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EXPERIMENTAL DATA-DRIVEN PREDICTION OF MAIN FUEL INJECTION QUANTITY USING ARTIFICIAL NEURAL NETWORKS AND GRADIENT BOOSTING MACHINES

Summary. Accurate prediction of the main fuel injection quantity is essential for performance optimization, fault diagnosis, and emission control in common rail diesel injection systems. While artificial neural networks (ANNs) have been widely applied to model nonlinear engine behaviors, the application of Gradient Boosting Machines (GBMs) for injection quantity prediction remains limited. This study presents a systematic comparison between ANN and GBM for predicting the main fuel injection flow rate using experimental injector test bench data. A dataset of 456 samples was collected under a wide range of operating conditions, including rail pressure, injection pulse width, injection frequency, and operating modes. The models were trained using 80% of the data and evaluated on the remaining 20% using R^2, RMSE, and MAE metrics. Both models achieved high predictive accuracy, with R^2 values exceeding 0.98 on the test dataset. However, the GBM consistently outperformed the ANN, reducing RMSE and MAE by up to 2.4% and 6.5%, respectively, on unseen data, and exhibiting a narrower error distribution. These results demonstrate the superior accuracy, robustness, and generalization capability of the GBM for fuel injection quantity prediction.

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1. INTRODUCTION

Although electric vehicles are increasingly widespread and strongly promoted, by the end of 2023 there were still more than 1.4 billion internal combustion engine (ICE) vehicles operating worldwide. Among them, diesel engines continue to play a crucial and largely irreplaceable role in many transportation sectors, particularly for heavy-duty applications that require high power output, large payload capacity, and durability under harsh operating conditions. However, the major drawback of diesel engines lies in their pollutant emissions. In response to growing environmental concerns, many countries and international organizations have introduced increasingly stringent emission regulations [1], thereby imposing urgent demands for technological advancements in engine and fuel supply systems.

In this context, the common rail electronic fuel injection system has emerged as an effective solution for improving engine performance and reducing emissions. This technology enables precise control of high-pressure fuel injection, thereby optimizing the combustion process, enhancing engine efficiency, reducing fuel consumption, and mitigating harmful exhaust emissions [2]. To ensure reliable and durable operation of the common rail system, periodic inspection, accurate diagnosis, and early fault detection are of critical importance. Accordingly, electronic diesel injector test equipment plays a vital role in performing precise measurements, identifying injector malfunctions, and supporting efficient maintenance and repair processes. Within the electronic Common Rail fuel injection system, main fuel injection quantity is a key parameter for evaluating injection accuracy and serves as an essential indicator for fault diagnosis and system optimization [3,4]. Consequently, numerous studies have focused on analyzing the factors influencing main fuel injection quantity and developing predictive models for this parameter. Carmen Mata et al. [5] conducted experimental investigations and modeling of injection rate characteristics in a Common Rail system equipped with solenoid type electronic injectors. Experiments were carried out under various rail pressures and injection pulse widths, enabling the acquisition of instantaneous injection rate data and characteristic parameters such as needle opening delay, rate of rise, peak injection rate, and needle closing behavior. Based on the experimental data, the authors developed an open-loop physical model incorporating nozzle flow equations, mass momentum balance, and injector needle dynamics. Although the model successfully reproduced the general trends of the injection rate profiles, it was found to be sensitive to modeling uncertainties, boundary conditions, and noise, thus requiring calibration using experimental data. With the rapid advancement of data-driven technologies, machine learning methods have increasingly been applied to predict complex phenomena due to their flexibility, strong nonlinear modeling capability, and high prediction accuracy. Xiangdong Lu et al. [6] proposed a predictive model for injection rate in a high-pressure Common Rail system of marine diesel engines by combining Quantum Particle Swarm Optimization (QPSO) with a deep bidirectional long short-term memory neural network. Furthermore, transfer learning with a parameter-freezing strategy was employed to extend the model to multiple injection strategies (pilot-main injection). The results demonstrated high prediction accuracy, low error, and stable real-time performance, meeting the stringent requirements for precise injection control in modern diesel engines. In automotive engineering, artificial neural networks (ANNs) are widely recognized as effective predictive tools due to their fast computation, high accuracy, and low implementation cost [7]. ANNs are particularly suitable for replacing conventional simulation-based approaches in complex and computationally expensive systems, making them a prominent choice in engine research and applications [8,9]. Mebin Samuel et al. [10] employed ANN models to predict performance and emission parameters of a single-cylinder direct-injection diesel engine using experimental data from a Common Rail Direct Injection (CRDI) engine fueled with various blended fuels. Six output parameters brake thermal efficiency (BTE), brake specific fuel consumption (BSFC), hydrocarbons (HC), nitrogen oxides (NOx), carbon monoxide (CO), and smoke were predicted with coefficients of determination (R^2) ranging from 0.982 to 0.997. Similarly, Babu et al. [11] investigated the effects of multiple injection strategies on a CRDI engine fueled with biodiesel and conventional diesel using ANN-based prediction, achieving high accuracy with RMSE values of 0.01-0.02 and R^2 values between 0.980 and 0.998. In addition to ANN, Gradient Boosting Machine (GBM) is a powerful machine learning approach in which predictions are generated by combining multiple weak learners to optimize a global objective function. Vijayaraghavan et al. [12] compared KNN, multilayer perceptron (MLP), and LightGBM models, demonstrating that LightGBM achieved the highest prediction accuracy with an R^2 of 0.990 on the test dataset. When integrated with a Natural Gradient Boosting algorithm in an ensemble framework, the performance further improved to an R^2 of 0.995, while also providing probabilistic uncertainty estimation. Similarly, Ahmad Sharafati et al. [13] compared ABR, GBM, and RFR models for predicting wastewater quality indicators and found that GBM delivered superior performance for nonlinear output variables, highlighting its robustness and predictive capability.

