



# OPEN A neural network based approach for thrust prediction in cold gas propulsion systems

Morteza Farhid<sup>✉</sup>, Mohammad Reza Ghavidel Aghdam & Moharram Shamel

In this paper, we present a machine learning method to accurately predict thrust in a cold gas thruster using a feedforward neural network (FFNN). The model leverages critical operational parameters, such as storage pressure, mass flow rate, nozzle length, exit pressure, and propellant mass density, to achieve high precision in thrust predictions. To make this technology accessible and practical, we introduce an intuitive graphical user interface (GUI) that allows users to estimate thrust in real-time systems. This tool simplifies design and analysis processes, offering engineers a powerful resource for optimizing the performance of the cold gas thrusters. Based on the simulation results, our proposed method achieves an accuracy of 0.98 and an F1 score of 0.981, showcasing its robustness and generalizability across various test cases. Our work highlights how machine learning methods can be effectively integrated into propulsion system development, paving the way for more innovative, more efficient designs.

**Keywords** Thrust prediction, Cold gas thruster, Neural network, GUI

Cold gas thrusters represent one of the most straightforward and versatile propulsion systems used in spacecraft<sup>1</sup>. These systems generate thrust by ejecting a pressurized gas through a rocket nozzle, with optional moderate heating to enhance performance<sup>2</sup>. Due to their straightforward design and operation, they are widely employed for various critical functions, including orbital maneuvers, collision avoidance, orbit maintenance<sup>3</sup>, and precise attitude control as part of reaction control systems (RCS)<sup>4</sup>. Unlike chemical propulsion systems, cold gas thrusters avoid combustion, enabling a range of propellants, usually including non-toxic and non-explosive options<sup>5</sup>. This simplifies storage, handling, and operational requirements, making them suitable for small satellite missions<sup>6</sup>.

The new space paradigm has intensified interest in cold gas thrusters, especially for CubeSats and nanosatellites<sup>7</sup>, which demand compact, cost-effective<sup>8</sup>, and efficient solutions<sup>9</sup>. With the reduction in launch costs and the standardization of satellite platforms, smaller spacecraft can now provide services like Earth observation<sup>10</sup>, communication<sup>11</sup>, and scientific research<sup>12</sup>. However, these advancements also impose unique challenges on propulsion systems, such as size, weight, complexity, and power consumption constraints.

Cold gas thrusters are well-suited to address several challenges in spacecraft propulsion, offering simplicity, low power requirements, and cost advantages<sup>13</sup>. Their compatibility with various propellants further enhances design flexibility while reducing the risks associated with high-pressure storage and toxic chemicals. These attributes and their suitability for low-thrust applications make cold gas thrusters essential for modern small satellite missions<sup>14</sup>. The reliability of cold gas thrusters as a propulsion solution stems not only from their operational simplicity but also from their ability to deliver consistent thrust under various conditions. In small satellite missions, where precision is critical, maintaining control over thrust output is essential for achieving mission objectives such as attitude adjustments or station-keeping<sup>15,16</sup>. This consistency inspires confidence in the system's ability to perform delicate maneuvers while minimizing the risk of overcorrections or propellant wastage. Their low-thrust nature facilitates subtle adjustments, making them ideal for mission scenarios where more significant, high-thrust systems might introduce instability or inefficiency<sup>17</sup>.

Despite their reliability, optimizing the thrust performance of cold gas thrusters requires addressing several interdependent parameters that directly impact their output. Operational parameters such as mass flow rate, nozzle length, throat diameter, storage pressure, nozzle exit pressure, and propellant density significantly affect the thrust produced by cold gas thrusters<sup>18</sup>. Understanding how these parameters affect thrust performance is crucial for enhancing system reliability and ensuring mission success in increasingly complex satellite applications. However, traditional analytical models for thrust prediction often rely on simplifying assumptions and fail to capture the complex, nonlinear interactions between these factors. This highlights the need for

Iranian Space Research Center, Tabriz, Iran. ✉ email: m.farhid@isrc.ac.ir

advanced methods to supplement traditional methods, which often lack the precision required for accurate thrust predictions.

