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Artificial Intelligence Deep Learning-Based Life Prediction and Fatigue Durability FEM Analysis Based on Control Arm Fatigue Accumulation

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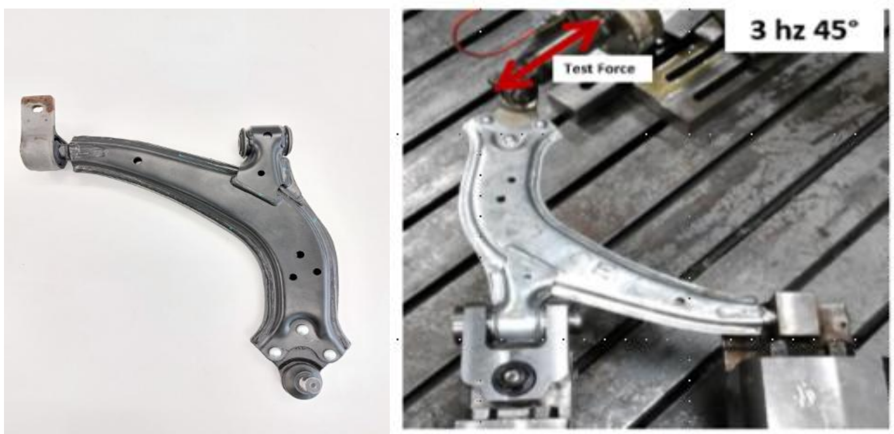
Abstract: *In this study, the life prediction and fatigue durability analysis based on artificial intelligence deep learning were mainly based on finite element analysis (FEA) and fatigue theory. The data-based artificial intelligence PRUL prediction was simulated based on Run to Failure data, that is, the sensing data of the conditions that occurred in the control arm during the execution from the last maintenance activity to the next activity. Based on the Pitch Angle signal calculated from the vehicle dynamics model during driving, random noises such as Random Road Profile were added to create a virtual sensor input signal, and then the previously designed algorithm was applied to calculate the actuator driving angle, and the simulation was performed to obtain the results. The basic characteristics of the control arm were FEM simulated and the displacement variation analysis was analyzed according to the failure. The Von Mises Stress analysis was performed for the structural destruction prediction and torsional analysis for load distribution. The PRUL prediction can be considered a special form of survival analysis, and basically, two types of technologies were considered for predicting the PRUL: model-based technology and data-based technology. Data-model-based techniques use physical models to predict the occurrence of component failures over time, while data-driven techniques predict PRUL based solely on past observations without making assumptions about how components may fail over time, which is why this study was conducted to derive the results*

Keywords: *Control Arm, Artificial Intelligence Deep Learning, Fatigue Durability FEM, Fatigue Accumulation, Dynamic Analysis*

1. Introduction

The direction of this study was to utilize AI-based deep learning techniques for fatigue life prediction and fatigue durability analysis of control arms, a core component of an automobile suspension system. Control arms are subject to repeated loads during driving and are vulnerable to fatigue failure, so accurately predicting their life and evaluating their durability is very important for securing vehicle safety and reliability. Existing fatigue durability analysis mainly relies on empirical models or finite element analysis (FEM), which requires a lot of time and money, and has limitations in reflecting the uncertainty of complex actual driving environments. In this study, sensor data such as acceleration, strain, and temperature of control arms acquired under various driving conditions are trained on a deep learning model to predict fatigue life, and through this, the remaining life is efficiently estimated and fatigue durability characteristics are analyzed in Fig. 1. The method of this study is expected to enable proactive maintenance by predicting potential risks before failure occurs, and to contribute to the design optimization and reliability improvement of control arms. In this study, the control arm is continuously subjected to complex loads such as impact, vibration, bending, and torsion from the road surface while the vehicle is driving, and these repeated loads cause micro-cracks inside the material to develop and grow gradually, ultimately leading to failure.



