

Experimental Data-Based ANN Modeling for Injection Flow Rate Prediction in Common Rail Fuel Systems Considering Fuel Temperature Effects

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ABSTRACT

In this study, an Artificial Neural Network (ANN) model is developed to predict the main injection flow rate of an electronically controlled injector in a Common Rail fuel injection system. Experimental data were collected using a Common Rail injector test bench equipped with an integrated temperature control unit, allowing the fuel temperature to be maintained at fixed values during testing. Two experimental datasets were obtained at fuel temperatures of 25 °C and 35 °C, each consisting of 344 data points, resulting in a total of 688 samples for model development and evaluation. The ANN model was trained using 80% of the dataset (550 samples), whereas the remaining 20% (138 samples) were used for testing. The predictive performance of the model was evaluated using the coefficient of determination (R^2), Mean Absolute Error (MAE), and Root Mean Square Error (RMSE). The results show that the ANN achieved high prediction accuracy on the training dataset, with $R^2 = 0.9861$, MAE = 0.0561, and RMSE = 0.0833. On the testing dataset, the model maintained strong predictive capability, yielding $R^2 = 0.9814$, MAE = 0.0624,

and RMSE = 0.0872. The small differences between the training and testing performance indicators demonstrate good generalization ability. The results confirm that ANN is an effective and reliable tool for predicting injection flow rate in Common Rail systems under different fixed fuel temperature conditions. The proposed approach enables simultaneous processing of multiple experimental datasets with high accuracy, contributing to reduced experimental time and operating costs, and offering significant potential for modeling, prediction, and optimization of electronically controlled fuel injection systems.

Keywords-Artificial Neural Networks (ANNs); injection flow rate; Common Rail; fixed temperature

I. INTRODUCTION

In recent years, electric vehicles have developed rapidly and are increasingly promoted due to their environmental benefits and high energy efficiency. However, by the end of 2023, more than 1.4 billion vehicles worldwide were still powered by internal combustion engines. Among them, diesel engines remain indispensable, particularly in heavy-duty transportation, owing to their high thermal efficiency, durability, and reliable operation under harsh conditions. Despite these advantages, diesel engines are a major source of pollutant emissions, posing significant challenges to environmental protection and public health. Consequently, increasingly stringent emission regulations have been introduced worldwide, driving continuous technological advancements in combustion optimization and emission reduction [1].

Within this context, the Common Rail fuel injection system has become a key enabling technology. By allowing precise electronic control of injection pressure, timing, and fuel quantity, Common Rail systems significantly improve combustion efficiency and reduce exhaust emissions [2]. To ensure stable and durable operation, accurate testing, diagnosis, and early detection of injector malfunctions are essential. Therefore, electronic diesel injector test benches are widely used for high-precision measurements to support calibration and maintenance processes. In such systems, the injected fuel quantity (or injection flow rate) is a critical parameter that directly reflects injection accuracy and stability and plays a central role in diagnosis, calibration, and performance optimization [3, 4]. Numerous studies have investigated the factors influencing injection flow rate and injection characteristics to develop reliable modeling and prediction methods. Artificial Neural Networks (ANNs) have been widely applied in engineering to model complex nonlinear systems that are difficult to describe using conventional analytical approaches [5]. In the field of fuel injection systems, authors in [6] conducted an extensive experimental and modeling study on solenoid-controlled Common Rail injectors, analyzing injection rate characteristics under various rail pressures and control signals. Although physical and phenomenological models can capture general injection trends, their accuracy strongly depends on modeling assumptions, boundary conditions, and extensive calibration, which limits their flexibility and practical applicability.

With advances in data science, machine learning methods have increasingly been adopted as effective alternatives for injector and engine modeling. Authors in [7] demonstrated that ANN-based models can accurately predict fuel consumption and emissions of marine diesel engines. Similarly, several studies in the automotive field have reported high prediction

accuracy and computational efficiency when applying ANN to engine performance and emission modeling [8-10]. Further investigations by authors in [11] and [12] confirmed that ANN models can achieve coefficients of determination exceeding 0.98 while substantially reducing experimental effort. Nevertheless, most existing ANN-based studies focus on global engine performance or emission characteristics under standard conditions.

