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RESEARCH ARTICLE

Study on Stochastic and Autoregressive Time Series Forecasting for Hydrogen Refueling Station

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ABSTRACT Hydrogen refueling stations are pivotal for renewable energy and carbon neutrality; however, they encounter challenges owing to equipment malfunctions. This study addresses the use of time-series forecasting techniques to predict and diagnose critical equipment failure at these stations. An analysis of the station equipment was conducted to create scenarios for potential malfunctions in compression equipment. Techniques such as the Recurrent Neural Network (RNN), Long Short-Term Memory network (LSTM), and Gated Recurrent Unit (GRU) have been employed to forecast the conditions of high-pressure compression equipment. Deep neural networks were constructed to enhance prediction accuracy, typically achieving an error margin of 0.01. Multi-step predictions using autoregression were utilized to bolster equipment resilience against aging and progressive failures. Autoregressive prediction models, particularly those using LSTMs and GRUs, outperform RNNs. However, predictions may be subject to errors due to algorithmic limitations and environmental factors. This study introduces a stochastic forecasting approach that, utilizes Gaussian distributions to predict probability distributions, not single-point estimates. This method yielded a 95% prediction interval with a standard deviation of 1.96. The reliability of multi-time step forecasts is significantly improved by adopting stochastic autoregressive forecasting and establishing prediction intervals. The proposed model enhances not only the accuracy of equipment failure predictions but also proactive maintenance, thus reducing downtime and boosting the efficiency of the hydrogen fuel infrastructure, which contributes to the wider utilization of hydrogen as a clean energy source.

INDEX TERMS Autoregressive, hydrogen refueling station, probabilistic forecasting, recurrent neural network, time series forecasting.

I. INTRODUCTION

Under the impetus of the Paris Climate Agreement, there has been a marked increase in the interest in renewable energy. South Korea is proactively investing in decarbonization by establishing a new value chain within the hydrogen industry to meet its carbon neutrality objectives. The rapid expansion of hydrogen refueling stations has elicited significant public safety concerns owing to abnormal operational conditions and key equipment failures, causing inconvenience for facility operators [1], [2]. Failures in on-site hydrogen refueling station facilities primarily occur in dispensers, high-pressure compressors, hydrogen production devices, and raw-material supply systems. Despite recent installations, high-pressure compressors have experienced a significant number of issues owing to maintenance and technical challenges. As hydrogen

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refueling stations continue to operate over time, the likelihood of encountering equipment aging-related problems is expected to rise [3], [4], [5].

To ensure the safe and efficient operation of hydrogen refueling stations, real-time information was collected from the Supervisory Control and Data Acquisition (SCADA) system, which is a remote monitoring and data acquisition system of the facilities. Intelligent maintenance activities, such as predicting and diagnosing future states and equipment failures based on date collected using time-series prediction techniques, are essential. Equipment failure diagnosis methods include experience-based, data-driven, and model-based approaches. To maintain health, periodic maintenance is based on regular observations or scheduled checks, and condition-based maintenance is performed at specific intervals [6], [7].

Recent studies have utilized deep learning techniques to ascertain the occurrence of failures, evaluate the severity of such failures, identify signs of anomalies, and estimate the remaining service life of equipment [8], [9]. Additionally, studies are actively ongoing to judge failures using time-series data from various sensors, such as vibration signals, and predict and diagnose failures [10], [11].

In hydrogen refueling stations, myriad signals measured throughout operational processes serve as data for failure diagnosis and health management. The measured signals form a history over time and suitable algorithms for such data include Recurrent Neural Networks (RNNs). RNNs process inputs and outputs at the sequence level and, possess a recurrent structure in which the output feeds back into the input. They perform well in processing sequential data, such as time-dependent data such as stock prices, weather, and sequential data such as natural language and audio [12]. To overcome the long-term dependency problem, LSTM was proposed, designed to maintain long and short-term memories by adding a cell state to the hidden state, preserving or discarding information from previous layers [13]. Subsequently, GRU, a simplified version of a complex LSTM cell, was proposed. It demonstrates relatively fast learning speeds and comparable performance to LSTM owing to its fewer parameters and simplified structure [14]. Furthermore, research has been actively conducted using Attention-based Seq2Seq and Transformers for time-series prediction and fault diagnosis [15], [16].

In this study, we performed state prediction for future time points using time-series forecasting algorithms to maintain health and diagnose failures of key equipment at hydrogen refueling stations. In hydrogen refueling stations, the prediction of equipment failure is complicated by the complexity of the multivariate data and the dynamic nature of the systems to be forecasted. For instance, the variability of pressure and temperature within the stations is highly dynamic, representing rapid fluctuations that are challenging to capture using simple time-series prediction models. The deep learning-based multi-step forecasting method proposed in this study is expected to better comprehend and predict these complex data patterns, thereby enhancing the accuracy of failure diagnostics.

The equipment data vary based on factors such as the charging of vehicles and process conditions such as pressure in each storage tank, and it does not follow trends, cycles, or seasonal patterns. Therefore, for multivariate prediction of major equipment, deep learning models in the RNN family, including RNN, LSTM, and GRU, are effective, and, capable of learning from discontinuous data compared to statistical analysis-based techniques such as Autoregressive Integrated Moving Average (ARIMA) or Exponential Smoothing (ES).

Time-series forecasting techniques are applied to predict and diagnose failures of crucial equipment at hydrogen refueling stations. Multivariate time-series prediction algorithms, such as RNN, LSTM, and GRU, were employed and compared to predict future states. To prepare for equipment aging and progressive failures, a multi-step time-series forecasting was conducted. To predict multiple future time points, we use an autoregressive forecasting technique rather than a single-shot prediction and perform a comparative analysis for each algorithm. Time-series forecasting can exhibit errors owing to the algorithmic accuracy and environmental factors. Therefore, our model is designed to analyze prediction intervals that are not merely based on predicted values with incorporated uncertainty but also rather on probability distributions. The prediction of these probability distributions enhances robustness against noise and enables more informed and optimal decision-making during fault diagnosis. Using an autoregressive model for uncertainty prediction, we analyzed the uncertainty of the model and set the upper and lower bounds for the prediction intervals. We ensured the reliability of the prediction algorithms for hydrogen refueling stations through an uncertainty prediction.

