the average of the squared differences between predicted values and actual values [38]. It is used to evaluate the model's performance.

- Prediction: The LSTM-AE model, trained with completed training, receives sensor data from a laser welder as input and classifies normal and abnormal states using the encoder layer (or the entire layer). Through this process, the LSTM-AE model is capable of detecting faults in the laser welder.

In this study, the LSTM-AE model was trained using the normal data of 191 items selected from the laser welder operation input. Figure 4 shows the laser welder data input and output structures of the LSTA-AE model used to create a laser welder failure prediction model.

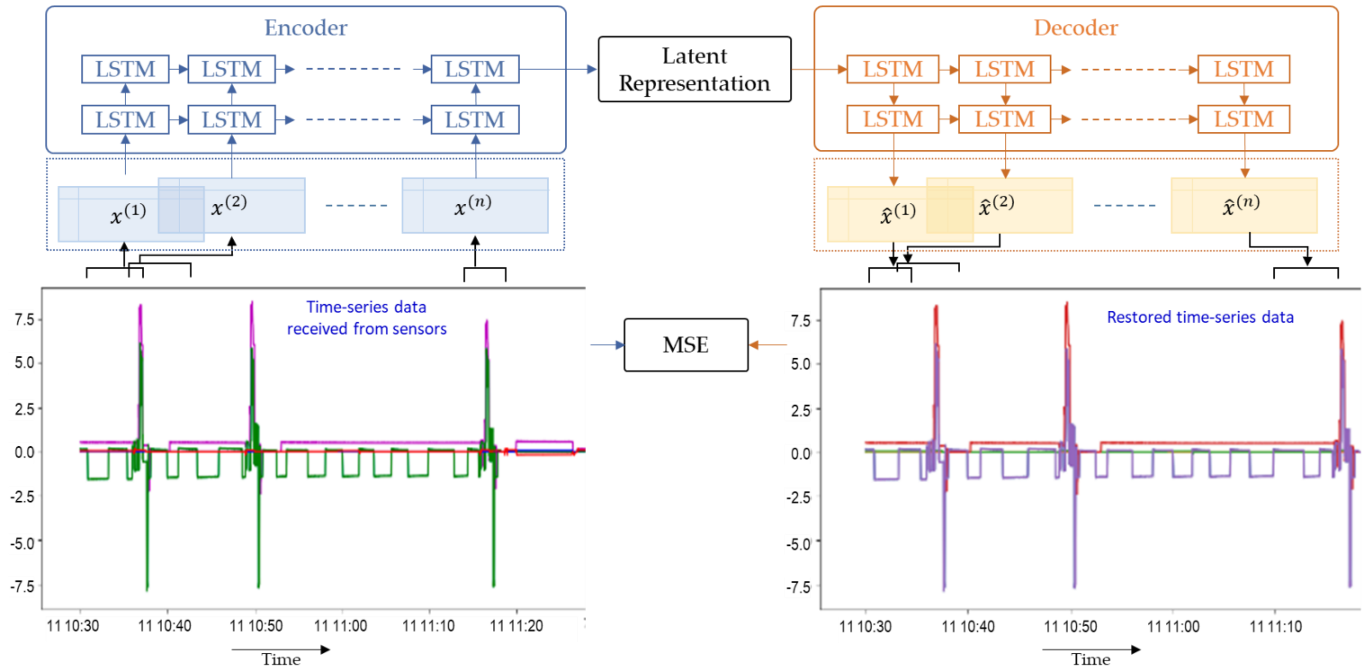

Figure 4. Architecture of the LW-PMM.

In the CGL, which require continuous production, interruptions from facility failure cause severe losses, including time to recover failed facilities and adjust operating conditions for regular production. Therefore, the manufacturing industry must be able to detect the signs of failure before a facility fail happens. In this study, AE and LSTM algorithms were selected considering the facility's characteristics and the features derived from the facility's operation data. Due to the nature of the facility, the laser welder can have a failure breakdown, but it occurs extremely rarely, with 1 to 2 cases per year. Therefore, most data are normal operating data, and abnormal data are rare. As a result, when training the model, it is extremely difficult (almost practically impossible) to label the distinguishes between normal and abnormal data. In this case, the AE, an unsupervised learning model, is suitable for training, assuming that most data are normal, without securing a label. In addition, by applying the LSTM algorithm, a model that can predict the possibility of failure in the future was developed by analyzing the time series data generated during the operation of the laser welder.

Many previous studies have examined models for determining mainly the welding quality by applying AI in the steel industry [23–32]. A study to assess welding quality involved the characteristics of corrective maintenance to detect defects after they occur [39]. On the other hand, the differentiating point of this study is predictive maintenance, which detects failures before facility failures and can allow predictive actions to be taken in advance. In addition, this study developed a model by applying actual operation data from facilities generated in steel plant production sites rather than imitation data or public data.

3.4. Model Training and Fine Tuning

3.4.1. Dataset for Model Training

The laser welder data that could be analyzed include operation and non-operation periods of three months, from 1 January 2021 to 31 March 2021. In other words, these data were from 191 items selected after removing unnecessary items through preprocessing for the analysis but included both normal and abnormal data. The detection of abnormalities in laser welders using LW-PMM, as described above, requires normal data for training. All data from the corresponding period were considered normal; however, it was necessary to exclude the data associated with failures during training to further improve the accuracy of the model. Therefore, as shown in Figure 5, for the section where an actual failure or fault signal occurred, the data from 1 h before and after were excluded from the training dataset.