Direct prediction of injection flow rate in Common Rail systems, particularly with explicit consideration of fuel temperature effects, remains insufficiently explored. Fuel temperature significantly influences diesel fuel properties such as density and viscosity, thereby affecting injection behavior, yet it is often neglected or treated indirectly. To address this gap, the present study employs an ANN model to predict the main injection flow rate of a Common Rail system using experimental data obtained at fixed fuel temperatures. Unlike conventional approaches based on single operating conditions or strong physical assumptions, this study simultaneously models injection behavior under multiple temperature conditions within a unified ANN framework. The objective is to evaluate the prediction accuracy, stability, and generalization capability of the proposed model, demonstrating its potential as a reliable data-driven tool for injector characterization, system diagnosis, and optimization of electronically controlled fuel injection systems.

II. METHODOLOGY

A. Experimental Setup and Test Bench Description

The experiments were conducted on a CARDIV V830 Common Rail injector test bench (Version 2021). The main technical specifications of the test system are summarized in Table I. The system is designed to accurately simulate the operating conditions of electronically controlled Common Rail fuel injection systems, enabling precise control of injection pressure, injection duration, and injection frequency.

TABLE I. GENERAL SPECIFICATIONS OF THE TEST BENCH

| Item | Specification |
|-----------------------------------|------------------------------------------------------------|
| Model | CARDIV V830 (Ver. 2021) |
| Power supply (injector unit) | Three-phase AC, 380 V, 50–60 Hz (with integrated inverter) |
| Power supply (high-pressure pump) | Single-phase AC, 220 V, 50–60 Hz |
| Motor power | 5 HP (injector), 2 HP (high-pressure pump) |
| Dimensions | 1,100 × 800 × 1,600 mm |
| Mass | 300 kg |
| Injector type | Bosch |
| Actuation | Solenoid |

As illustrated in Figure 1, fuel in the Common Rail experimental system is stored in the fuel tank (2) and drawn by the low-pressure pump (3) through a fuel filter (4) to remove impurities. The fuel is then supplied to the high-pressure pump (6), which is driven by an electric motor (5) to compress the fuel to high pressure before delivering it to the Common Rail (7). A Common Rail pressure sensor (8) continuously monitors the rail pressure and transmits the signal to the Electronic Control Unit (ECU) (15). The ECU compares the measured pressure with the target value and regulates the pressure control valve (9) and the high-pressure pump to maintain stable operating pressure. Upon receiving control signals from the ECU, the injector (10) is actuated to perform the fuel injection

process. The injected fuel passes through the injection flow rate measuring line (11), where the injected fuel sensor (12) records the injection flow rate. Simultaneously, the return fuel from the injector flows through the return fuel measuring line (13) and is measured by the return fuel sensor (14) before returning to the fuel tank. All sensor signals are collected and processed by the ECU and displayed on the monitoring interface (16) for real-time supervision and subsequent experimental analysis. In addition, a fuel temperature control unit (1) is integrated into the system to stabilize the fuel temperature, ensuring accurate, repeatable, and safe experimental conditions throughout the tests.