Through this study, we contribute to the prediction and diagnosis of major equipment failures at hydrogen refueling stations using time-series prediction algorithms. By employing multivariate prediction, we can provide accurate predictions considering the complex temporal interactions of the equipment. In addition, utilizing multi-step time-series prediction allows us to forecast the long-term conditions of the facilities. The use of probabilistic forecasting enhances resilience to noise, improves the reliability of prediction algorithms, and enables more effective equipment failure diagnosis. It is anticipated that these dependable optimal decision-making processes will contribute to enhancing the stability and reliability of hydrogen refueling stations.

II. ANALYSIS OF HYDROGEN REFUELING STATAION FACILITIES

A. P&ID (PIPING & INSTRUMENTATION DIAGRAM)

This study focused on an off-site hydrogen refueling station located in Seosan, Chungnam Province, South Korea. The station consists of a process and refueling equipment. Off-site hydrogen refueling stations receive hydrogen from external sources via tube trailers or pipelines, which are ideal

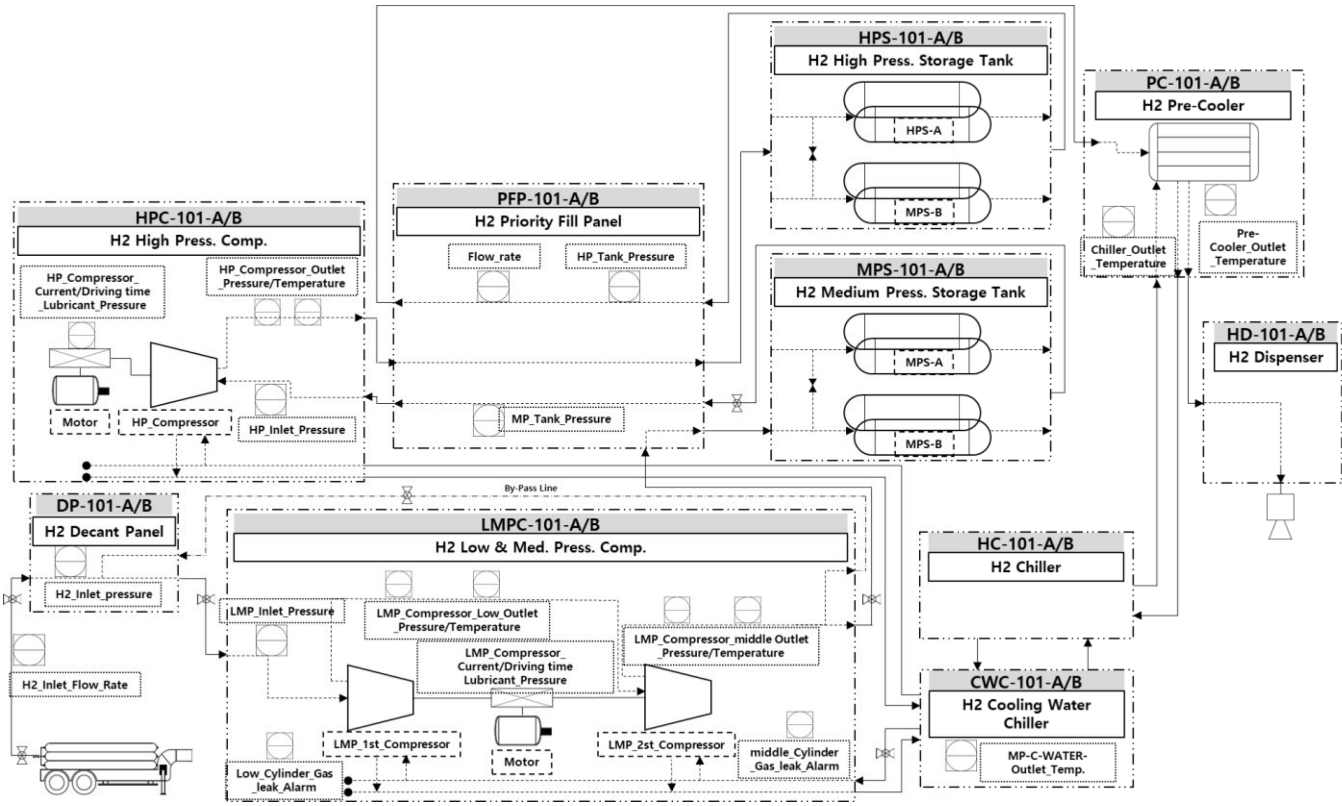

FIGURE 1. P&ID diagram of hydrogen refueling station.

for short transportation distances from the hydrogen supply source [2], [5].

Hydrogen refueling stations, despite handling high-pressure gases, feature relatively simple operational systems. The process facilities consisted of unit A and B. As both units operate identically, Figure 1 schematically illustrates only one unit. It includes compressors for low, medium, and high pressures, as well as storage tanks. Hydrogen at 20MPa is delivered to the refueling station in trailer form and passes through a decant panel and, then through low- and medium-pressure compressors, compressing it to approximately 50MPa. Compressed hydrogen passes through a priority panel and is stored in a medium-pressure tank. The medium-pressure hydrogen was further compressed to approximately 87MPa using a high-pressure compressor and is stored in a high-pressure tank after passing through a control panel. Hydrogen is supplied to fuel-cell vehicles through a dispenser. During this process, owing to the Joule-Thomson effect, the temperature of the hydrogen vehicle container increased. To avoid compromising the durability of the container when the temperature exceeds 85 °C, the hydrogen is cooled to −40 °C via a cooler before being supplied to the fuel cell vehicle. The charging process is terminated once the temperature and pressure of the hydrogen container reach specific levels, ensuring a State of Charge(SOC) of over 95% [17].

B. MULTIVARIATE DATA ANALYSIS OF HYDROGEN REFUELING OPERATIONS

The data measured from the process and refueling equipment consisted of over 450 variables. The data include tag data representing various physical quantities, such as pressure and temperature, status data indicating the state of the equipment, and alarm data representing risk signals, such as gas leaks, high pressure, and high temperature. The data at the refueling station were measured at a one-second interval over the course of a year.