Despite the growing application of machine learning techniques in automotive engineering, most existing studies have primarily focused on artificial neural networks, while the potential of Gradient Boosting Machine models remains underexplored, particularly in the prediction of main fuel injection quantity in Common Rail systems. Limited studies have comparatively evaluated ANN and GBM models for main fuel injection quantity prediction based on experimental injector test data under different operating conditions. The novelty of this study lies in the comparative evaluation of ANN and GBM models for predicting the main fuel injection quantity of Common Rail diesel injectors, together with a quantitative comparison of prediction accuracy, robustness, and practical applicability. The proposed approach provides valuable insights into the applicability of machine learning techniques for fuel injection diagnosis and optimization while significantly reducing experimental effort, cost, and development time in diesel engine research and applications [14,15].

2. METHODOLOGY

2.1. Experimental Setup

The experimental setup was designed to acquire measurement data from a high-pressure common-rail (CR) fuel injection system equipped with a diesel injector, as illustrated in Fig. 1. A dedicated electronic control unit (ECU) was employed to adjust key operating parameters, including rail pressure, injection frequency, pulse duration, dwell time, and control currents. Bosch calibration fluid was used as the working medium and circulated through a low-pressure and high-pressure pumping system before entering the common rail, which acted as a fuel accumulator supplying the injector. Various sensors were installed to monitor system performance: rail pressure was measured using Kistler and Trafag sensors; fuel temperature was monitored with Pt100 and type-K thermocouples; injector needle lift was measured with a Micro-Epsilon displacement sensor; and current, frequency, and flow rates were recorded using high-precision transducers. All signals were acquired by the ECU and transmitted to a computer for data processing and analysis. Experiments were conducted across a range of injection pressures (300-1700 bar), injection speeds (600-1700 cycles/min), and pulse widths (500-1700 μs), while pilot injections were limited to 200-600 μs. Data were averaged over multiple cycles, yielding a maximum uncertainty of 0.6% and a relative error below 5%, ensuring reliable measurement accuracy.