In recent years, machine learning methods have been increasingly incorporated into aerospace applications to address the limitations of traditional methods. These methods offer significant advantages over conventional approaches, particularly in predicting thruster performance. By leveraging advanced algorithms such as neural networks<sup>19</sup> and support vector machines (SVM)<sup>20</sup>, machine learning can analyze large datasets and identify complex patterns that are difficult to model using traditional methods. This allows for more accurate and reliable predictions of thruster behavior, even under varying operational conditions, which is critical for optimizing spacecraft performance and mission outcomes<sup>21</sup>.

Additionally, machine learning has proven to be a valuable tool for thruster prediction, enabling more precise forecasts of system behavior across diverse scenarios<sup>22–24</sup>. These methods can dynamically adapt to new data, continuously improving their predictive accuracy as they learn from real-time sensor inputs and historical performance data. This adaptability makes machine learning particularly effective for addressing the inherent complexities of space missions, where conditions can change rapidly and unexpectedly.

Previous research has primarily focused on thrust prediction for Hall and micro Newton thrusters, which, while crucial, often overlook the complexities of cold gas thrusters. Cold gas thrusters, however, present a unique challenge as their performance is highly dependent on a range of interrelated parameters such as mass flow rate, nozzle design, storage pressure, and propellant characteristics. These factors make thrust prediction for cold gas thrusters particularly intricate and critical, especially in space missions where precision and reliability are paramount. In response to this gap, our proposed method aims to provide a more accurate and adaptive approach for predicting thrust performance, specifically for cold gas thrusters. To achieve this, we utilize accurate data<sup>18</sup> to predict thrust for various operational scenarios, enhancing the reliability and applicability of our model.

In this paper, we introduce a feedforward neural network (FFNN) to model the nonlinear relationships between input parameters and the generated thrust in cold gas thrusters. Neural networks have proven to be practical tools for capturing complex patterns in data, making them ideal for modeling the intricate dependencies in propulsion systems. This approach allows for accurate, data-driven predictions, even when traditional models fail to capture the full complexity of the underlying physics.

In addition to the neural network model, a graphical user interface (GUI) was developed to facilitate the real-time application of the predictive model. The GUI provides a user-friendly platform for engineers and researchers to input relevant operational parameters and receive immediate thrust predictions, making evaluating different spacecraft designs and operational scenarios easier. Integrating machine learning with a practical interface enables the model to be used effectively in real-world situations where rapid decision-making is often required.

We aim to demonstrate the power of machine learning in enhancing the prediction capabilities of cold gas thrusters and to provide a user-friendly tool that can be easily incorporated into spacecraft propulsion system design. By combining a high-performance neural network with a simple interface, this work paves the way for more efficient mission planning, optimized spacecraft designs, and better decision-making processes for space engineers.

The remainder of this paper is organized as follows: section “[Proposed method](#)” describes the proposed method, FFNN structure, and GUI development used in this paper. Simulation results and FFNN performance analysis are provided in section “[Simulation results](#)”, and the conclusion is presented in section “[Conclusion](#)”.

## Proposed method

This paper presents a machine-learning method to predict the thrust generated by cold gas thrusters. The main focus is leveraging the FFNN to model the complex and nonlinear relationships between key operational parameters and the generated thrust. Traditional analytical models for thrust prediction in cold gas thrusters often rely on simplifications that may not fully capture the underlying physics, especially in cases where nonlinear interactions between variables play a significant role. Neural networks, on the other hand, excel at capturing such complexities, making them an ideal tool for this task. In FFNN, there is no feedback loop such that the previous input data would not affect the current output, i.e., memoryless. The FFNN is used when the data is not correlated, e.g., image data. Also, this type of FFNN can be used to predict thrust values in cold gas thrusters because the thrust values are not correlated.

To develop our model, we utilized a dataset of experimental measurements from cold gas thrusters, where the operational parameters include mass flow rate, nozzle length, nozzle throat diameter, storage pressure, nozzle exit pressure, and propellant mass density. These parameters were selected because they directly influence the thermodynamics and fluid dynamics within the thruster, affecting the thrust output. FFNN was trained using this dataset to map from the input parameters to the output thrust. The network’s architecture and training process were carefully designed to achieve high predictive accuracy, and the model’s performance was thoroughly evaluated using standard metrics such as mean squared error (MSE) and coefficient of determination ( $R^2$ ).