In this study, we performed an analysis of tag data, excluding status and alarm data, for time-series forecasting. The data to be used for time-series prediction algorithms were selected from high-pressure compressors and storage tanks, as these are the components that experience the most failures, along with the dispenser at the off-site refueling station [18]. Figure 2 illustrates the pressure data for the high-pressure storage tank and inlet pressure of the high-pressure compressor. Abnormal pressure-drop periods were observed for the high-pressure compressor. We identified instances of pressure removal for tank maintenance as outliers and removed them because they did not represent normal system operation. The measured data do not exhibit periodicity, seasonality, or trends, rendering statistical analysis-based time-series prediction methods unsuitable. In the case of refueling equipment, events such as receiving hydrogen from an external source or a hydrogen vehicle initiating charging can cause data changes. Algorithms utilizing recurrent neural networks learn the weights of the impact of preceding sequences on the next sequence, thus predicting future time points. As data changes occur owing to process variations accompanying events, univariate prediction is not suitable because it relies on a single variable. The facility's conditions are affected by different variables at different time points; hence, this study employed multivariate analysis and prediction for time-series using variables related to high-pressure compressors and storage tanks, selected through P&ID analysis.

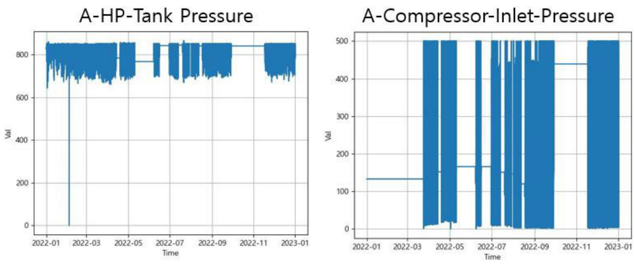

FIGURE 2. Hydrogen refueling station acquisition data.

III. TIME SERIES FORECASTING ALGORITHMS

A. THEORETICAL BACKGROUND OF RECURRENT NEURAL NETWORK

An RNN is an artificial neural network that processes input and output in sequence units, having a recurrent structure where the output feeds back into the input. The fundamental forward propagation structure of an RNN cell is shown in Figure 3. The computational result of the cell receives the hidden state value from the previous cell, and the hidden state and prediction at each time step are given by Eq. (1). RNN suffer from the gradient vanishing problem during backpropagation, leading to the issue of long-term dependencies [12], [19].

$$\begin{aligned} a^t &= \tanh\left(W_{ax}x^t + W_{aa}a^{t-1} + b_a\right) \\ \hat{y}^t &= softmax(W_{ya}a^t + b_a) \end{aligned} \tag{1}$$

where, t is the timestamp, a^t represents the hidden layer at t. x^t is the input vector at t, and W_{ax} is the weight between the input vector and hidden layer. a^{t-1} represents the hidden layer at $t-1$ and W_{aa} is the weight between the hidden layer at time $t-1$ and hidden layer at time t. b_a represent the bias. $\hat{y}^t$ is the output vector, and W_{ya} and b_a represent the weight and bias of the hidden layer, respectively.

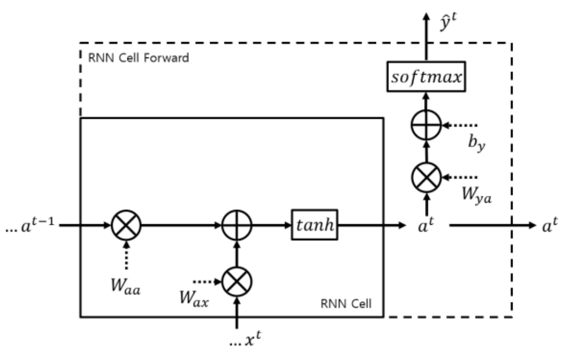

FIGURE 3. Forward propagation for RNN.

LSTM is a model that addresses the vanishing gradient problem by incorporating a memory cell and has shown high performance in predicting time-series data. The fundamental forward propagation structure of an LSTM cell is shown in Figure 4. It has a cell state for long-term memory at each time step, and operations are performed for the forget gate (Γ_{f}), update gate (Γ_{i}), output gate (Γ_{o}), and candidate value ($\bar{c}^t$). The equations for each gate are shown in Eqs. (2). The forget gate operates on the previous result and the current input and produces a value between 0 and 1 through an activation function. The candidate value carries a tensor containing information from the current step, and is influenced by the update gate. The update gate determines candidate information to be added to the cell state. The cell state determines the memory passed to the next time step [13], [19], [20], [21].

$$\begin{aligned} \Gamma_{\mathrm{f}}^t &= \sigma(W_f\left[a^{t-1}, x^t\right] + b_f) \\ \Gamma_{\mathrm{i}}^t &= \sigma(W_i\left[a^{t-1}, x^t\right] + b_c) \\ \Gamma_{\mathrm{o}}^t &= \sigma(W_o\left[a^{t-1}, x^t\right] + b_o) \\ \bar{c}^t &= \tanh(W_c\left[a^{t-1}, x^t\right] + b_c) \end{aligned} \tag{2}$$

where, W_{nm} represents the weight between the hidden layer at time t-1 and the input vector for each gate and b denotes the bias for each gate. σ represents the activation function.

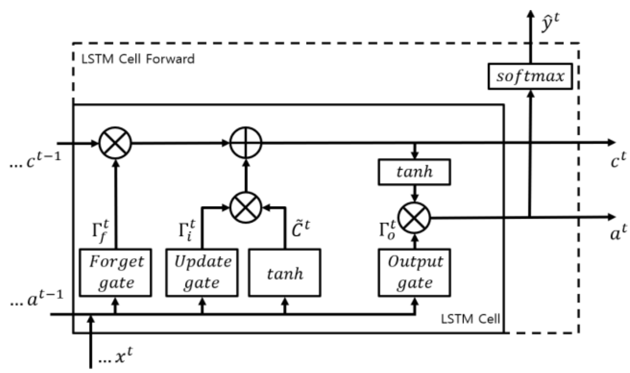

FIGURE 4. Forward propagation for LSTM.

The GRU is a variation designed to address the vanishing gradient problem more effectively than LSTM. This simplifies the cell from LSTM, resulting in a faster learning speed and similar performance. The fundamental forward propagation structure of a GRU cell is depicted in Figure 5. It consists of a Reset gate and an Update gate, as shown in Eq. (3). The Reset gate determines the amount of the previous state information retained from the current state. The Update gate plays a role similar to that of LSTM's forget gate and input gate, determining the proportion of the previous information and corresponding to the current information. In other words, it determines how much of the past information is retained and how much of the current new information is incorporated [20], [21], [22], [23], [24].

$$\begin{aligned} \mathrm{r_t} &= \sigma(W_{xr}x_t + W_{hr}h_{t-1}) \\ \mathrm{z_t} &= \sigma(W_{xz}x_t + W_{hz}h_{t-1}) \\ \mathrm{g_t} &= \tanh(W_{hg}\,(t_t \otimes h_{t-1}) + W_{xg}x_t \\ \mathrm{h_t} &= (1 - z_t) \otimes g_t + z_t \otimes h_{t-1} \end{aligned} \tag{3}$$

where the weight matrices are denoted as W, and the bias vectors are denoted as b in Eq. (3).