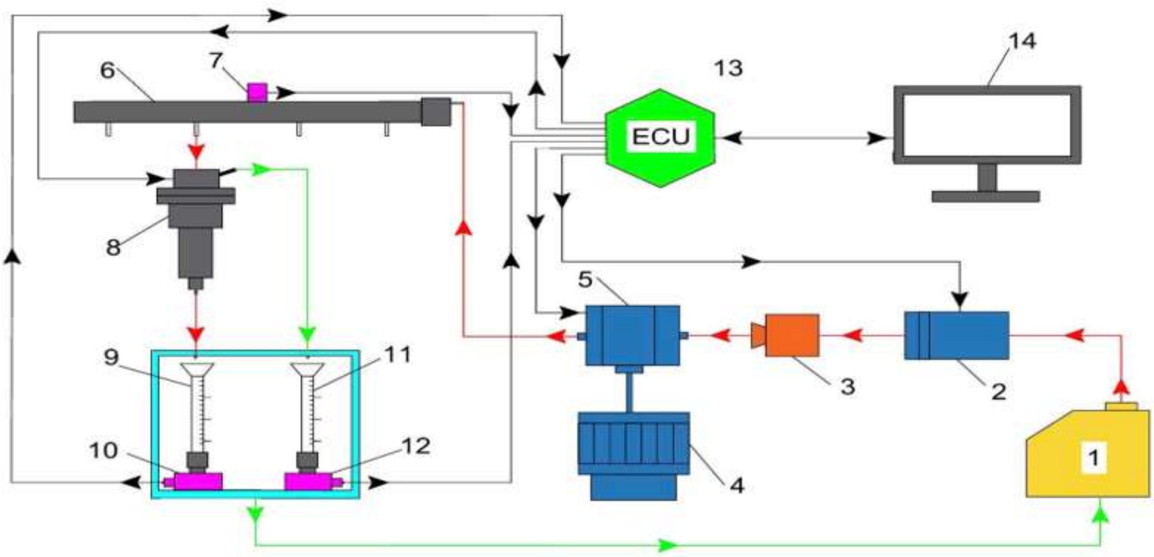

Fig. 1. Experimental setup of the common rail fuel injection system
1 – fuel tank; 2 – low-pressure pump; 3 – fuel filter; 4 – electric motor; 5 – high-pressure pump; 6 – common rail (accumulator); 7 – rail pressure sensor; 8 – injector; 9 – injection measuring tube; 10 – injection flow sensor; 11 – return fuel line; 12 – return flow sensor; 13 – ECU (electronic control unit); 14 – computer

2.2. Artificial neural networks (ANN) and gradient boosting machines (GBM)

In this study, two machine learning models were employed to predict the fuel main fuel injection quantity: artificial neural networks (ANN) and gradient boosting machines (GBM), a regression variant of gradient boosting machines (GBM). Both models are well suited for capturing complex nonlinear relationships in experimental data. ANN is a machine learning approach inspired by biological neural systems and consists of an input layer, one or more hidden layers, and an output layer. Each neuron performs a weighted summation of the input signals followed by a nonlinear activation function, such as Sigmoid, ReLU, or Tanh. The ANN model is trained using the back-propagation algorithm, which involves a forward propagation stage to generate predictions and a backward propagation stage to update network weights by minimizing a predefined loss function. Gradient Boosting Machine (GBM), originally proposed by Jerome Friedman, is a powerful ensemble learning algorithm that builds models sequentially by combining multiple weak learners to progressively reduce prediction errors. Based on this principle, Gradient Boosting Machine (GBM) is specifically designed for regression tasks, where the model is trained by optimizing a differentiable loss function.

In this study, three commonly used performance metrics were employed: the coefficient of determination (R^2), the root mean square error (RMSE), and the mean absolute error (MAE). These metrics are widely adopted in artificial intelligence and machine learning applications to quantify prediction errors [16-17].

Root Mean Squared Error (RMSE) calculates the average deviation between predicted values and actual values.

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - {y'}_i)^2} \tag{1}$$

Mean Absolute Error (MAE) calculates the average of the absolute errors between the actual and predicted values.

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \tag{2}$$

R² (Coefficient of Determination): A statistical indicator that shows the proportion of variance in the target to be predicted that is explained by the input variables in the model.

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \tag{3}$$

Where y_i is the actual value and $\hat{y}_i$ is predicted value, $\bar{y}$ is the average of the actual values.

The dataset used for the model consists of experimental data, with the fuel main fuel injection quantity as the target output. Each measured output corresponds to a specific set of control parameters, including test pressure (bar), injector holding time (µs), injection frequency (Hz), and test operating modes (CH1 represents the low-speed condition, CH2 corresponds to the medium-speed condition, CH3 refers to injector testing under pilot injection mode, and CH4 denotes the high-speed condition).

A total of 456 experimental data points were obtained, and their distribution is illustrated in Figure 2. The dataset used in this study was divided into subsets for training and validating the ANN and GBM models. Specifically, 80% of the data (364 samples) were allocated for model training to enable the models to learn the underlying patterns in the output distribution, while the remaining 20% of the data (92 samples) were reserved for validation to evaluate the prediction accuracy of the developed models.

Before being introduced into the models, the dataset was standardized after the data splitting process in order to improve model stability and enhance training performance. All normalization parameters were determined exclusively from the training dataset and subsequently applied to the validation dataset to ensure that data leakage did not occur. For the numerical input variables, including test pressure, injector holding time, and injection frequency, the data were standardized using the StandardScaler method to ensure numerical consistency among the features. The operating modes (CH1-CH4) were treated as categorical variables and encoded using OneHotEncoder prior to model training.