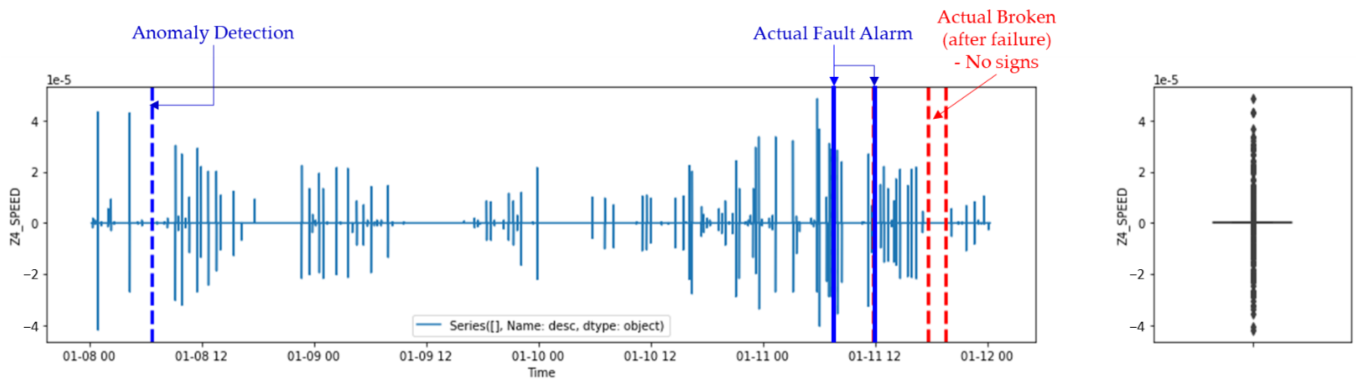

Figure 5. Actual fault data for the z4 servo motor speed.

For the dataset selected in this method, the training and test datasets were separated at a ratio of 8:2 through random sampling, and model training was performed as described in the next section.

3.4.2. Model Training and Fine Tuning

Hyperparameters refer to the values the model user sets directly in the deep learning model and are used to control the training process [40]. Furthermore, hyperparameters are optimized to maximize the performance of deep learning models. Examples include the epoch, learning amount, and learning rate, determining how far to proceed. In addition, the performance of the deep learning model varies depending on the combination of these values. In this way, exploring the combination of hyperparameters to maximize model performance is called hyperparameter optimization [41].

Epochs are defined as the number of times the model has been repeatedly trained once for the entire dataset through feed forwarding and backpropagation [42]. In addition, the epochs of LW-PMM in this study amounted to 200. The batch size is the size of the data sample given for each batch. If there are problems learning the entire dataset in terms of the system or time, then the dataset is trained by dividing it into a specific size. As a result, the size of the divided dataset becomes the batch size. Furthermore, the batch size of this study was 128. When optimizing hyperparameters, the parameter that changes the model performance most dramatically and easily is the optimizer. This study used adaptive moment estimation (Adam) as the optimizer. Adam is a widely used optimization algorithm for improving accuracy in deep learning because it is easy to implement, computationally efficient, and has few memory requirements [43]. The learning rate is a rate for converging to an appropriate value. If the value is low, it takes a long time to converge, and if it is high, it fluctuates near the minimum value or even deviates from preventing convergence. Therefore, in this study, 0.001 was applied as the learning rate. The LW-PMM model was developed with the Python programming language and the TensorFlow library. Table 5 shows the hyperparameters applied to the LW-PMM model. For other parameters, the authors used the TensorFlow library's default settings.

Table 5. Hyperparameter of LW-PMM using the LSTM-AE.

Hyper Parameters	Value Determined
Epochs	200
Batch size	128
Optimizer	Adam
Learning rate	0.001

The predicted value also changed drastically depending on how the model was trained. It is important to select a balanced trained model rather than an overfitting or underfitting model to obtain good results. Model parameter optimization was performed using K-fold cross-validation, which is a model training method that divides the data into K folds according to the situation, whereby the K-1 fold data were used as training data, and the remaining unselected data were classified as test data [44]. Subsequently, the training and test data are changed by repeating the exact process K times. The data were divided into K groups according to the trends displayed. Parameter optimization was performed by classifying the training and test data using K = 10, which is a commonly used value.

The window size of the LSTM affects the accuracy of the LW-PMM model. This factor determines the number of data windows used to predict the dataset. When the factor is too small or large, the accuracy can be reduced. Therefore, a value with demonstrated effectiveness through repeated tests according to the characteristics of the data must be selected, such as setting K to 10 in the K-fold cross-validation. The window size was tested by dividing the window into 30, 60, 90, 120, 150, and 180 windows. Figure 6 shows the results of checking the anomaly detection frequency according to the window size. It was confirmed that more anomalies were detected with a window size of 60 than with a window size of 30, and even more with a window size of 90 than with 60. However, the window size of 120 did not significantly differ from the window size of 90 for anomaly detection.

The test results showed that the abnormality detection frequency increased for window sizes below 90, which was similar to the time of one cycle of the laser welder. For the 120, 150, and 180 cycles (exceeding one welding cycle), results similar to those for 90 were obtained. In conclusion, learning was performed with a final window size of 90, which is similar to one welding cycle.

Finally, a threshold value, which was the reference value for the reconstruction error, was set for the AE algorithm. The optimal threshold value was experimentally determined by repeating the test and changing the threshold value of the model. Figure 7 shows the case in which the threshold value was set to 0.05, indicating that errors in detecting anomalies occurred frequently because the sensitivity was too high.