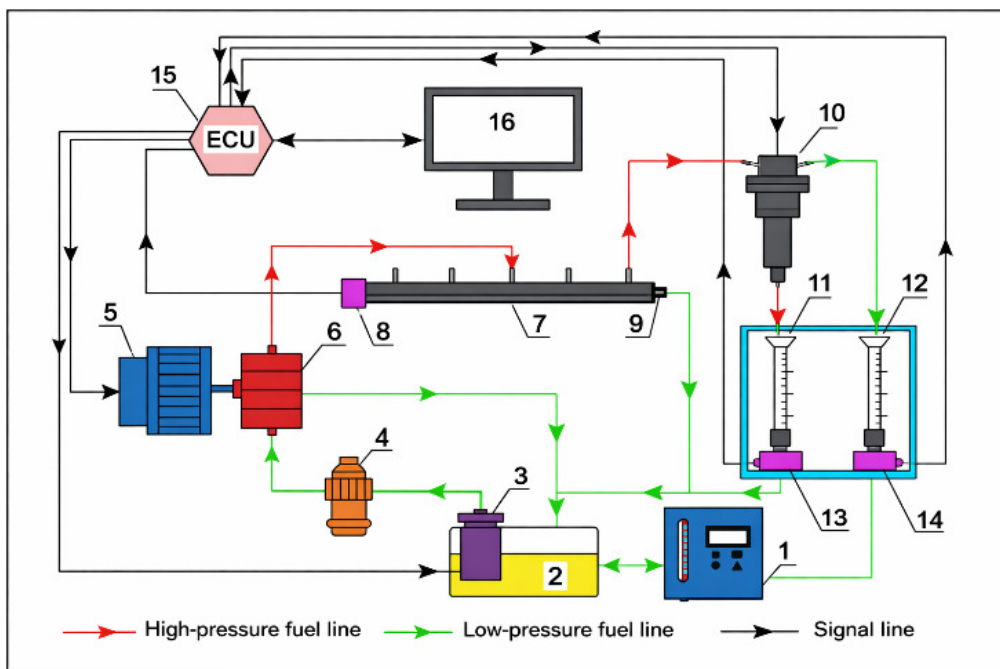


Fig. 1. Experimental system configuration.

B. Artificial Neural Network Model

In this study, an ANN model is employed to predict the main injection flow rate of an electronically controlled injector in a Common Rail fuel injection system. ANN is a powerful machine learning approach capable of capturing complex nonlinear relationships between input and output variables using experimental data. The ANN architecture consists of an input layer, one or more hidden layers, and an output layer, where connection weights are optimized through the backpropagation algorithm to minimize prediction errors. Figure 2 illustrates the general architecture of the ANN employed in this study, consisting of an input layer, one or more hidden layers, and an output layer. The input signals are processed through weighted connections and activation functions to capture the nonlinear relationships between the input variables and the predicted output.

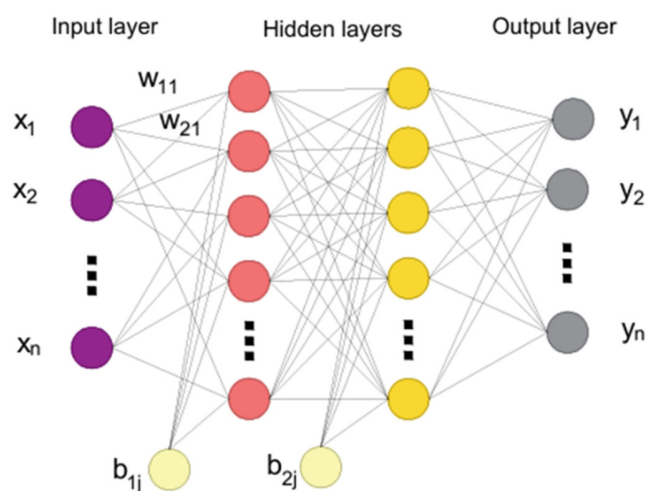


Fig. 2. General architecture of the ANN.

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

$$\text{RMSE} = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2} \quad (1)$$

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

$$\text{MAE} = \frac{1}{n} \sum_{i=1}^n |y_i - \hat{y}_i| \quad (2)$$

The coefficient of determination (R^2) is 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:

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

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

Figure 3 illustrates the workflow of the ANN model development and evaluation. Data from CH1, CH2, and CH4 are acquired and normalized, then divided into training-validation and testing datasets. The model is optimized through hyperparameter tuning to minimize prediction error, followed by performance evaluation using statistical metrics.