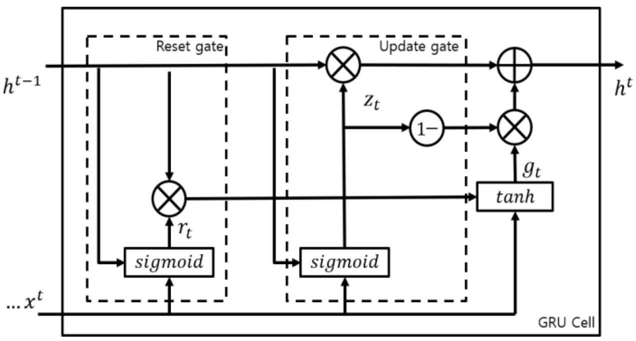

FIGURE 5. Forward propagation for GRU.

B. DATASET FOR APPLYING TIME SERIES FORECASTING ALGORITHMS

The dataset for applying time-series forecasting algorithms is related to equipment Unit A at the hydrogen refueling station. It includes the inlet and outlet pressures, outlet temperature, lubricant oil temperature of the high-pressure compressor, and the pressure of the high-pressure storage tank. The input data included the input and outlet pressures of the high-pressure compressor, the outlet temperature, the lubricant oil temperature, and the storage tank pressure. The output data are the lubricant oil temperature of the compressor, with time-series predictions made accordingly.

In the event of an issue with the storage tank, the compressor will operate continuously to maintain the pressure of the storage tank, causing an increase in the lubricant oil temperature. Furthermore, if the compressor malfunctions, it will operate longer to maintain the outlet pressure, resulting in an increase in the lubricant oil temperature of the compressor. If there is a problem with the input pressure, the incoming hydrogen will continuously escape through the vacuum valve, and because the compressor is not operating, the temperature of lubricant oil will steadily decrease. Because issues with high-pressure equipment can lead to changes in the compressor lubricant oil temperature, it was selected as the predicted value for maintenance. A schematic of the high-pressure compressor equipment is shown in Figure 6.

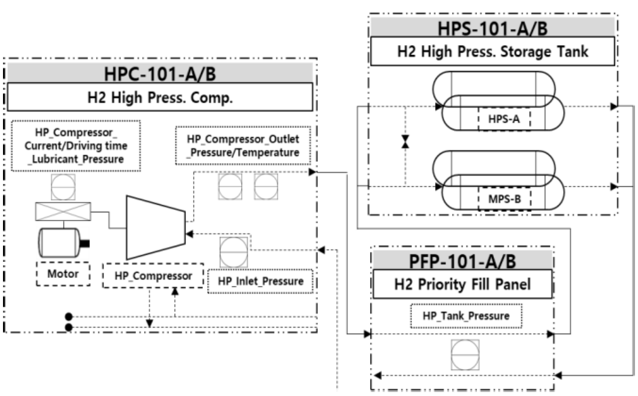

FIGURE 6. High-pressure compressor equipment diagram.

C. CORRELATION ANALYSIS OF APPLIED ALGORITHM DATA

The correlation is considered stronger as it approaches 1, as shown in Figure 7 [25]. The results of the correlation analysis are shown in Figure 8. The outlet pressure of the compressor exhibits strong correlations, being most pronounced with the input pressure and significant with temperature. The label data, lubricant oil temperature, show a distinct correlation with both outlet pressure and temperature, a weak correlation with the high-pressure tank, and a low correlation with the input pressure. Predicting multivariate time series achieves higher accuracy when the variables involved have strong correlations. However, with equipment, correlations can vary over time and variables may not correlate at the same time points. Therefore, it is necessary to consider various variables according to the process flow when predicting a multivariate time series for equipment, even if the correlations are very weak.

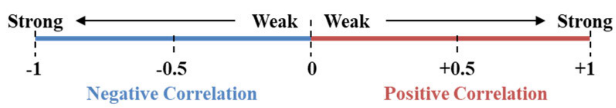

FIGURE 7. Strength and direction of correlation coefficient.

The measurement data spans approximately one year. To focus on the summer months, from June to August, which have the most significant impact on hydrogen facilities operating at lower temperatures among the four seasons, the data were narrowed down. Additionally, considering computer resources, the data were up-sampled at 5-minute intervals. The preprocessed dataset for the application of the algorithm is shown in Figure 9.

The operational cycle of the high-pressure equipment is illustrated in Figure 10. The pressure in the high-pressure tank decreased when the vehicle was refueled with hydrogen. As the tank pressure decreased, both the pressure and temperature at the compressor outlet increased for compensation. To achieve this, the input pressure rises to replenish hydrogen from the intermediate pressure tank, and the compressor operates to compress from intermediate pressure to high pressure.

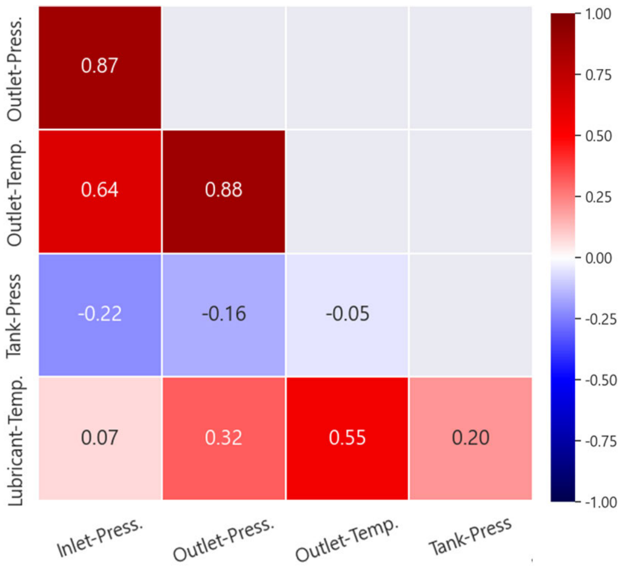

FIGURE 8. Correlation coefficient high-pressure compressor.