Accordingly, sudden failure of the control arm due to fatigue accumulation can lead to the inability to steer the vehicle and loss of driving stability, which can cause serious casualties, so fatigue accumulation management is very important. Passenger cars are constantly evolving in terms of ride comfort, steering stability, and safety. Among these, the suspension system is a key component directly related to the vehicle's driving performance, and in particular, the control arm plays an important role in connecting the wheel and the body, absorbing shock and vibration transmitted from the road surface, and controlling the position of the wheel. Since the control arm is continuously subjected to repetitive dynamic loads in the vertical and horizontal directions during driving, there is a high risk of damage due to accumulated metal fatigue. Since fatigue damage of the control arm can lead to serious accidents during driving, accurately predicting its fatigue life and evaluating its durability are very important research fields in the automobile industry.

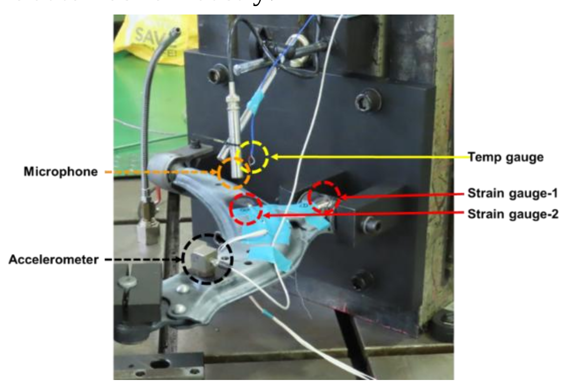


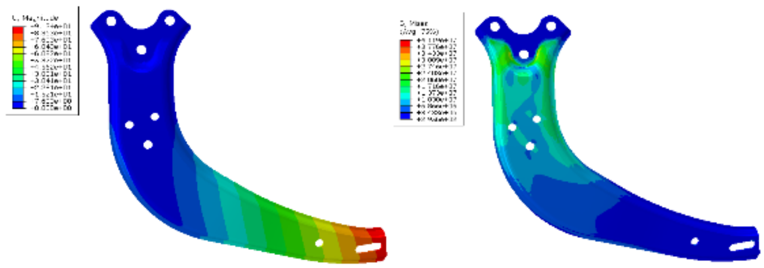
Fig. 2: Control Arm HALT Test Strain gauge : KFGS-1-350-C1-11L5M3R

Existing control arm fatigue durability analysis has been mainly based on empirical models such as the S-N curve (Stress-Number of Cycles curve), stress analysis using the finite element method (FEM), and actual vehicle driving tests. However, empirical models have difficulty reflecting the complexity of actual load conditions, and finite element analysis has the disadvantage of having a high dependence on accurate load input and material properties and long analysis time. Actual vehicle driving tests provide the most realistic results, but they require a huge amount of time and money, making it difficult to perform for all design variables[2]. Recently, the development of artificial intelligence, especially deep learning technology, has shown excellent performance in learning and predicting complex data patterns and has been applied to various engineering fields. In this study, we aim to overcome the limitations of existing methods by applying this deep learning technology to fatigue life prediction and durability analysis of control arms. We collect load and response data acting on the control arm in various driving environments and train the deep learning model to monitor the fatigue accumulation status of the control arm in real time and predict the remaining life. This can improve vehicle safety by enabling preventive maintenance and, in the long term, can contribute to optimizing durability during the design and material selection process of control arms in Fig.2.

2. Fatigue and Durability

2.1. Fatigue Life Prediction and Durability Analysis

Fatigue life prediction is a research field that predicts the point at which a material will break when repeated loads are applied to the material behavior by Palmgren −Miner Rules have been used. Finite element analysis is used to precisely analyze the stress distribution of a component to identify the location where fatigue failure is likely to start. Recently, research is actively being conducted to evaluate fatigue durability without a physical object by utilizing virtual testing and digital twin technology. In Fig. 3 and Fig 4., Von Mises stress, also known as equivalent tensile stress or the Von Mises yield criterion, is a scalar value that combines the complex multi-axial stress states[1].



(a) Von- Mises stress on displacement (b) Von- Mises stress

Fig. 3 : Von- Mises stress distribution of Control arm

The direction of movement of the body is three-axis movement, and moves together with the internal body systems of control arm system.