The main parameters used for constructing and training the ANN model are as follows. A feed-forward backpropagation network trained with the Levenberg–Marquardt algorithm was employed. The network consists of two hidden layers with 128 and 64 neurons, respectively. Five operational variables speed, pressure, injection speed, pulse time, and temperature, were selected as inputs, whereas flow rate was defined as the output. The experimental dataset consisted of 688 data samples obtained from two test campaigns at fixed fuel temperatures of 25 °C and 35 °C, with 344 data points for each temperature condition. The dataset was divided into 80% for training (including 10% for validation) and 20% for testing. Model performance was evaluated using R^2 , RMSE, and MAE. Training was terminated using an early-stopping criterion based on validation error or the maximum number of epochs. The input parameters of the machine learning model are presented in Table II, whereas the injection flow rate is defined as the model output.

TABLE II. INPUT PARAMETERS OF THE ANN MODEL

| Input parameters | Range |
|-------------------------|-------------------------------------------------------|
| Test pressure | 100–1,800 bar (maximum 2,000 bar) |
| Main injection duration | 100–3,000 μs |
| Injection frequency | 100–1,800 Hz |
| Test modes | CH1 (low speed), CH2 (medium speed), CH4 (high speed) |
| Fuel temperature | 25–35 °C |

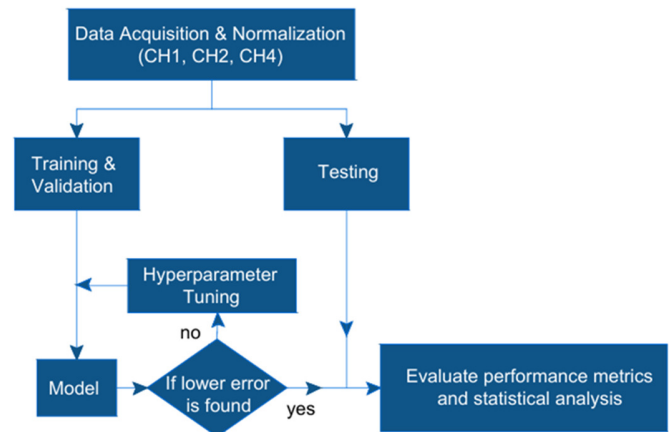


Fig. 3. Workflow of the ANN model development and evaluation.

III. RESULTS AND DISCUSSION

The ANN training process was conducted using both datasets, with 80% of the total data allocated to the training set to evaluate the model's learning capability and its ability to capture nonlinear relationships. The remaining 20% of the data were reserved for the testing set to assess the accuracy and reliability of the model when applied to unseen data. This data-splitting strategy plays a crucial role in mitigating overfitting, which occurs when the model memorizes the training data rather than learning the underlying general patterns of the system. Therefore, the predictive performance of the ANN model was evaluated on both the training and testing datasets using standard statistical metrics, including R^2 , RMSE, and MAE. Initially, regression plots for the training and testing datasets were analyzed to visually examine the relationship between the experimental values and the ANN-predicted values at fuel temperatures of 25 °C and 35 °C. These plots provide a qualitative assessment of the model's fitting performance and potential prediction deviations.

Figure 4 presents the regression plots between the experimental measurements and the ANN-predicted values on the training dataset at fuel temperatures of 25 °C and 35 °C. For both temperature conditions, the predicted values are closely aligned with the ideal $y=x$ line, indicating a strong agreement between the model predictions and the experimental data over the entire measurement range. At 25 °C, the data points exhibit a tighter clustering around the regression line, reflecting a more stable learning behavior of the ANN model. In contrast, a slightly increased scatter is observed at 35 °C, particularly in the medium-to-high value range, which can be attributed to changes in fuel physical properties, such as reduced viscosity at elevated temperatures, leading to increased sensitivity of the injection flow rate to operating conditions. Despite this minor dispersion, the overall linear trend remains well preserved at both temperatures, demonstrating that the ANN model effectively captures the underlying relationship between the input variables and the fuel injection flow rate and maintains robust training performance across different fuel temperature conditions.