The threshold value was determined to be 100 by comparing the data at the time of the actual fault or failure with those of the implemented LW-PMM (Figure 8), reflecting the final model.

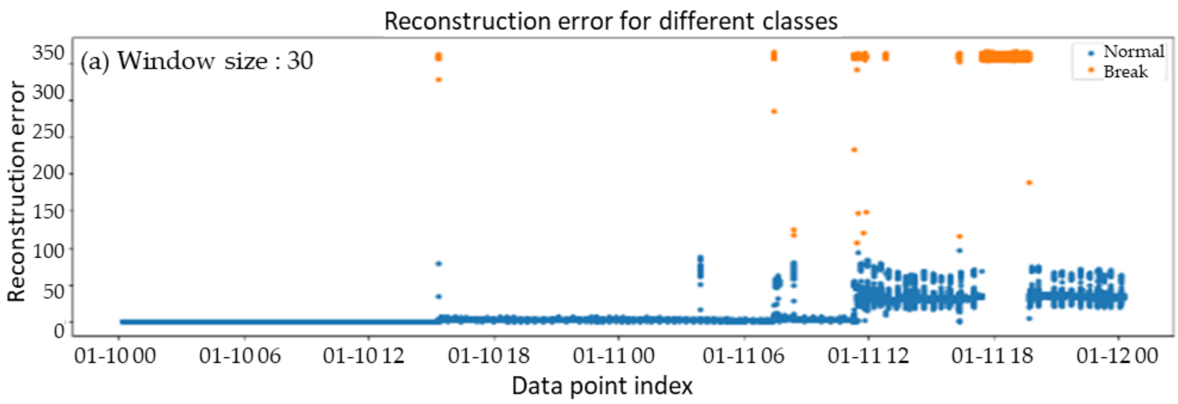

Figure 6. *Cont.*

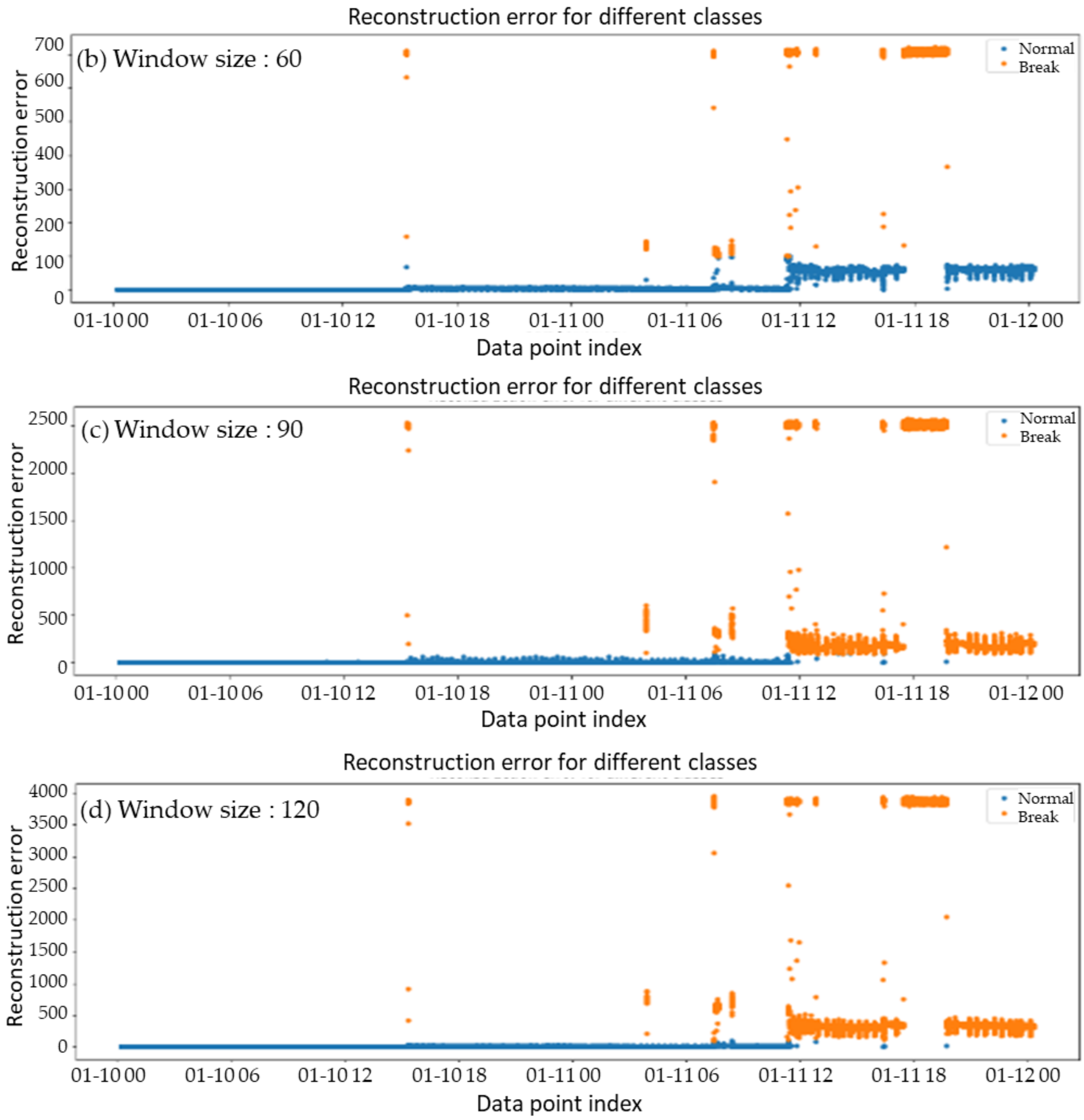

Figure 6. Anomaly detection performance according to the window size of the LSTM.