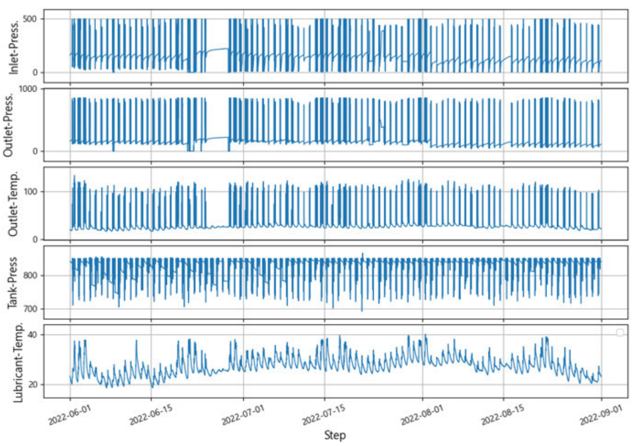

FIGURE 9. High-pressure compressor equipment dataset.

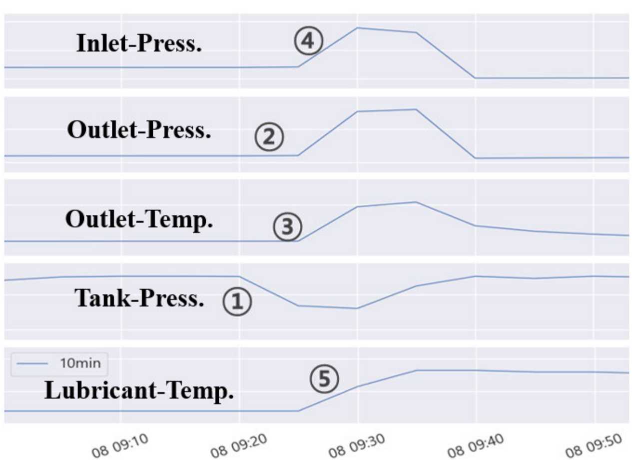

FIGURE 10. Cycle of high-pressure compressor equipment.

The operation of the compressor resulted in an increase in lubricant oil temperature.

The dataset for the algorithm application is Sequence to Vector, where the input sequence consists of multivariate variables. The window size for the input sequence was 12, and the label size for the output sequence was 1, as illustrated in Figure 11. The window and label data for a single training data sample are shown in Figure 12. Normalization was performed to prevent overfitting during training. The training, validation, and test data were split at a ratio of 6:2:2, and the data separation for the lubricant oil temperature corresponding to the Label is shown in Figure 13.

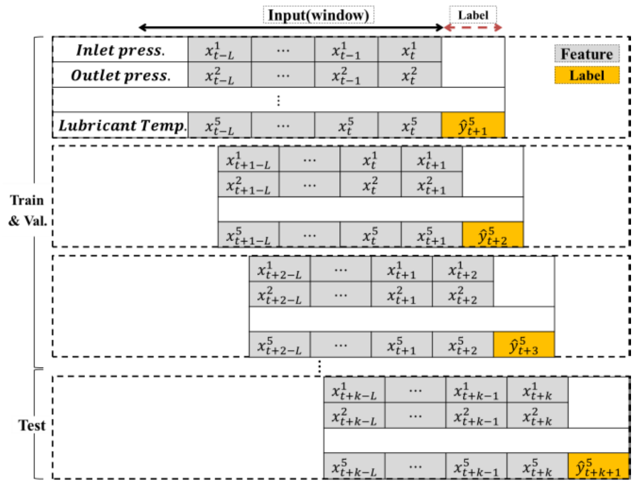

FIGURE 11. Train and test for time forecasting algorithm diagram.

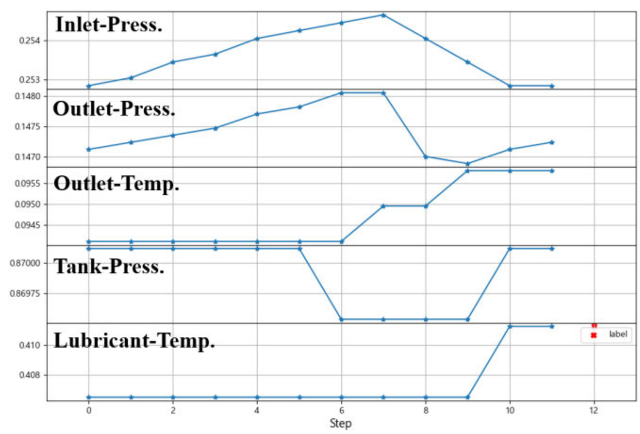

FIGURE 12. Train and test date for time forecasting algorithm.

Structural designs for the RNN, LSTM, and GRU were developed to predict the lubricant oil temperature of a high-pressure compressor at a hydrogen refueling station. The hyperparameters were selected and optimized, as listed in Table 1. The network architecture consists of an RNN layer with depth, comprising two recurrent neural network layers and two hidden layers. For a fair comparison and analysis of the hyperparameters and algorithms, the seed was fixed, and experiments were conducted.

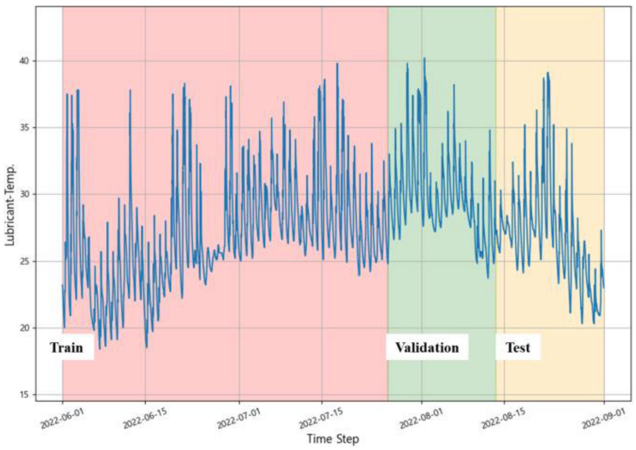

FIGURE 13. Split label data for time forecasting algorithm.

TABLE 1. Hyperparameters of various deep learning models.

	Epoch	Learning rate	Batch	Optimizer
RNN	100; 300	0.01; 0.001	64; 512	Adam
LSTM	100; 300	0.01; 0.001	64; 512	Adam
GRU	100; 300	0.01; 0.001	64; 512	Adam

D. EVALUATION METRICS

To evaluate the prediction performance of the time series prediction algorithm, we employed the Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE) as shown in Eq. (4) to (6) [26], [27].