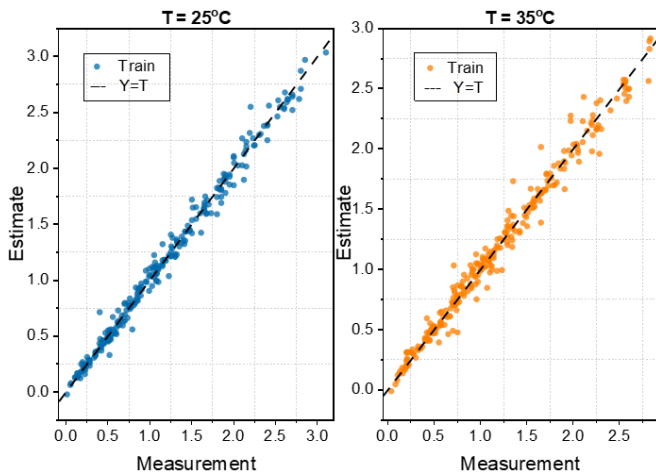


Fig. 4. Regression relationship between experimental and predicted values on the training dataset at fuel temperatures of 25 °C and 35 °C.

Figure 5 illustrates the regression plots between the experimental measurements and the ANN-predicted values on the test dataset at fuel temperatures of 25 °C and 35 °C.

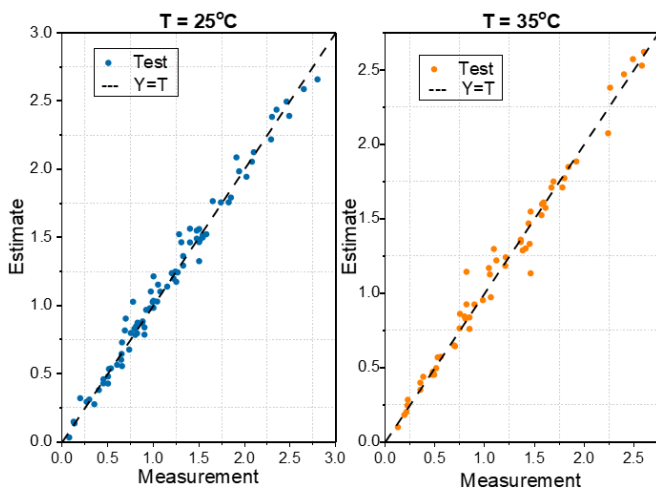


Fig. 5. Regression relationship between experimental and predicted values on the test dataset at fuel temperatures of 25 °C and 35 °C.

For both temperature conditions, the predicted values closely follow the ideal $y=x$ line, demonstrating a strong agreement between the ANN predictions and unseen experimental data. At 25 °C, the data points remain tightly clustered around the regression line, indicating good generalization capability and stable predictive performance of the trained ANN model. At 35 °C, a slightly higher dispersion is observed, particularly in the medium-to-high measurement range, which can be attributed to increased nonlinearity in fuel injection behavior caused by reduced fuel viscosity at elevated temperatures. Despite this minor increase in scatter, the overall linear trend is well preserved, confirming that the ANN model maintains robust predictive accuracy and is capable of reliably extrapolating fuel injection flow rate behavior under different fuel temperature conditions without significant performance degradation.

As shown in Table III, the ANN model demonstrates strong predictive performance on both the training and testing datasets. For the training set, the model achieves R^2 , RMSE, and MAE values of 0.9861, 0.0833, and 0.0561, respectively, whereas the corresponding values on the testing set are $R^2 = 0.9814$, RMSE = 0.0872, and MAE = 0.0624. The close agreement between training and testing performance indicates a high level of prediction accuracy and suggests that the proposed ANN architecture effectively captures the underlying relationships in the data across different operating conditions. The fuel injection flow rates measured at fuel temperatures of 25 °C and 35 °C are well represented by the model, resulting in accurate predictions for both datasets. The coefficient of determination shows only a slight decrease of approximately 0.48% from training to testing, whereas RMSE and MAE increase moderately by 4.68% and 11.23%, respectively. These relatively small performance differences indicate stable model behavior and good generalization capability when applied to unseen data.