Figure 7. Classification of normal and abnormal data when the threshold is 0.05.

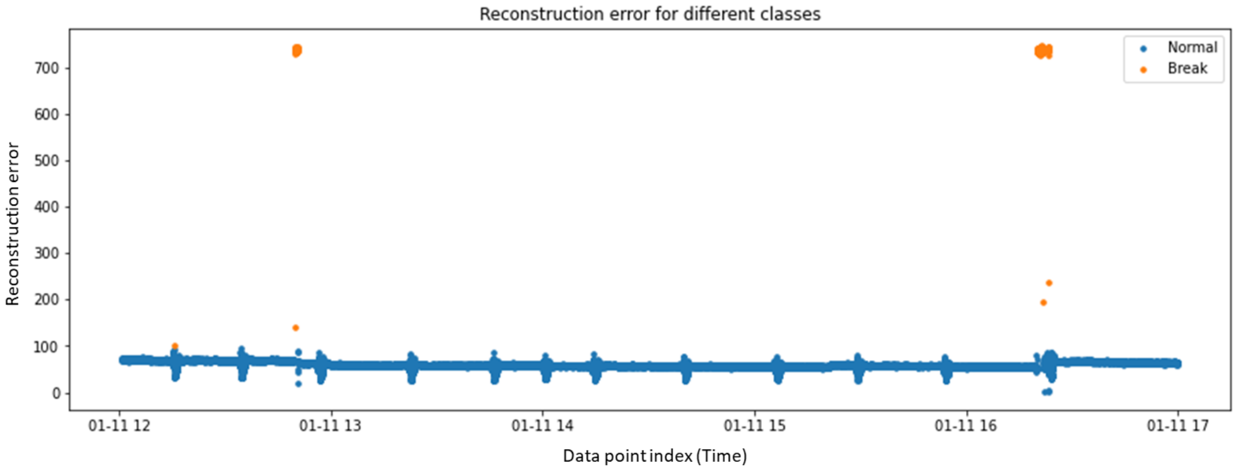

Figure 8. Classification of normal and abnormal data when the threshold is 100.

4. Validation through Case Study

4.1. Performance Metrics for Model Test

In this study, the performance of LW-PMM was evaluated using a validation dataset. Verification was achieved using the F1-score, which evaluates the model performance when there is a significant data imbalance between the objects to be classified [45]. A confusion matrix was used to confirm the precision, recall, and accuracy required for the F1-score verification. Table 6 lists the confusion matrix of the four variables.

Table 6. Confusion matrix for the LW-PMM model.

		Predictive Value	
		Positive	**Negative**
The Actual Value	Positive	True Positive (TP)	False Negative (FN)
	Negative	False Positive (FP)	True Negative (TN)

A true positive (TP) refers to a case in which an actual failure has occurred, and it is predicted that an actual failure has occurred. A false negative (FN) is a case in which an actual failure has occurred, but it is incorrectly predicted that no failure has occurred. A false positive (FP) is a case in which an actual failure has not occurred, but it is incorrectly predicted that a failure has occurred. Finally, a true negative (TN) is a case in which an actual failure has not occurred, and it is correctly predicted that no failure has occurred. The accuracy, precision, and recall were evaluated using the TP, FN, FP, and TN. Accuracy was defined as the number of correctly predicted data points divided by the total number of data points. Precision is the ratio of the data predicted by the model to the actual data that failed. Recall is the ratio of data in which the model predicts the failure of the data as a failure. Finally, the F1-score is the harmonic average of precision and recall. The formulae for calculating the accuracy, precision, recall, and F1-score using information from the confusion matrix are as follows [46]:

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \times 100\% \quad (1)$$

$$\text{Precision} = \frac{\text{TP}}{(\text{TP} + \text{FP})} \times 100\% \quad (2)$$

$$\text{Recall} = \frac{\text{TP}}{(\text{TP} + \text{FN})} \times 100\% \quad (3)$$

$$\text{F1} - \text{Score} = 2 \times \frac{(\text{Precision} \times \text{Recall})}{(\text{Precision} + \text{Recall})} \times 100\% \quad (4)$$

In parallel with the F1-Score, which is widely used, an additional verification process was conducted to determine whether failures of the laser welder could be predicted during actual use in the CGL site. Verification was achieved using the operation data of the laser welder in "A" CGL for six months, from 1 January 2022 to 30 June 2022. The verification of the actual operation data confirmed whether a failure was predicted at the time of failure or whether a failure signal appeared before failure.

4.2. Evaluation Results and Validation

Table 7 lists the values of the TP, FN, FP, and TN, and the corresponding accuracy, precision, recall, and F1-score are listed using the confusion matrix.

Table 7. Validation results of the LW-PMM model.