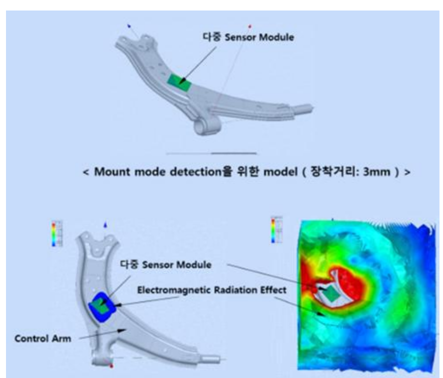


Fig. 4 Von- Mises stress with mount mode insensor module

2.2. Prognostics and Health Management(PHM)

PHM is a technology that monitors the health status of a system or component, predicts potential failures, and supports preventive maintenance decisions. Previously, statistical methods and physics-based models were mainly used, but recently, machine learning and deep learning techniques have been in the spotlight in the PHM field. In particular, LSTM (Long Short-Term Memory) and GRU (Gated Recurrent Unit), which are types of recurrent neural networks (RNNs), have shown excellent performance in learning time series data, and are widely applied to predicting the remaining useful life (RUL) of equipment[3]. Convolutional neural networks (CNNs) are used not only for image data processing, but also for converting sensor data into image formats to extract features and for fault diagnosis and prediction in Fig.5.

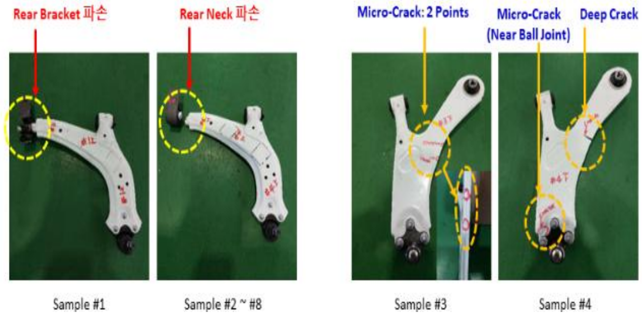


Fig. 5. PRUL Sensor layout of Control Arm

2.3. Fatigue Analysis and AI Application Cases

In the automotive field, artificial intelligence is being used to predict fatigue life and diagnose failures of vario us parts such as engines, transmissions, and chassis. For example, research has been conducted to determine whe ther there are any abnormalities in the suspension system based on vehicle vibration data, or to predict tire wear patterns[4]. For important structural parts such as control arms, in the past, physics based models and experiment al data were mainly relied on, but recently, there has been an increasing need for research that combines sensor d ata and deep learning to evaluate fatigue accumulation in real time and prevent failures

3. AI-based life prediction interpretation

3.1. Data collection and preprocessing

In this study, we conducted research on fatigue life prediction and durability analysis of control arms using the following deep learning-based methodology[5]., The results were measured using a strain gauge at a load of 600 kgf (8,790 cycles), an angle of 45º, and a frequency of 4 Hz in Fig. 6.

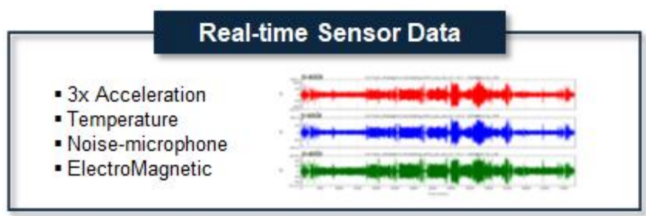


Fig. 6 PRUL Sensor real time sensor data measurement of Control Arm

Data is collected from sensors attached to the control arm via an actual vehicle or test equipment under various driving conditions (high-speed driving, low-speed driving, sudden braking, cornering, unpaved road driving, etc.). The main sensor data are as follows. The vibration and shock acceleration data (X, Y, Z axes) acting on the control arm were measured with an acceleration sensor[6]. In addition, strain data of the main stress concentration area of the control arm was used. Temperature data around and inside the control arm can be used to influence the fatigue characteristics[7]. Data was collected by measuring the fatigue accumulation evaluation according to the driving conditions and cumulative driving distance with the vehicle speed and driving distance at HALT test results in Fig. 7.