TABLE III. PERFORMANCE OF THE PREDICTION MODEL

| Method | R^2 | RMSE | MAE |
|--------|--------|--------|--------|
| Train | 0.9861 | 0.0833 | 0.0561 |
| Test | 0.9814 | 0.0872 | 0.0624 |

Figure 6 illustrates the error distribution between the predicted and experimental values on the training dataset at fuel temperatures of 25 °C and 35 °C. The errors are predominantly concentrated around zero, with most values falling within the range of ± 0.1 . Although a few larger errors are observed sporadically, the maximum deviation is limited to approximately ± 0.3 , indicating a negligible level of discrepancy. The high-density region near the zero-error axis reflects the high predictive accuracy of the model in the majority of cases. At a fuel temperature of 35 °C, the error distribution remains symmetric around zero, with most data points located within ± 0.12 . Errors exceeding ± 0.35 occur with very low frequency and do not exhibit any noticeable bias or systematic trend. This behavior demonstrates that the model maintains stability and consistency under varying temperature conditions.

Overall, for both temperature levels of 25 °C and 35 °C, the error distributions are narrowly concentrated around zero, with large deviations occurring infrequently. These results confirm that the proposed model provides accurate, unbiased predictions and is well-suited for estimating the fuel injection flow rate in Common Rail systems.

Figure 7 illustrates the error distribution between the predicted and experimental values on the testing dataset at fuel temperatures of 25 °C and 35 °C.

The errors are predominantly concentrated around zero, indicating that the ANN model maintains high predictive accuracy when applied to unseen data. At 25 °C, most errors fall within a narrow range, similar to the training results, whereas at 35 °C, a slightly wider dispersion is observed, particularly in the higher measurement range.

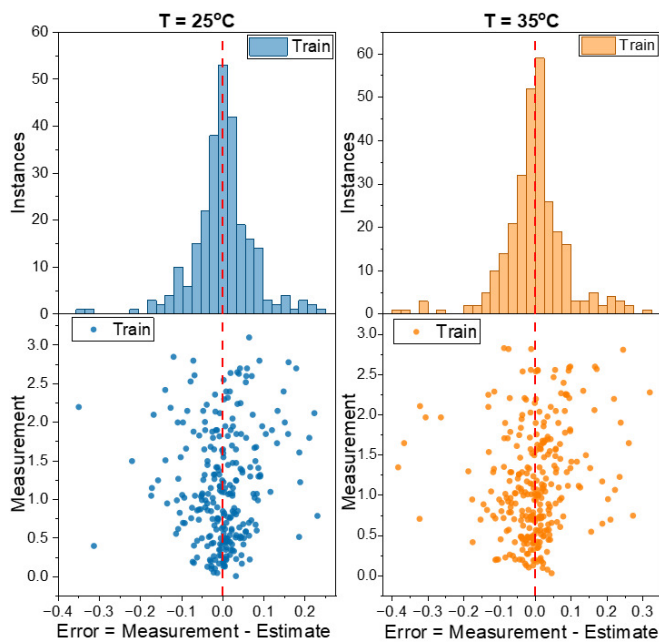


Fig. 6. Error distribution between experimental and predicted values on the training dataset at fuel temperatures of 25 °C and 35 °C.