To determine the optimal hyperparameter configurations for the ANN and GBM models, the Grid Search method was employed in this study. This process was carried out by systematically evaluating multiple combinations of hyperparameters within a predefined search space in order to identify the configuration that provided the best predictive performance.

The optimal parameter sets were selected based on the validation results using prediction accuracy and error evaluation metrics of the developed models.

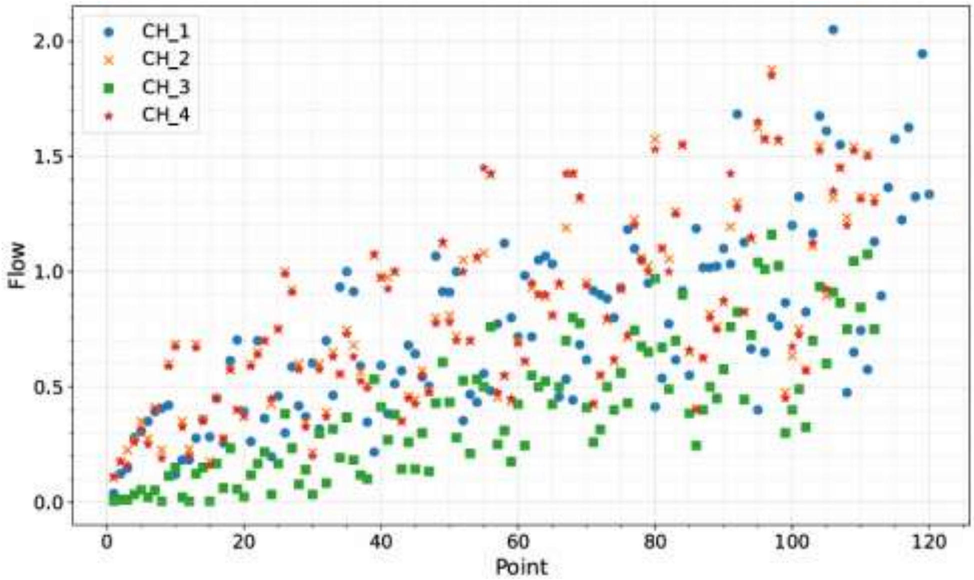

Fig. 2. Experimental results

Tab. 1
Hyperparameter configuration and optimal values of the ANN model

Model	Hyperparameter	Candidate values	Optimal value
ANN	Hidden layer sizes	[(50,30), (64,32), (80,20), (128,64)]	(80,20)
	Activation function	['relu', 'tanh', 'identity']	'relu'
	Solver	['sgd', 'adam', 'lbfgs']	'adam'
	Learning rate	[0.1, 0.01, 0.001]	0.001
	Maximum iterations	[200, 500, 1000, 1500]	1000

Tab. 2
Hyperparameter configuration and optimal values of the GBM model

Model	Hyperparameter	Candidate values	Optimal value
GBM	Number of estimators	[50, 100, 200]	200
	Learning rate	[0.1, 0.01, 0.001]	0.1
	Maximum depth	[3, 4, 5, 6]	4
	Minimum samples split	[2, 5, 10]	2
	Minimum samples leaf	[1, 2, 4]	1
	Subsample ratio	[0.6, 0.8, 1.0]	1.0
	Loss function	['squared_error', 'absolute_error', 'huber']	'squared_error'

3. RESULTS AND DISCUSSION

During the machine learning training process, the dataset was divided into two subsets: 80% for training and 20% for testing. The training set was used to develop the models, while the testing set was employed to evaluate prediction accuracy and practical applicability. This data-splitting strategy plays a crucial role in preventing overfitting, where the model memorizes the training data instead of learning generalized patterns. Model performance was evaluated on both datasets using the metrics R^2, RMSE, and MAE. Regression plots of the training and testing datasets were first analyzed to visualize the relationship between the actual and predicted values for both ANN and GBM models. These plots provide an intuitive assessment of model accuracy, where points closer to the diagonal line Y=T indicate higher accuracy, and also facilitate the identification of overfitting or underfitting. If the training data points closely follow the diagonal while the testing data points are widely scattered, the model is considered overfitted.