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(target_i - prediction_i)^2} \quad (4)$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|target_i - prediction_i| \quad (5)$$

$$MAPE = \frac{1}{N}\sum_{i=1}^{N}\left|\frac{target_i - prediction_i}{target_i}\right| \quad (6)$$

IV. EXPERIMENTAL RESULTS AND DISCUSSION

A. SEQUENCE TO VECTOR MODEL

The hardware configuration used for the experiments included an Intel(R) Core(TM) i9-9940X CPU @ 3.3 GHz, and all models utilized GPU computation with an NVIDIA GeForce RTX 3090 Ti for fast training and computation. Deep learning models were constructed using TensorFlow, version 3.10 as the algorithm framework.

The future data are unknown from the current state; therefore it is not appropriate to normalize the entire dataset, including the test data, uniformly. First, normalization was performed on the training dataset, and the validation and test data were normalized based on the training data.

The hyperparameters for the normalized data were optimized on the validation set. The performance evaluation metrics for the validation datasets of the RNN, LSTM, and GRU are listed in Table 2. All the results exhibited a high accuracy below 0.01. Based on this, experiments were conducted on the test data. The performance evaluation metrics for the test data are listed in Table 3. A comparison of the actual and predicted values for each model is shown in Figure 14.

TABLE 2. Evaluation metrics of validation data for various deep learning models.

	RNN	LSTM	GRU
RMSE	0.0072	0.0098	0.0067
MAE	0.0040	0.0064	0.0035
MAPE	0.0079	0.0110	0.0062

TABLE 3. Evaluation metrics of test data for various deep learning models.

	RNN	LSTM	GRU
RMSE	0.0078	0.0077	0.0063
MAE	0.0054	0.0043	0.0032
MAPE	0.0187	0.0124	0.0102

For the test dataset, RNN, LSTM, and GRU showed high accuracy below 0.01 in RMSE and MAE, and RNN also showed a high accuracy of approximately 0.02 in MAPE. As shown in Figure 14, the actual and predicted values tended to closely match.

The Sequence to Vector model predicts single-step predictions. It uses multivariate and multiple input values as sequences and outputs a vector of single-step predictions. It demonstrates high accuracy using a basic structure that connects the sequentially predicted results for single-step predictions.

However, in actual processes, predicting only the immediate next step is insufficient to ensure Prognostics and Health Management (PHM), which includes monitoring equipment aging and progressive failures, predicting only the immediate next step is insufficient. For PHM, predictions of multiple steps are required. In this study, an autoregressive forecasting model, in which the predicted output values are fed back as inputs to predict multiple steps (i.e., sequences), was used to predict multiple steps using the trained model.

B. AUTOREGRESSIVE FORECASTING

To facilitate multi-step forecasting, an autoregressive modeling approach was employed. Autoregressive models leverage the previous output as the input for subsequent predictions, a process graphically represented in Figure 15. We assessed the model performance using RMSE, MAE, and MAPE, and the results are tabulated in Table 4.

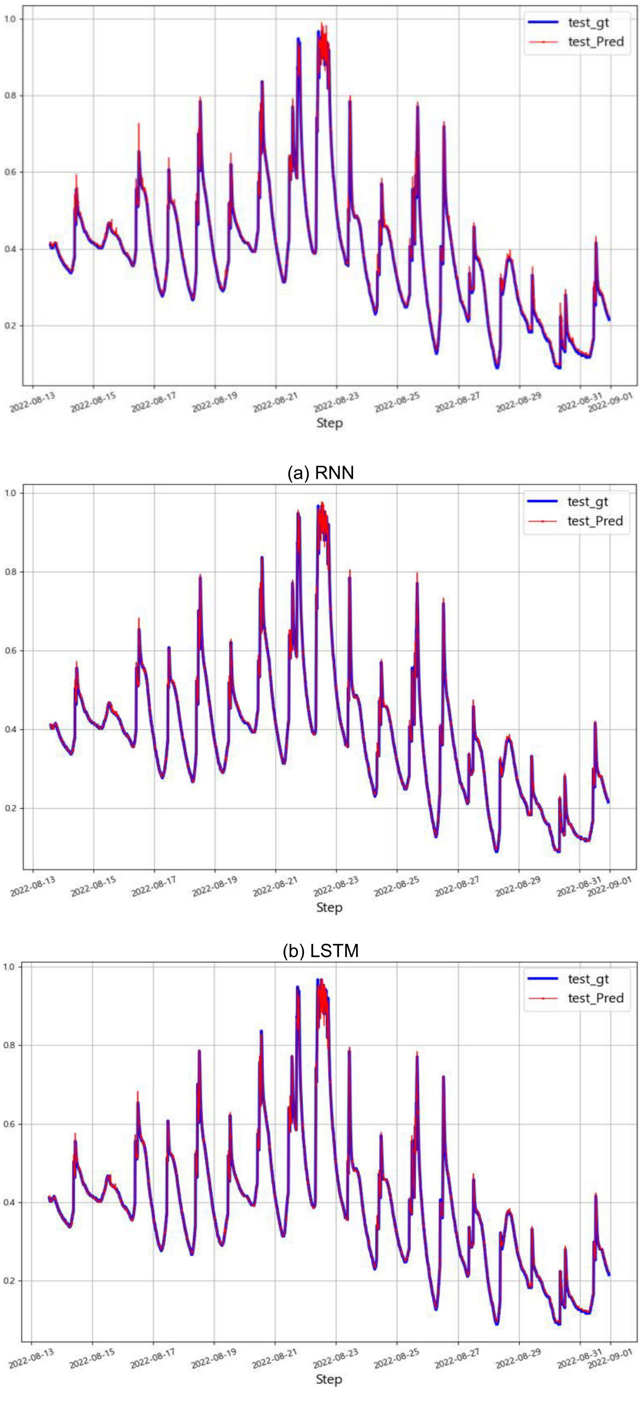

FIGURE 14. Lubricant temperature forecasting for various deep learning models.

RNN exhibits a relatively lower performance in terms of RMSE, MAE, and MAPE compared with LSTM and GRU. Figure 16(a) illustrates this discrepancy, showing that the predicted values of the general trend, deviate significantly from the actual measurements while following the general trend.