Value				Performance			
TP	**FN**	**FP**	**TN**	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F1-Score (%)**
265,140	0	66,930	2,142,790	97.3	79.8	100	88.8

For the validation results using the confusion matrix, of the 2,474,860 data points, 265,140 failures were correctly classified (TP). Among the verification results listed in Table 7, the FN and FP indicate prediction errors. An FN of zero indicates that there are zero cases where a failure occurred; however, the LW-PMM model did not predict the failures. Of the 2,474,860 test data points, 66,930 were predicted as failures, although they were not actual failures (FP). The authors determined that 2,142,790 of the total test data did not have actual failures and that no failures would have occurred in the predictions (TN). Accordingly, the accuracy of the LW-PMM model implemented in this study was 97.3%, the precision was 79.8%, and the recall was 100%. As a result, the F1 score was 88.8%.

The failure prediction model aims to detect anomalies before actual failures occur and provides them to facility engineers. In other words, actual failures can be predicted. As the numerical value related to this is the recall, the LW-PMM developed in this study showed a numerical value of 100%. Next, we assume that the data judged as abnormal by the failure prediction model do not lead to actual failures. In such cases, it is essential to determine the number of times that a facility engineer can tolerate such errors. The related number is the precision. A precision of 79.8% compared to a recall value of 100% indicates that the actual equipment failure is predicted by the model as well, but approximately 20.2% of the prediction results are duplicate values; that is, the precision of the LW-PMM model of 79.8% indicates that the actual predicted value and the model's failure prediction match rate are approximately 80%. When five failure signals are provided, one can be interpreted as not an actual failure.

Therefore, it is essential to develop and use a failure prediction model. If the threshold value is strictly adjusted to increase the precision value, there is a high risk of dysfunction, such that an actual failure can be missed. Considering that this study was a proof of concept (POC), in the developed LW-PMM model, an error of approximately one out of five was tolerable with the current technology, as confirmed through an interview with an actual facility engineer.

To compare the failure prediction performance of the LW-PMM model, the authors attempted to compare the performance of the proposed model with the results of other studies, but there was no previous study on failure prediction of the corresponding facility using AI. Therefore, it is presumed that the research results are lacking due to the limitations of their use because the facility is used only for steel plants, not general industrial plants. If similar studies on steel facilities are published in the future, the results of these studies can be compared.

4.3. Performance on the Operation Site

Instead of comparing the CGL laser welder with previous studies, the model performance was compared with existing equipment used in the operation process at the actual site.

To verify whether failure can be predicted in the actual field, in addition to the verification using the F1-score described above, the operation data of the laser welder for six months from 1 January 2022 to 30 June 2022 were entered into the LW-PMM.

The field operation conditions for the actual site test were as follows. The production line for the test was the CGL, the minimum temperature was −14.4 °C and the maximum was 37.9 °C, rainfall and snowfall did not occur as the test was conducted indoors, the maximum wind speed was 35 m/s, the maximum relative humidity was 89%, and the line speed was 180 mpm. In addition, a product welded using a laser welder was required to test the LW-PMM model. The test strip was a galvanized iron strip produced via welding with a laser welder at 'A' CGL in Company P. Table 8 lists the site operating conditions for the LW-PMM model test.

Table 8. Operation conditions for the LW-PMM model test in the site.

Operation Condition for Site Test	Strip for Site Test
Temperature: Min. −14.4 °C, Max. 37.9 °C	Material: Galvanized steel
Rainfall and snowfall: Indoors	Production Line: Welding with laser welder in 'A' CGL
Wind: Max. 35 m/s	Strip Thickness: 0.4–3.2 mm
Relative Humidity: Max. 89%	Strip Width: 800–1900 mm
Line Speed: 180 mpm	Strip Weight: Max. 45 ton

While no special anomaly detection occurs for most of the period, as shown in Figure 9, during the verification period, the first anomaly is detected 27 h before the occurrence of the actual failure, and an additional anomaly is detected 12 h before the actual failure. This shows the performance for detecting a signal approximately 18 h earlier than the existing facility monitoring system detecting a fault signal for the first time 9 h before actual failure, confirming that the system detected anomalies that are not recognized as faults. It is expected that this method can be applied to a field with higher accuracy than existing systems if continuous abnormalities can be detected before failures occur and alarms can be generated in time.