As shown in Figure 3, for both ANN and GBM models, the data points in the training and testing sets are distributed close to the diagonal line Y=T, indicating the absence of overfitting. Both models demonstrate strong predictive capability and maintain a good balance between training accuracy and generalization performance, confirming their stability and reliability in modeling the combustion process and ignition delay. However, a more detailed comparison reveals that the GBM model exhibits a tighter clustering of data points around the diagonal for both training and testing sets, with fewer outliers and lower noise levels compared to ANN. In contrast, the ANN model shows greater dispersion in the high-value region (1.5), indicating higher prediction variability. This difference is more clearly illustrated in Figure 4.

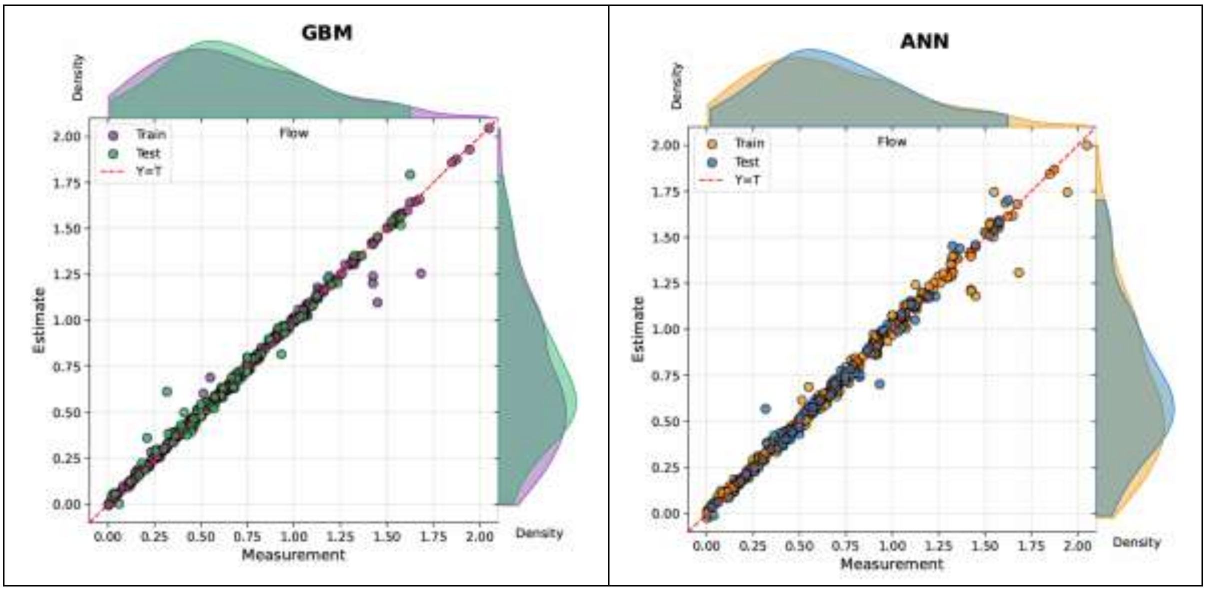

Fig. 3. Comparison between experimental and predicted values for the training and test datasets obtained from the ANN and GBM models

From Table 1, it can be observed that both the ANN and GBM models achieve very high prediction performance. On the training dataset, the ANN model yields R^2, RMSE, and MAE values of 0.9908, 0.0406, and 0.0228, respectively, whereas the GBM model provides better results with R^2 = 0.9926, RMSE = 0.0364, and MAE = 0.0133. A quantitative comparison shows that the R^2 of GBM is higher than that of ANN by 0.0018, corresponding to an improvement of approximately 0.18%. Meanwhile, the RMSE of GBM is reduced by 0.0042 (about 10.3%) compared to ANN. Most notably, the difference is more pronounced in terms of MAE, where GBM achieves a value of only 0.0133, which is 0.0095 lower than ANN, representing a reduction of approximately 41.7%. These results indicate that although both models learn the training data effectively, GBM exhibits a clear advantage in reducing absolute errors, reflecting predictions that are closer to the actual values. On the testing dataset, both ANN and GBM maintain high accuracy with R^2 values greater than 0.98 and low error levels, demonstrating good generalization capability. However, GBM continues to outperform ANN across all three-evaluation metrics, achieving $R^2 = 0.9835$, RMSE = 0.0487, and MAE = 0.0289. Specifically, the R^2 value of GBM is approximately 0.08% higher than that of ANN, while the RMSE and MAE are reduced by about 2.4% and 6.5%, respectively. Overall, these findings confirm that the GBM model provides higher accuracy and superior generalization performance compared to ANN in the main fuel injection quantity prediction task.