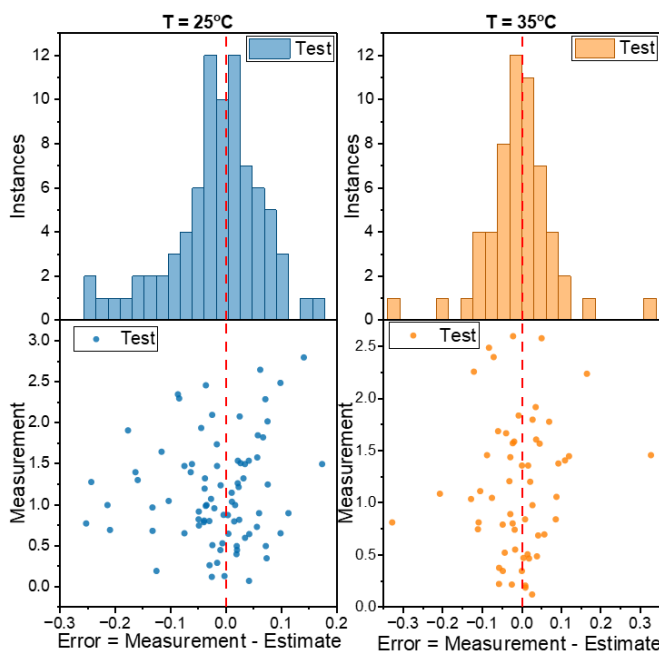


Fig. 7. Error distribution between experimental and predicted values on the testing dataset at fuel temperatures of 25 °C and 35 °C.

This behavior can be attributed to increased nonlinearity in fuel properties at elevated temperatures. Despite this slight increase in dispersion, the error distribution remains symmetric around zero for both temperature conditions, with no evident systematic bias. The majority of prediction errors remain within a limited range, and larger deviations occur infrequently. Compared to the training dataset, a marginal increase in error spread is observed, which is expected when evaluating model

performance on unseen data. Overall, these results confirm that the ANN model retains good generalization capability and provides reliable predictions under different fuel temperature conditions.

Figure 8 shows the comparison between measured and ANN-predicted flow rates on the test dataset at 25 °C. The predicted values closely follow the measured data over the entire operating range, indicating a strong agreement in both trend and magnitude. Quantitatively, the prediction errors remain small for most points, particularly in the medium flow-rate region (0.5–1.5), where deviations are generally within a few percent of the measured values. Even at high flow-rate peaks (up to ~2.8), the ANN accurately reproduces rapid fluctuations with only minor local discrepancies. The absence of observable phase lag further confirms the model's ability to capture the dynamic behavior of the injection system at 25 °C. Overall, the low dispersion between measured and predicted data implies a small RMSE and a high coefficient of determination (R^2 close to unity) on the test set.

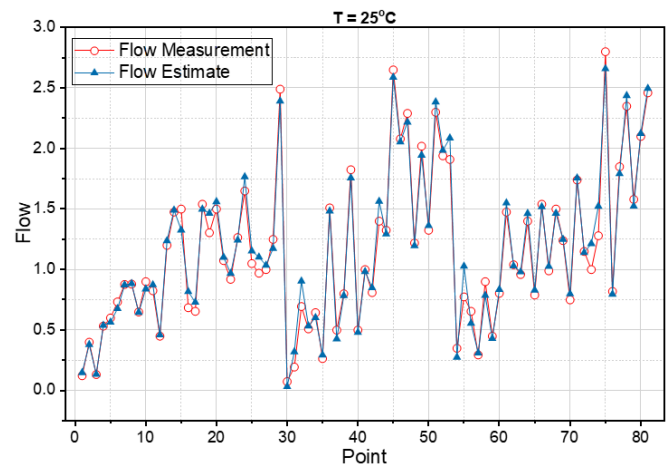


Fig. 8. Comparison between measured and ANN-predicted flow rates on the test set at 25 °C.

Figure 9 presents the corresponding results at 35 °C. Although the ANN model continues to capture the overall trend and peak flow rates accurately, slightly larger deviations are observed, particularly in the low flow-rate region (0.2–0.5) and during abrupt transitions. Quantitatively, the prediction error increases modestly compared to 25 °C, reflecting the stronger nonlinearity induced by temperature-dependent changes in fuel properties. Nevertheless, the errors remain within an acceptable range, and no systematic over- or underestimation is observed, indicating stable generalization performance. In summary, the ANN model achieves higher accuracy at 25 °C than at 35 °C, as evidenced by smaller prediction errors and tighter agreement with experimental data. These results confirm that the proposed ANN model provides reliable and quantitatively accurate flow-rate predictions, while highlighting temperature as a key factor influencing prediction uncertainty.