Conversely, the LSTM model achieved a MAPE of 0.13, indicating an enhanced predictive accuracy over the RNN.

TABLE 4. Evaluation metrics of autoregressive model for deep learning models.

	RNN	LSTM	GRU
RMSE	0.1449	0.0613	0.0540
MAE	0.1320	0.0472	0.0393
MAPE	0.5096	0.1370	0.1337

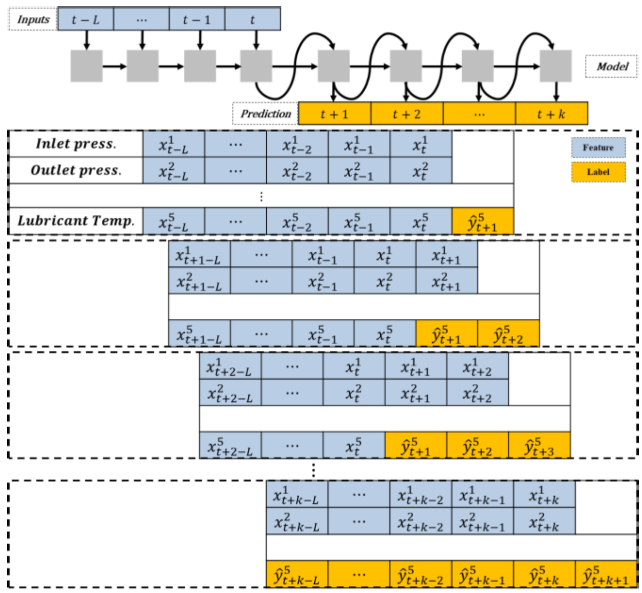

FIGURE 15. Visualization of autoregressive models.

Figure 16(b) shows how LSTM closely mirrors the fluctuations in lubricant temperature, capturing the peaks with precision. However, it exhibited discrepancies, particularly at the extremities of the data series, suggesting a limitation in capturing lower temperature values.

The GRU model outperformed LSTM in terms of MAE and MAPE, demonstrating its superior predictive capability. It accurately traced the lubricant temperature variations and showed a marked improvement in early value predictions compared to the LSTM model, which is also visually corroborated by Figure 16(c).

C. PROBABILISTIC TIME SERIES FORECASTING

In time-series forecasting, point prediction shows the expected future value, but depending on the accuracy of the algorithm, there is uncertainty. The predicted value is not always precise and errors can occur because of environmental changes and random factors. This study aims to enhance the reliability of forecasting information by applying prediction intervals. The prediction intervals represent a range around a specific predicted value, which accounts for the uncertainty. They indicate the likelihood that the actual observed value will fall within this range when, considering environmental and random factors. This approach can enhance

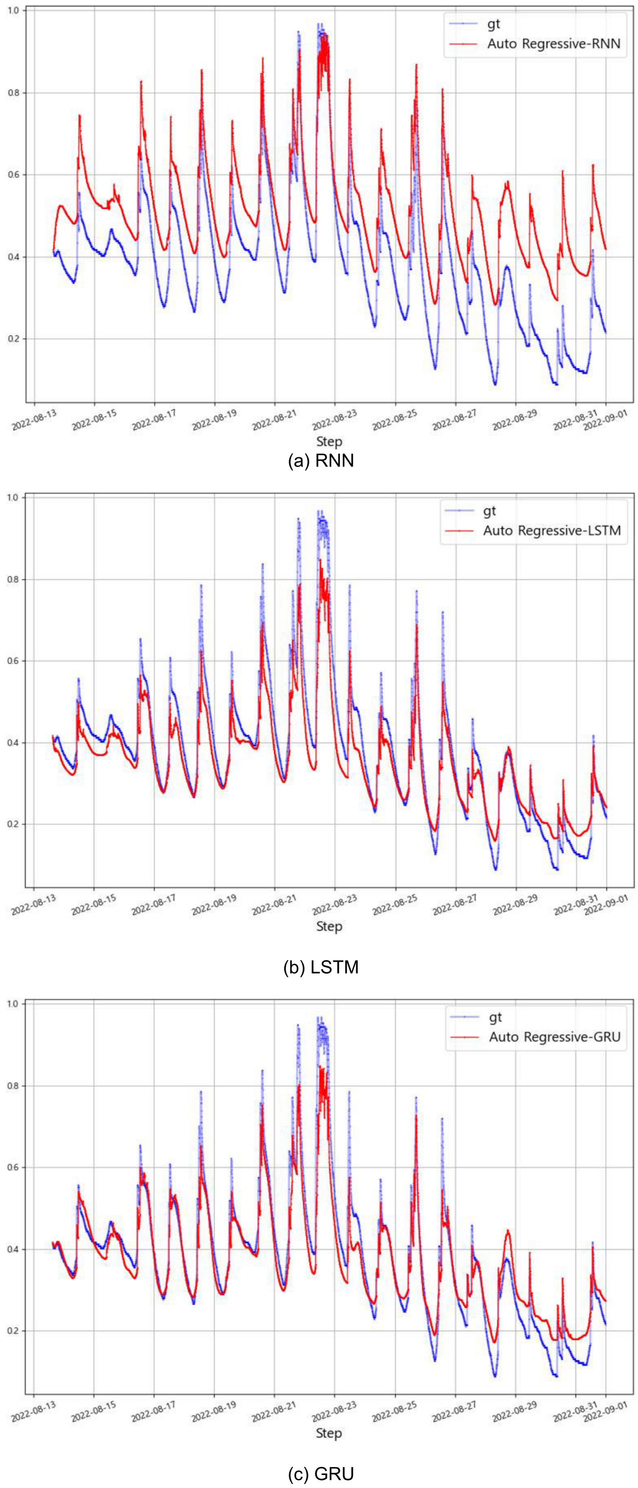

FIGURE 16. **Lubricant temperature forecasting for various autoregressive models.**