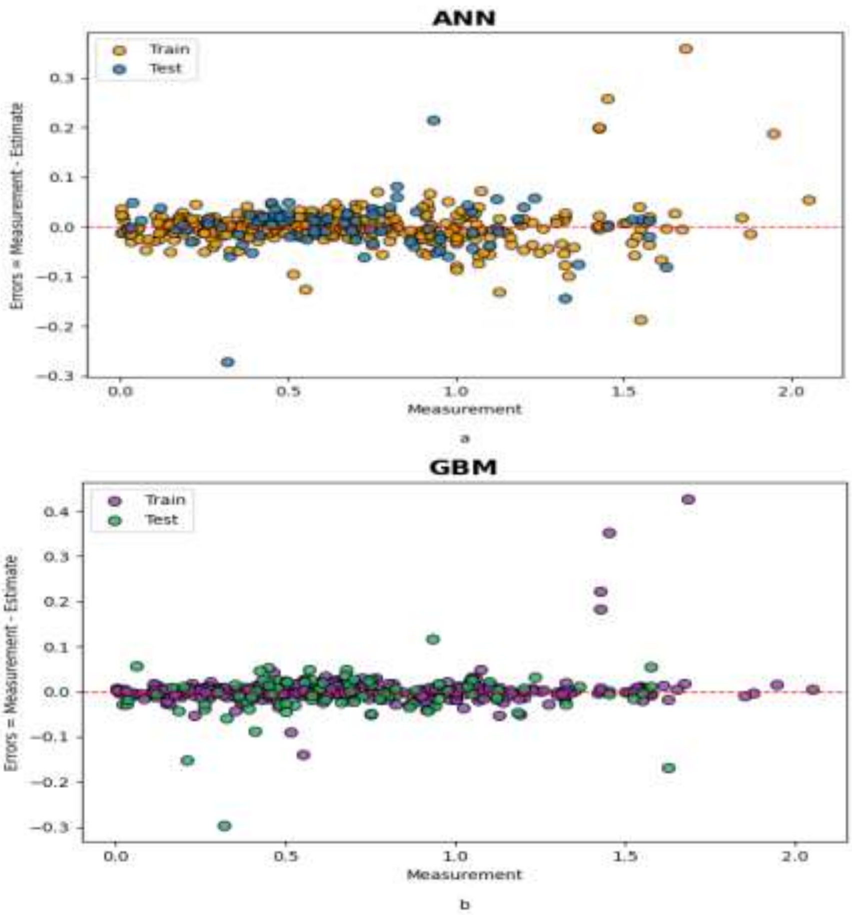

Fig. 4. Residual error distributions of the ANN and GBM models

Figure 5 presents the quantitative comparison of the error distributions (measurement − estimate) obtained from the ANN and GBM models, offering a detailed interpretation of their predictive performance. For both models, the error distributions are centered close to zero, with the mean error remaining near zero, indicating that neither model exhibits a significant systematic bias. This observation is consistent with the high coefficients of determination (R^2 > 0.98) reported in Table 3, confirming that both models accurately capture the relationship between the input variables and the main fuel injection quantity. Nevertheless, notable quantitative differences are observed in the dispersion of prediction errors. The ANN model shows a wider error range, with most errors distributed approximately between −0.20 and +0.35, whereas the GBM model exhibits a more compact distribution, with the majority of errors concentrated within approximately −0.05 to +0.05. This reduced spread directly explains the lower RMSE achieved by GBM (0.0364) compared to ANN (0.0406), corresponding to a reduction of about 10.3% on the training set. Similarly, the sharper peak around zero for GBM indicates a lower average absolute deviation, consistent with the MAE of 0.0133 for GBM versus 0.0228 for ANN, representing a substantial reduction of approximately 41.7%.