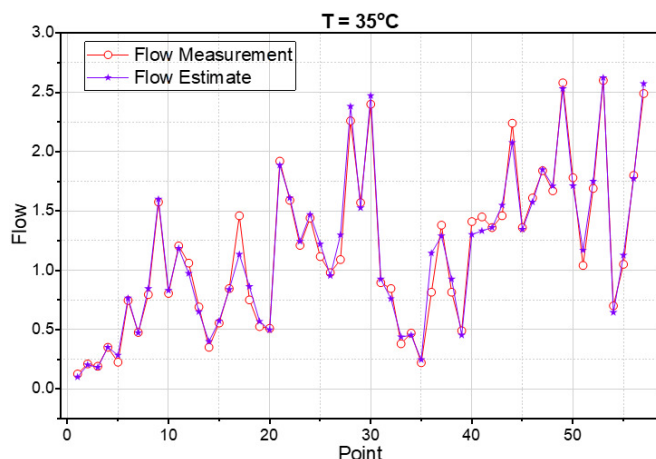


Fig. 9. Comparison between measured and ANN-predicted flow rates on the test set at 35 °C.

IV. CONCLUSION

This study proposed and validated an experimental data-driven Artificial Neural Network (ANN) model for predicting the main injection flow rate in a Common Rail fuel injection system, with explicit consideration of fuel temperature effects. Unlike conventional physics-based or single-condition data-driven approaches, the proposed model was developed using experimental datasets obtained at two fixed fuel temperatures (25 °C and 35 °C) and trained within a unified ANN framework.

Experimental results demonstrate that the ANN model exhibits excellent predictive performance for both training and testing datasets. Quantitatively, the model achieved a coefficient of determination (R^2) of 0.9861 during training and 0.9814 on the test dataset, accompanied by low Root Mean Square Error (RMSE) (0.0833–0.0872) and Mean Absolute Error (MAE) (0.0561–0.0624) values. The small reduction in performance between the training and testing phases confirms that the model possesses strong generalization capability. Regression analyses and time-series comparisons further reveal a close agreement between measured and predicted injection quantities, with errors predominantly concentrated around zero and no observable systematic bias.

Comparative analysis between the two temperature conditions indicates that prediction accuracy at 25 °C is slightly higher than that at 35 °C. This behavior can be attributed to temperature-induced variations in fuel physical properties, such as viscosity and density, which increase the nonlinearity of the injection process at elevated temperatures. Nevertheless, the ANN model maintains stable and reliable performance under both conditions, demonstrating its robustness and suitability for practical applications.

The findings confirm that a single ANN architecture can accurately predict injection flow rate across different fuel temperature conditions using experimental data alone, without relying on complex physical assumptions or extensive calibration. This highlights the potential of the proposed approach as an efficient and reliable tool for injector

characterization, performance evaluation, and fault diagnosis in electronically controlled Common Rail fuel injection systems.

A. Future Work

Future work will focus on extending the proposed model to a wider range of fuel temperatures and operating conditions, with fuel temperature treated as a continuous input variable. Hybrid modeling approaches integrating ANN with physics-informed or other machine learning techniques will be investigated to enhance robustness and interpretability. In addition, real-time implementation and validation on engine or hardware-in-the-loop test platforms will be pursued to assess practical applicability.

DECLARATION OF COMPETING INTERESTS

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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DATA AVAILABILITY

The data supporting the findings of this study are available from the corresponding author upon reasonable request.

DECLARATION ON THE USE OF GENERATIVE AI

The authors declare that no generative artificial intelligence tools were used in the writing of this manuscript.

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