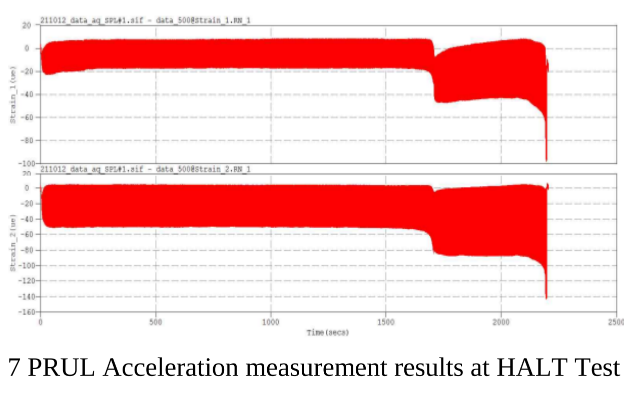


Fig. 7 PRUL Acceleration measurement results at HALT Test results

3.2. Data preprocessing and deep learning model design

The collected raw data undergoes preprocessing processes such as noise removal, sampling rate adjustment, and normalization. In addition to time domain data, features can be extracted through frequency domain analysis (FFT: Fast Fourier Transform)[8]. For example, energy changes in a specific frequency band can be associated with fatigue accumulation. Since fatigue accumulation of the control arm has time-series characteristics, a deep learning model based on a recurrent neural network (RNN) that has strengths in learning time-series data is utilized. In particular, it is designed based on an LSTM or GRU model that can solve the long-term dependency problem detected by Fig. 8 and Fig. 9.

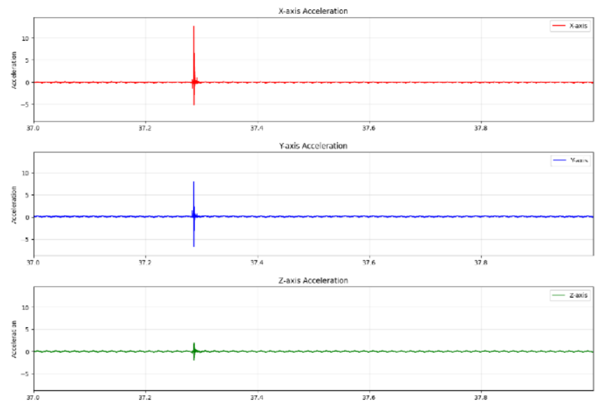


Fig. 8 Detection data due to control arm fatigue failure at x, y, z axes.