Tab. 3

Prediction Results of the Models

Method	Pharse	R^2	RMSE	MAE
ANN	Train	0.9908	0.0406	0.0228
	Test	0.9827	0.0499	0.0309
GBM	Train	0.9926	0.0364	0.0133
	Test	0.9835	0.0487	0.0289

Although both models display a small number of positive-error outliers with magnitudes exceeding 0.25, the occurrence frequency of such outliers is visibly lower for GBM than for ANN. This difference further contributes to the improved robustness of GBM, as reflected in its lower MAE and RMSE values. On the testing dataset, the same trend is maintained, with GBM yielding lower RMSE (0.0487 vs. 0.0499) and MAE (0.0289 vs. 0.0309), corresponding to reductions of approximately 2.4% and 6.5%, respectively. The quantitative analysis of the error distributions in Figure 5 supports the numerical performance metrics reported in Table 3. While both ANN and GBM provide highly accurate predictions, the GBM model demonstrates a narrower error dispersion, fewer extreme deviations, and consistently lower error magnitudes, thereby confirming its superior accuracy and stronger generalization capability in main fuel injection quantity prediction.

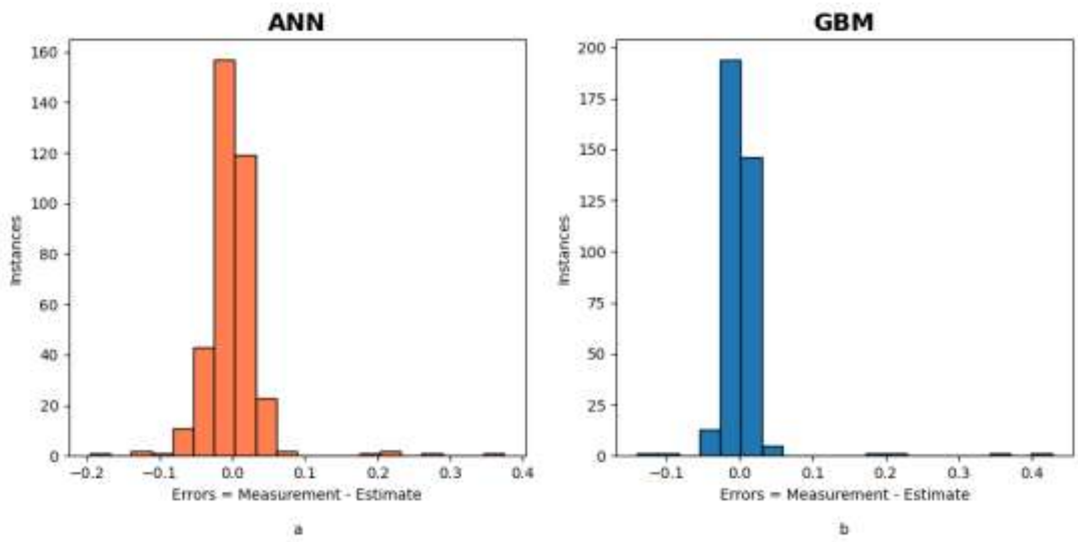

Fig. 5. Error distribution between the experimental and predicted values of the ANN and GBM models on the test dataset

Figure 6 illustrates the comparison between the experimental main fuel injection quantity and the values predicted by the ANN and GBM models on the testing dataset, providing a direct assessment of their predictive accuracy under unseen conditions. As shown in the figure, the predicted curves of both models follow the overall trend and fluctuations of the measured data closely across the entire operating range, indicating strong generalization capability. However, a closer inspection reveals that the GBM predictions exhibit better agreement with the experimental measurements, particularly at peak and valley regions where rapid variations in fuel flow occur. In several high-gradient segments, the ANN model shows slightly larger deviations from the measured values, whereas the GBM model tracks the experimental curve more consistently.

This visual observation is quantitatively supported by the statistical indicators reported in Table 3. On the test set, GBM achieves a higher coefficient of determination (R^2 = 0.9835) compared to ANN (R^2 = 0.9827), reflecting a stronger correlation with the measured data. Moreover, the prediction errors of GBM are smaller, with RMSE and MAE values of 0.0487 and 0.0289, respectively, which are lower than those of ANN by approximately 2.4% (RMSE) and 6.5% (MAE). These reductions indicate that GBM not only reduces large deviations but also improves overall prediction consistency. The results shown in Figure 6 confirm that both ANN and GBM are capable of accurately predicting main fuel injection quantity on unseen data. Nevertheless, GBM demonstrates superior robustness and accuracy, particularly in capturing sharp variations and extreme values, which is consistent with its narrower error distribution and lower error metrics. This further substantiates the conclusion that GBM provides improved predictive reliability and generalization performance compared to ANN for main fuel injection quantity estimation.