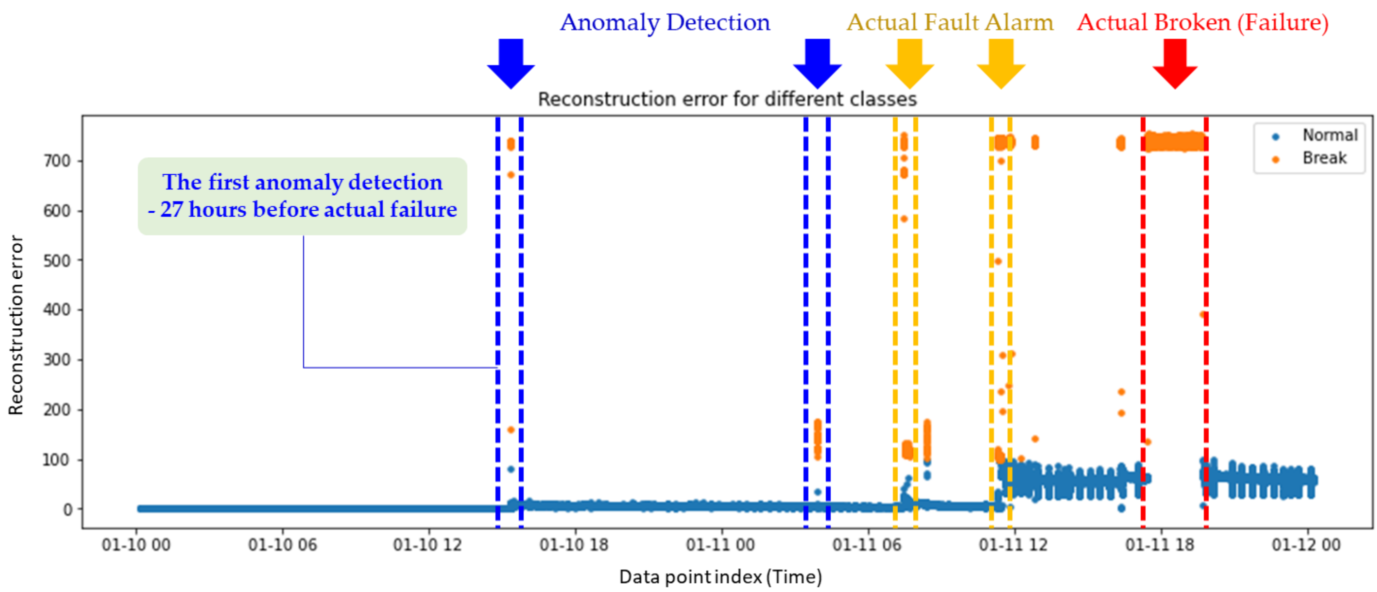

Figure 9. Actual performance in anomaly detection on the operation site.

After the model validation process, the authors analyzed other related studies of laser welder anomaly detection for benchmarking. Company P has recently studied the detection of anomalies before equipment failures occur. Among them, the authors examined the method of detecting equipment anomalies using pattern-matching technology for benchmarking in this study [47]. It is inefficient to compare each piece of data individually to analyze the operation data from the facilities for the comprehensive detection of the anomalies. In this situation, it is necessary to create a normal operation pattern that integrates all operational data, considering the fact that each piece of data is organically connected.

Pattern-matching technology is a method in which the permissible upper and lower limit threshold values are set based on the normal operation pattern generated, and as such flags abnormalities if the pattern created during actual facility operation deviates from the standard value. First, based on the data collected from various sensors attached to the laser welder, a statistical analysis was conducted to establish a normal operation pattern, setting upper and lower limit thresholds. Thus, an anomaly detection method using pattern matching (ADPM) model that detected anomalies deviating from the normal operation pattern was developed. The model's accuracy was 81% at the time of initial development.

To increase the accuracy of the failure prediction model, it is necessary to accurately distinguish between normal and abnormal situations without causing problems such as overfitting, even under conditions in which there is significant deviation between normal and abnormal data.

However, this ADPM model was unable to actively respond to the operating environment where various unexpected situations occur because the normal operation pattern and range calculated initially statistically were determined by absolute values. As a result, this ADPM model was not applied to facility management in the actual process site. One of the reasons for this is that the failure prediction accuracy of the model decreases as the model is used. ML engineers continuously input new data to adjust the regular pattern, which requires system intervention to maintain the model's accuracy. If there is no continuous management by engineers, the system's reliability will decrease, and eventually it will not apply to the operation.

By benchmarking this study's results, the authors learned that the involvement of ML experts should be minimized in future studies. Figure 10 shows a brief overview of the anomaly detection process using the pattern-matching technique. This involves creating a normal operation pattern through a statistical analysis method and comparing it to the actual operation pattern.

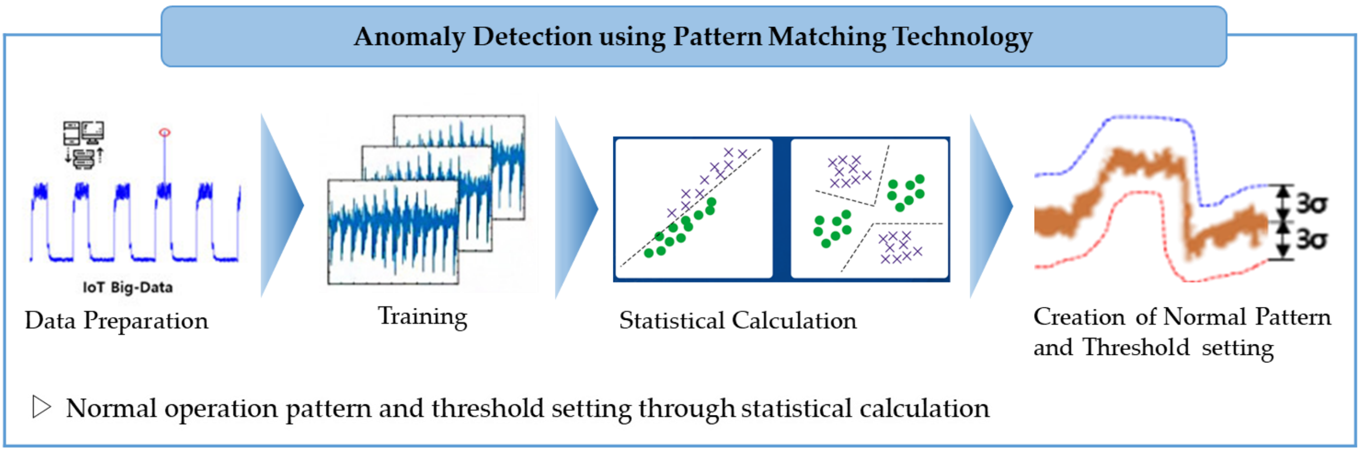

Figure 10. Case 1 of anomaly detection using pattern matching technology.

The authors reviewed prior studies on anomaly detection using ML technology in the steel industry, as presented in Sections 1.3.1 and 1.3.3 Most studies have applied AI technology for the defect detection of steel strips or steel surfaces, not steel production facilities [27–29].