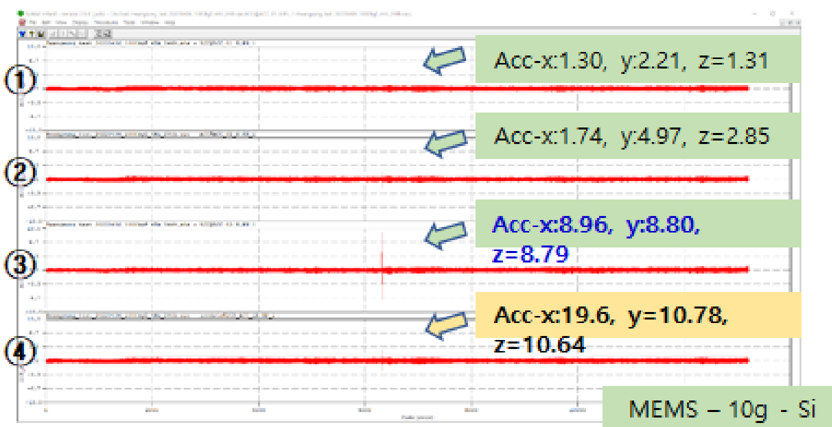


Fig. 9 Failure detect due to control arm fatigue

3.3. Model Structure, Loss Function, and Optimization

Input layer uses a sequence of preprocessed sensor data (acceleration, strain, temperature, etc.) as input. Each sequence consists of data points at a certain time interval. LSTM/GRU layer: Stack multiple LSTM or GRU layers to learn long-term patterns of time series data. Each layer updates the hidden state based on the information of the previous time step and the input of the current time step. The Dense layer receives the output of the LSTM/GRU layer and derives the final predicted value for predicting fatigue accumulation or remaining life. The output layer uses a linear activation function (regression problem) or a sigmoid/softmax activation function (classification problem) depending on the value to be predicted. In this study, we focus on a regression model for predicting remaining life[9]. Through the HALT Test results (12,790 cycles), the durability of the AI-based smart arm complex sensor was measured using a strain gauge (2 channels). The loss function uses the mean squared error (MSE) or mean absolute error (MAE) to minimize the error between the predicted remaining life and the actual remaining life. The optimizer updates the model's weights using efficient optimization algorithms such as Adam, RMSprop, etc.3.1.3. Model Structure, Loss Function, and Optimization[10].

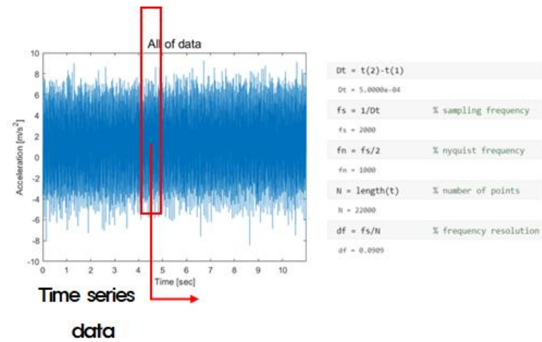


Fig. 10. Artificial intelligence model for anomaly detection and life prediction

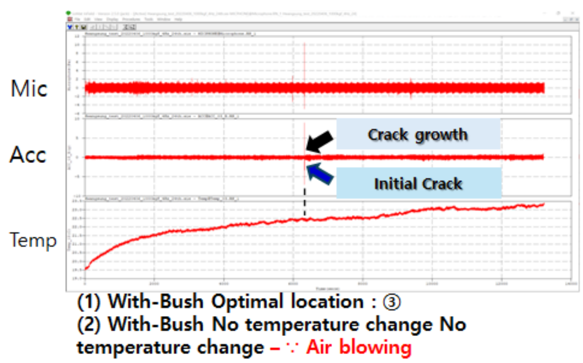
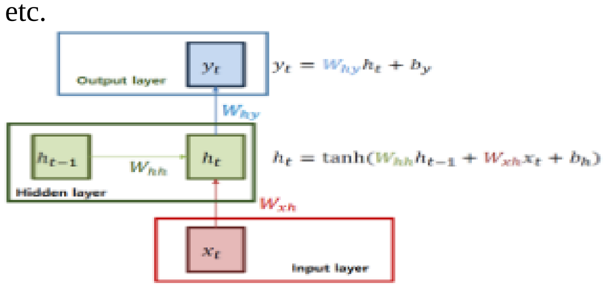


Fig. 11. Results of AI Prediction with crack failure

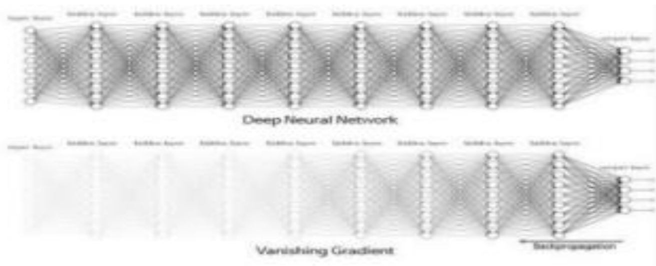
Input layer uses a sequence of preprocessed sensor data (acceleration, strain, temperature, etc.) as input. Each sequence consists of data points at a certain time interval. LSTM/GRU layer: Stack multiple LSTM or GRU layers to learn long-term patterns of time series data. Each layer updates the hidden state based on the information of the previous time step and the input of the current time step. The Dense layer receives the output of the LSTM/GRU layer and derives the final predicted value for predicting fatigue accumulation or remaining life. The output layer uses a linear activation function (regression problem) or a sigmoid/softmax activation function (classification problem) depending on the value to be predicted. In this study, we focus on a regression model for predicting remaining life by AI LSTM in Fig. 10 and Fig.11.