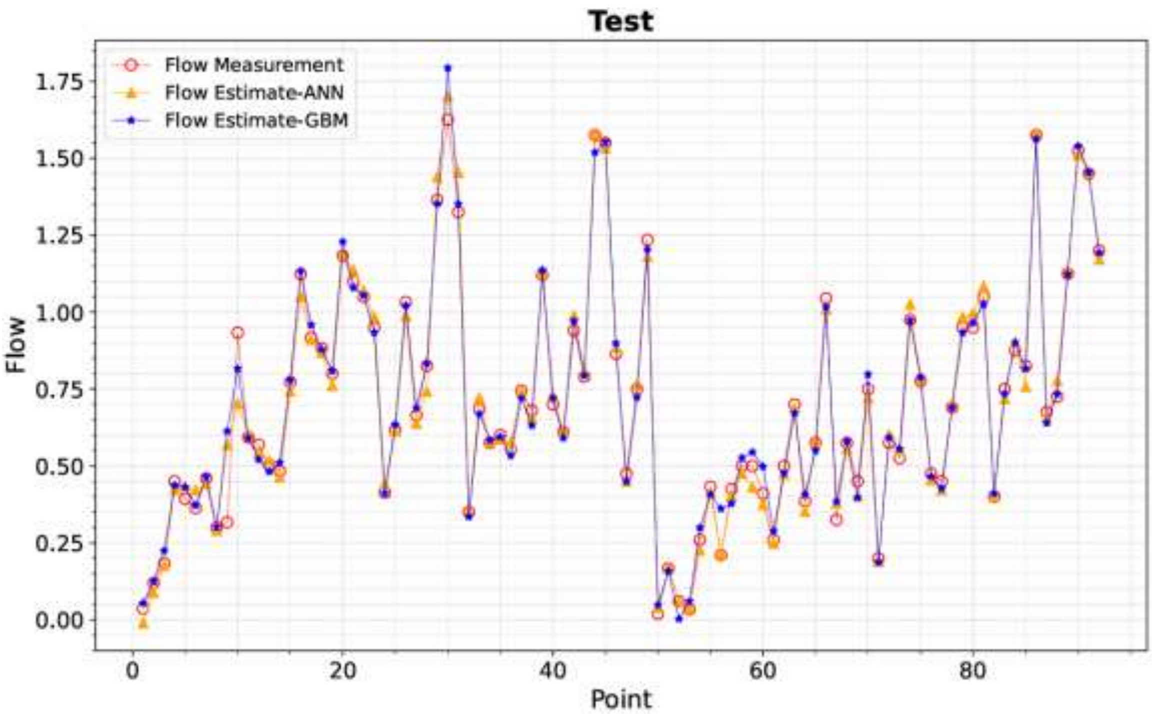

Fig. 6. The comparison between the experimental main fuel injection quantity and the values predicted by the ANN and GBM models on the testing dataset

4. CONCLUSION

This study presented a comprehensive comparison between Artificial Neural Networks (ANN) and Gradient Boosting Machines (GBM) for predicting the main fuel injection quantity of a common rail diesel injector using experimental test bench data. The results demonstrate that both models effectively capture the nonlinear relationship between control parameters and main fuel injection quantity, achieving high prediction accuracy with R^2 values exceeding 0.98 on both training and testing datasets. A quantitative evaluation indicates that GBM consistently outperforms ANN in terms of prediction error, with RMSE and MAE reductions of up to 10.3% and 41.7% on the training dataset, and 2.4% and 6.5% on the testing dataset, respectively. Furthermore, error distribution and regression analyses reveal that GBM produces a narrower dispersion of prediction errors with fewer extreme deviations, indicating more stable predictive performance on the evaluated dataset and test conditions. Overall, the findings suggest that GBM is a promising data-driven approach for injector flow rate prediction and diagnostic applications, contributing to reduced experimental effort and development time while supporting advanced modeling of modern diesel fuel injection systems.

Limitations and Future Work: Despite the high prediction accuracy achieved, this study is limited by the use of experimental data obtained from a single injector under controlled test bench conditions, which may restrict model generalization to different injector types and real-engine operating environments. In addition, only the main injection event was considered, while multiple injection strategies were not addressed. Moreover, the present study compares only ANN and GBM models without including simpler baseline approaches such as linear or polynomial regression. Future studies should incorporate baseline statistical models to provide a more comprehensive assessment of the relative advantages of advanced machine learning techniques for injection flow rate prediction. Future work will focus on extending the proposed models to multi-injection strategies, validating their performance under real engine conditions, and incorporating uncertainty quantification and real-time implementation to enhance practical applicability.

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