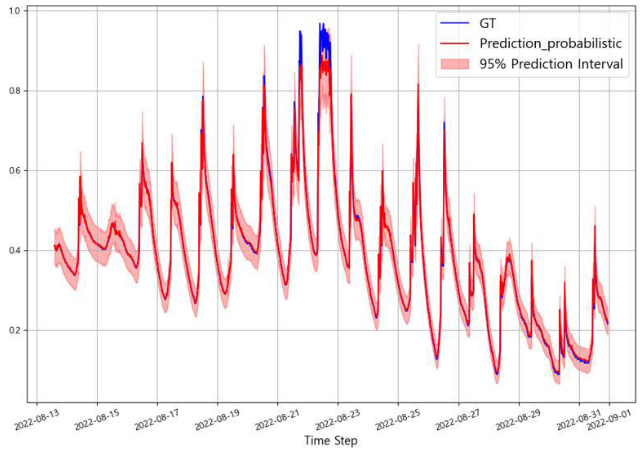

FIGURE 17. **Single-step stochastic forecasting (95% prediction interval).**

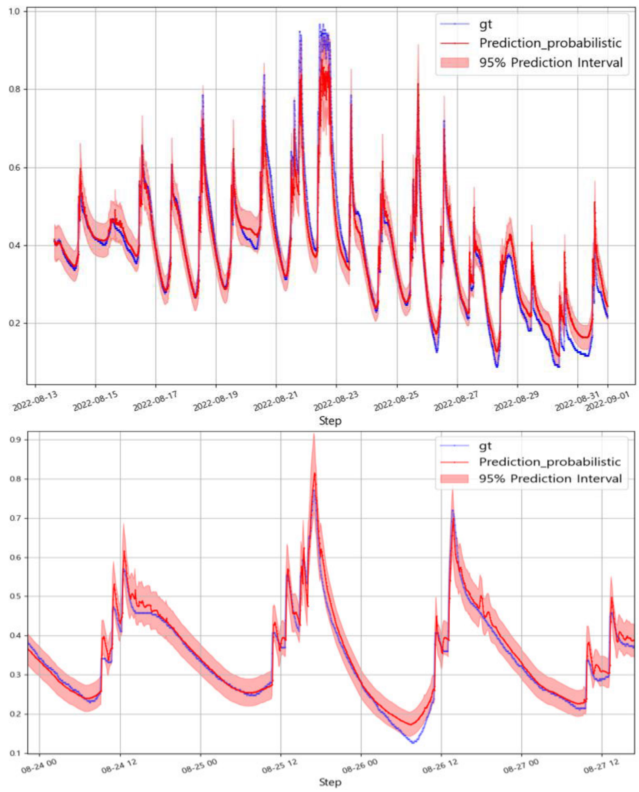

FIGURE 18. **Autoregressive stochastic forecasting (95% prediction interval).**

prediction reliability and build an optimal decision-making system [28], [29].

In the output layer of the time-series forecasting algorithm, instead of a single point, a probability distribution of the Gaussian distribution is used to measure the mean and standard deviation of the prediction. The Gaussian distribution indicates that 95% of the observations are within 1.96 standard deviations from the mean, and this information is used to determine the upper and lower prediction intervals. The probability loss function was optimized using a negative log-likelihood loss function, focusing on the probability distribution. Recurrent Neural Networks (RNNs) were tested based on the GRU, which showed the highest reliability among autoregressive models.

For the sequence-to-vector model, Figure 17 shows the probability forecasting using the basic structure that sequentially connects the single-step prediction values. As with the previous model, because it is a structure that sequentially connects the predicted results, the accuracy is high, and 95% of the observed values are within the prediction interval.

The autoregressive model also performs forecasting using a probability distribution. The predicted mean value of the probability result was used again for prediction, and the results are shown in Figure 18. Although the prediction accuracy was somewhat lower than that of single-step predictions, 95% of the observed values were within the prediction interval. This indicates that even with a slightly lower accuracy or existing uncertainty, the actual values fall within the 95% confidence interval.

V. CONCLUSION

This study conducted a comparative investigation of various Recurrent Neural Networks applied to hydrogen refueling station equipment, encompassing low-pressure, medium-pressure, and high-pressure compressors. Our focus was primarily on high-pressure compressors, which are recognized for their susceptibility to frequent malfunctions. The operational parameters of this equipment, including inlet pressure, compressor outlet pressure and temperature, lubricant oil temperature, and high-pressure storage tank pressure, were considered for multivariate time series forecasting utilizing RNN(Recurrent Neural Network), LSTM(Long-Short Term Memory), and GRU(Gated Recurrent Unit) algorithms. Prior to algorithm implementation, outlier detection, normalization, and data set division were rigorously performed.

Our findings reveal an effective analysis of connected sequential data using the sequence-to-vector time series forecasting methodology. Employing performance metrics such as RMSE, MAE, and MAPE, all algorithms demonstrated high precision with accuracy levels at or below 0.01.

The autoregressive model extends the prediction scope to multi-step forecasting and recycles the output for subsequent predictions. Within this model, the RNN exhibited trends consistent with the other algorithms but demonstrated comparatively lower predictive performance. In contrast, the LSTM and GRU algorithms exhibited higher efficacies, with MAPE values of approximately around 0.1. The study's proposed autoregressive algorithm model confirmed the reliability in both single-step and multi-step forecasting scenarios.

A principal contribution of this research is the incorporation of prediction uncertainty, employing a Gaussian distribution for probabilistic forecasting, achieving over 95% reliability, which corresponds to a prediction interval of 1.96 standard deviations. The stochastic sequence-to-vector model, akin to single-point predictions, demonstrated a robust predictive performance, with observed values falling within the 95% prediction interval. For the stochastic autoregressive model, although the probability distribution forecasting showed reduced performance compared to single-step forecasting, the observed values remained within the 95% forecasting prediction interval.

The study underscores the adaptability of recurrent neural networks to equipment with event-driven time series changes, moving beyond periodicity or trending behaviors. It ascertains the dependability of multi-point predictions through autoregression and, by extension, through probability distribution prediction, validating a reliability of 95% or greater. Such a framework reflects the model's inherent uncertainty, thereby improving the reliability of forecasts and establishing an optimized decision-making system.

Future work should extend the proposed stochastic forecasting methods not only to high-pressure equipment but also to medium and low-pressure apparatuses or dispensers. Furthermore, robustness should be verified by applying these methods to hydrogen refueling stations across different regions beyond the Seosan station, the focus of this forecast. The exploration of transfer learning for the application of time series forecasting to a variety of equipment, beyond hydrogen refueling stations, to ensure generality is also warranted. We will continue to investigate the use of ensemble techniques that combine various algorithms to achieve more accurate predictions. This is anticipated to contribute to increased accuracy and reduced computational time, ultimately aiding the establishment of safety standards for hydrogen refueling stations in terms of fault diagnosis and condition prediction in the future.

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