Wang et al. applied a deep neural network to monitor the quality results of ultrasonic welding (USW) [30]. This approach is similar in predicting quality abnormalities using this study's LSTM algorithm. In particular, as a study showing that quality classifications can be accurately predicted (97.8%) without traditional feature engineering for multiple input signals when welding steel sheets by ultrasonic composite welding, this is expected to be applied in future research. However, in the prediction method using deep learning, even if the same prediction model and parameters are used, the results may not be constant depending on the characteristics of the dataset [48]. Wang et al.'s study detected abnormalities in quality for welding results, and there are various similar studies with the same purpose. Even though the applied models are different, benchmarking and performance comparisons of the models are possible. This study involved an MRO model for facilities, and this facility targeted to specific equipment used solely in steel mills is an obstacle to benchmarking Wang et al.'s study.

In addition, the models proposed in numerous previous studies related to failure prediction are facility abnormality detection models that simply detect the abnormal signals generated in each facility and send an abnormal alarm when the standard value is exceeded. Consequently, these models are limited in their ability to detect anomalies because the occurrence of minor irregularities in the facilities is below the standard value. However, the method developed in this study was used for detecting anomalies by integrating minor irregularities in various facilities and showed the performance in quickly detecting signs of failure for approximately 18 h compared to the existing facility monitoring system of Company P.

Steel production facilities have inferior operating conditions owing to their high temperatures and high levels of dust (fine iron powder) compared with those commonly used in general industries. Therefore, it is challenging to predict failures caused by various causes using a failure prediction system applied to general industrial facilities.

The failure prediction level for steel facilities is lower than that for general industrial structures. In the future, if a failure prediction model that comprehensively analyzes the complex environment and operating conditions of steel plants is developed, the results of mutual studies can be compared. The early detection of facility abnormalities has the advantages of accurately identifying faulty devices, preparing replacement parts before equipment failure occurs, and having a certain amount of time to secure the workforce. Continuous technological developments are required to perfectly predict all fault cases.

5. Economic Benefits Analysis

In Sections 3 and 4, the development methodology of the LW-PMM, a model that automatically detects laser welder failures using laser welder operation data, is explained. Section 5 presents a simple analysis of the economic effects of the LW-PMM, which is a PoC-level model. The economic analysis in this section is an auxiliary part of the study and demonstrates the economic benefits of the model.

The economic impact of this study, which prevents failures by detecting laser welder anomalies, is equivalent to the opportunity costs of welder failures and the losses from not producing normal products due to such measures. This loss cost is divided into direct and indirect loss costs according to the cause of the production time loss.

The direct cost of the loss is based on the time required to repair the facility, and in the case of strip tears to reweld the torn strip to resume facility operations. Indirect loss costs are based on the time spent on safety measures before work and inspections of other facilities for normal production, in addition to facility failure measures, including the time it takes to bring a product to a sellable level, even if the facility is in operation. In other words, the economic effect is the sum of direct and indirect loss costs. Table 9 lists the laser welder failure status and operation data from January 2021 to September 2022 used for the loss cost calculation.

Table 9. Primary data for calculating loss costs (1 January 2021–30 September 2022).

Category	Definition	Data	Specification
Laser Welder Fault Status	Cases	29.7 cases/year	Number of laser welder failures
	Hours	40.5 h/year	Time taken for actual laser welder failure action
	Action time	2 h/case	Average time taken to produce a normal product, other than the failure time
Operational Data	Production	50 ton/h	Amount of product produced per hour
	Variable processing cost	USD 50/ton	Costs that change as product production increases

The loss cost is the actual operating profit that can be obtained if a product that should have been produced is sold during non-production times. Based on the primary data listed in Table 9, the economic effect was analyzed for "A" CGL operating a laser welder. The loss cost was calculated as the number of failures (cases/year) × ② the failure time (h/year) × ③ the production volume (Ton/Hr) × ④ the variable processing cost (USD/ton). Table 10 lists the results from calculating the direct and indirect loss costs by applying the loss cost calculation formula based on the actual failure status and operational data of the laser welder.

Table 10. Calculation results for the loss costs.

Category	Calculation Result
Direct Loss Cost	① 2 Cases/Year × ② 2.5 h/Year × ③ 50 Ton/h × ④ USD 50/Ton = USD 12.5 K (KRW 0.125 billion)
Indirect Loss Cost	① 2 Cases/Year × ② 2.0 h/Year × ③ 50 Ton/h × ④ USD 50/Ton = USD 10 K (KRW 0.10 billion)

The direct loss cost is approximately USD 12.5 K (0.125 billion KRW/year) per year, the indirect loss cost is approximately USD 10 K (0.1 billion KRW/year) per year, and the economic effect through laser welder failure prevention is approximately USD 23.5 K (0.23 billion KRW/year) per year. This study reviewed the economic benefits based on a CGL that became a POC model. In the future, if the application is expanded to 13 factories that use laser welders among the CGLs of Company P, it is expected that more than 400 K (KWR 400 million) of economic profits will be generated annually.