3.4. RNN(Recurrent Neural Network) and LSTM (Long Short-Term Memory model)

RNN can encounter the vanishing gradient problem when learning long sequences. RNN is a powerful tool fo r effectively learning and analyzing sequential data. In particular, it can increase learning efficiency through para meter sharing and can be applied to various sequential data processing problems. However, various modified mo dels such as LSTM and GRU are being developed to solve problems that may occur when learning long sequenc es. The following Fig. 12 shows the structure that shows the basic operation of RNN. The loss function uses the mean squared error (MSE) or mean absolute error (MAE) to minimize the error between the predicted remaining life and the actual remaining life. The optimizer updates the model's weights using efficient optimization algorit hms such as Adam, RMSprop, etc.



Basic operation of RNN



(b) Basic operation of LSTM

Fig. 12 Comparison of basic operations of RNN and LSTM

3.5. Fatigue life prediction and remaining life estimation

The trained deep learning model receives a new sensor data sequence as input, evaluates the current fatigue accumulation status of the control arm, and predicts the remaining life. The predicted remaining life can be utilized in the following ways. Real-time monitoring continuously monitors the fatigue status of the control arm during vehicle operation and generates an alarm when the threshold is reached. Preventive maintenance plans the replacement period in advance based on the predicted remaining life to prevent sudden failures and optimize maintenance costs.

3.6. Fatigue durability analysis

The fatigue durability characteristics of the control arm are analyzed based on the fatigue life information predicted by the deep learning model. Identification of fatigue-vulnerable sections: By correlating the sensor data with the fatigue life prediction results, we analyze whether specific driving conditions or load patterns have a greater impact on fatigue accumulation. This can be used to reinforce fatigue-vulnerable sections or change materials when designing control arms. Analysis of the relationship between design variables and fatigue durability: By training data of control arms with various shapes and materials, we can infer which design variables have a greater impact on fatigue durability through weight analysis of the deep learning model. This becomes an important indicator for optimal control arm design.

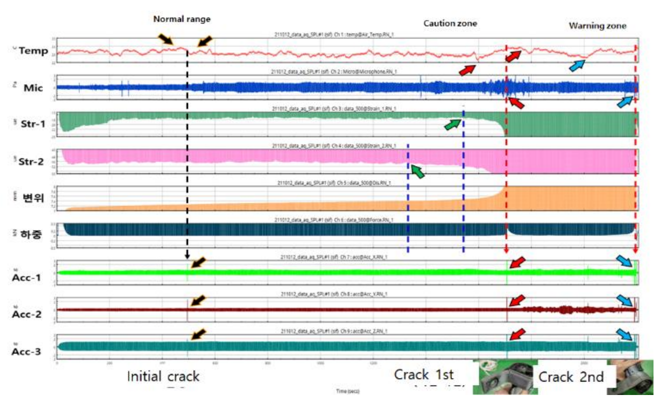


Fig. 13. Results of AI Prediction Accelerated Life Testing

Linking with Accelerated Life Testing Results: By training the deep learning model with limited accelerated life test data and actual driving data, we can build a more accurate and generalized fatigue life prediction model in Fig. 13.

4. Results Analysis and Discussion

4.1. Analysis of dataset setup results

This section presents a hypothetical experimental design and expected results for the paper. In actual research, experimental results based on real data should be presented. The Continuous Wavelet Transform (CWT) is a powerful tool for transforming data into the time-frequency domain, offering a rich representation that highlights how signal frequencies evolve over time. Here's a breakdown of what the results of a CWT typically show and why it's so useful in Fig. 14.