In addition, if the LW-PMM technique applied in this study is expanded and applied to the side trimmer and tension leveler, which are critical facilities of the steelworks production line, additional profits are expected to be created, similar to those of laser welders, by preventing production from stopping due to the chronic failures of these facilities. Furthermore, facility failure measures reduce the burden on engineers in charge of risky facilities. In addition to these effects, it would be meaningful to conduct research on facility failure prediction, which is relatively lagging in technological applications compared to the application of various AI technologies in the field of production automation and intelligence in promoting smart factories in the steel industry. As a facility that requires precision control, failures can occur because of various factors; therefore, there is a limit to detecting and preventing failures in advance using only a monitoring system and the technical skills of the engineer in charge of the facility. By developing a failure prediction model for a laser welder that facility managers can trust, it is possible to reduce the burden on facility management engineers, who must take urgent action in the event of a failure. Failure prediction can also contribute to minimizing safety risks because measures against strip tears always involve fieldwork with the risk of disaster occurrence. Finally, this study is expected to contribute to the facility management paradigm shift in the steel industry from general preventive maintenance to predictive maintenance by conducting repairs before a failure occurs to maximize the use of facilities.

6. Conclusions and Future Works

6.1. Conclusions and Contribution

This study developed the LW-PMM using the LSTM-AE algorithm to automatically detect a failure in laser welders in CGLs in a steel plant. The LW-PMM model was developed and validated at POC, and its performance was tested with a pilot system at the operation site.

- First, the authors collected operational data from a CGL laser welder equipment from Steel plant at Company P for three months, from 1 January 2022 to 31 March 2022. After preprocessing, a total of 191 data items were finally selected.
- Second, considering the time series characteristics of the data, an LSTM-AE-based LW-PMM model was developed and trained by selecting the AE as the base algorithm and adding the LSTM algorithm.
- Finally, the performance of LW-PMM was evaluated, and the accuracy of the LW-PMM model was 97.3%, the precision was 79.8%, the recall was 100%, and the F1-score was 88.8%. Moreover, abnormalities were detected 27 h before the failure during operation site tests, demonstrating detection approximately 18 h faster than the existing equipment monitoring system.

The steel Industry processes iron, the basis of human civilization, into its most usable form and provides it as a product. Making high-strength automobile steel plates are used in vehicles to provide a safer environment for drivers in the case of an automobile accident and manufacturing high-strength rebars that do not collapse even after an earthquake. Steel can contribute to making human life more prosperous and sustainable in many fields through fusion with other metals.

6.2. Limitations and Further Research

This study was applied as a POC model for CGL laser welder failure prediction, and its effectiveness was verified. The limitations and discussions for future research are as follows. First, although the model was trained using as much data as possible, considering the influence of various factors on failures, there is a limit because not all possible situations can be learned during facility use, such as replacing laser welder parts. In addition, the model may have been overfitted because the threshold, which is the criterion for learning from the collected data to judge the anomaly, was set by a facility engineer with domain knowledge. To prevent overfitting, validation was performed using the data in addition to those used to train the model. However, because the frequency of facility failures is low, the accuracy of the model may be lower during actual use than during performance verification.

Considering these limitations, a discussion of future research directions is presented. First, to analyze the various characteristics of laser welder operation, additional research is required to improve and verify the accuracy of the model by expanding and applying the model developed in this study to laser welders in other factories that operate under the same mechanism. Moreover, it is necessary to additionally secure data that affect the welding quality, such as the characteristics of the steel type and the production speed of the strips.

Unlike conventional ML algorithms, such as neural networks, SVMs, and ensembles, which cannot handle the learning of hierarchical representations of time series data, the LSTM is suitable for modeling sequential data through training based on previous observations. The LW-PMM developed in this study can detect facility failures; however, it cannot identify the root causes of the failures. The LW-PMM is expected to be applied not only to laser welders but also to various facilities throughout the production process; therefore, additional research is required.

The CGL laser welder facility, which was the subject of this study, is used only for steel plants and is not commonly used for general industrial plants. Therefore, similar studies have not yet been conducted to compare these findings. In the future, if a similar type of research is published in a different facility or an equivalent steel facility, the results of mutual studies can be compared.

The analysis of the economic effect of the LW-PMM presented in Section 5 is an auxiliary part of this study and requires additionally proven justifications. Comprehensive financial research on the model developed in this study is also required in the future.

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Abbreviations

The following abbreviations and parameters are used in this paper:

Adam	Adaptive Moment Estimation
AE	Auto-Encoder
AI	Artificial Intelligence
ANN	Artificial Neural Network
Bi-LSTM	Bidirectional LSTM
BNN	Bayesian Neural Network
CGL	Continuous Galvanizing Lines
CNN	Convolutional Neural Network
DBN	Deep Belief Network
DNN	Deep Neural Network
HDR	High Dynamic Range
IoT	Internet of Things
IQR	Internet of Things
IT	Information Technology
LOF	Local Outlier Factor
LS-PMSM	Line Start-Permanent Magnet Synchronous Motor
LSTM	Long Short-Term Memory
LW-PMM	Laser Welder Predictive Maintenance Model
ML	Machine Learning
MSE	Mean Square Error
MSPC	Multivariate Statistical Process Control
NDE	Non-Destructive Evaluation
NSGA-III	Non-Dominated Sorting Genetic Algorithm- II
PCA	Principal Component Analysis

PHM	Prognostics and Health Management
QCDS	Quality Control Data System
RF	Random Forest
RNN	Recurrent Neural Network
RT	Regression Tree
RUL	Remaining Useful Life
SAE	Sparse Auto-Encoder
SCADA	Supervisory Control and Data Acquisition
SVM	Support Vector Machine
TF-IDF	Term Frequency–Inverse Document Frequency
U-LSTM	Unidirectional LSTM
USW	Ultrasonic Welding

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