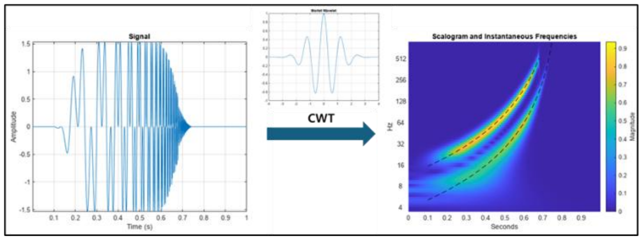


Fig. 14. Results of Transform data into time-frequency domain using CWT

The dataset is constructed by constructing a dataset consisting of sensor data (acceleration, strain, temperature) generated from a virtual control arm test device or simulation environment and time (cycle) data until actual failure. The dataset is divided into training, verification, and test sets. The model uses a deep learning model based on LSTM, and searches for the optimal model by adjusting the number of hidden layers, the number of units, and the dropout ratio. For evaluation indices, MAE, MSE, and R-squared (R2) are used to evaluate prediction accuracy by results of AI Prediction accelerated Life Testing in Fig. 14.

4.2. Expected Results

In terms of fatigue life prediction performance, the learned deep learning model shows that it can predict the remaining life of the control arm more accurately than the existing empirical model or simple statistical model. In particular, it proves that deep learning effectively learns complex and nonlinear fatigue behavior. Robustness to driving environment changes: By learning data collected in various driving environments, it is confirmed that it shows stable prediction performance even under general driving conditions, not limited to a specific environment. Fatigue durability characteristic analysis results: Based on the prediction results of the deep learning model, it is analyzed and presented that stress is concentrated in a specific part of the control arm, accelerating fatigue failure, or that a specific driving pattern has a greater effect on fatigue accumulation. For example, it is possible to derive analysis results such as high strain occurs in a specific weld of the control arm under sudden braking and high-speed cornering situations, which greatly contributes to the shortening of the fatigue life. The simulation was performed considering the dependency of PRUL on the operation time of the control arm parts of the model as well as the dependency on several related factors such as the severe operating temperature of the parts and the severe multi-axis vibration. PRUL prediction can be considered as a special form of survival analysis, and basically, two types of techniques are considered for predicting PRUL: model-based techniques and data-based techniques.

The model-based techniques use physical models to predict the occurrence of component failures over time, while data-based techniques predict PRUL based only on past observations without making assumptions about how components may fail over time.

5. Conclusion

This paper proposes an artificial intelligence deep learning-based approach for predicting the life of a control arm and analyzing its fatigue durability according to fatigue accumulation, and presents its feasibility. The proposed deep learning model shows that it can accurately predict the remaining life of a control arm by learning sensor data acquired in various driving environments. This can improve the safety and reliability of a vehicle through preventive maintenance and contribute to the design optimization of the control arm. The following directions can be considered for future research. Acquire and verify actual vehicle data: Acquire actual long-term driving data to further improve the prediction accuracy of the model, and verify the practicality of the model through comparison with actual failure data. Apply transfer learning. Through the optimization method technology through fault analysis, a fault analysis process was performed to measure and verify the assumption of FMEA, which is one of the life prediction techniques, and through this, the essential elements for safety were identified. In addition, a list of block constraints (debugging, testing, operation mode) and a fault injection list were created. Through this, the safety goals and essential influencing elements in the control arm were analyzed and verified. Use data on various types of control arms or similar parts to improve the generalization performance of the model through transfer learning. Apply explainable AI (XAI) techniques: Interpret the prediction results of the deep learning model to analyze which sensor data has the most significant effect on fatigue life prediction, and thereby deepen the understanding of the fatigue mechanism. Multi-sensor fusion and optimization: Fuse more types of sensors (e.g., acoustic sensors, vibration spectrum analysis, etc.) and optimize sensor placement and data fusion strategies to maximize predictive performance. Integration with digital twin technology: Integrate deep learning-based fatigue life prediction models into digital twin systems to synchronize the virtual model and the actual component status in real time and establish precise remaining life prediction and maintenance plans.

6. References

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