## Data acquisition

The dataset used in this study was obtained from experimental results of cold gas thrusters operating under various conditions<sup>18</sup>. The dataset used in this study, as cited in<sup>18</sup>, consists of 2300 chemical substances—300 inorganic and 2000 organic—screened for their potential as spacecraft propellants. All substances were evaluated under standard reference conditions of 20 °C and 1 atm to ensure consistency and relevance to propellant handling and storage on Earth. Units for temperature (K), pressure (Pa), and vapor pressure were standardized across the dataset.

To ensure practical feasibility, substances were filtered based on six key criteria: (1) compatibility with an operational temperature range of 20–100 °C; (2) phase stability to avoid phase changes between 0–40 °C during handling or testing; (3) exclusion of radioactive or economically infeasible materials (threshold: 10/g \$ elemental

cost); (4) upper vapor pressure limits of 1 atm at 20 °C to avoid pressure-related storage risks; (5) vapor pressure at 100 °C between 500 Pa and 2 atm to ensure sufficient volatility without requiring high-pressure systems; and (6) maximum gas storage pressure of 100 atm, with substances grouped by phase behaviour relative to their critical temperature. These rigorous filtering and classification criteria help ensure that the dataset reflects both practical constraints and scientifically reliable data, enhancing confidence in the results derived from this analysis.

The key parameters considered in the dataset include:

- Mass flow rate ( $\dot{m}$ ): Propellant flow rate in (mg/s).
- Nozzle length (NL): Geometrical length of the nozzle in (mm).
- Nozzle throat diameter (NTD): Geometrical diameter of the nozzle throat in (mm).
- Storage pressure (SP): Chamber pressure measured in (kPa).
- Nozzle exit pressure (NEP): Exit pressure of the nozzle in (kPa).
- Propellant mass density (PMD): Density of the propellant in ( $\text{kg}/\text{m}^3$ ).
- Thrust ( $F$ ): Average thrust generated, recorded in (mN).

The dataset was used to train a neural network model to predict thrust generation based on these operational parameters. Also, the input parameter used for training spans for the thrust value ranges from 10.1 to 11.4. No data points outside this range were included during model development.

#### Data pre-processing

The dataset was subjected to several pre-processing steps to ensure its suitability for training a neural network model to predict thrust. Missing values were handled by imputing numerical features with their respective medians. Outliers are detected using Z-scores and capped where necessary. Finally, the dataset is partitioned using the holdout method to assess model performance<sup>25</sup>.

#### Neural network model

The FFNN is designed to capture the nonlinear relationships between operational parameters and thrust output. In this architecture, information flows sequentially from the input layer through the hidden layers to the output layer.

The input layer consists of six neurons, each corresponding to one of the following parameters: mass flow rate, NL, NTD, SP, NEP, and PMD. These parameters represent the key operational and design variables that influence thrust generation. The hidden layers consist of two fully connected layers. Both layers use the sigmoid activation function, allowing the network to model complex and nonlinear interactions between input features. This structure enables the network to learn both broad and refined representations of the input data. The output layer contains a single neuron with a linear activation function, producing a continuous thrust value based on the transformed features. This setup is suitable for regression tasks and ensures that the output remains interpretable and aligned with real-world measurements.

The selection of key hyperparameters, including the learning rate (0.1) and the number of hidden neurons (15/10), was determined through a combination of manual tuning and insights derived from prior studies. Initially, a range of values for these hyperparameters was explored to assess their impact on model performance. The learning rate of 0.1 was chosen based on its established effectiveness in balancing convergence speed with stability. The number of hidden neurons, set at 15 for the first layer and 10 for the second, was selected to strike an optimal balance between model complexity and generalization capability. These values were further informed by prior research, which frequently employed similar configurations in related tasks. Although a formal grid search was not conducted, manual tuning facilitated an efficient exploration of the hyperparameter space, ultimately leading to the selection of values that maximized model performance.

Figure 1 illustrates the architecture of the proposed FFNN. The network comprises multiple layers, including an input layer, two hidden layers, and an output layer, each consisting of interconnected neurons. The input layer receives raw data, while the hidden layers perform feature extraction and transformation through weighted connections and activation functions. The output layer generates the final predictions based on the processed input. This design demonstrates the model's capacity to learn complex patterns from cold gas thruster data.

This architecture balances learning capacity with computational efficiency, making it well-suited for modelling thrust behaviour in cold gas thrusters.

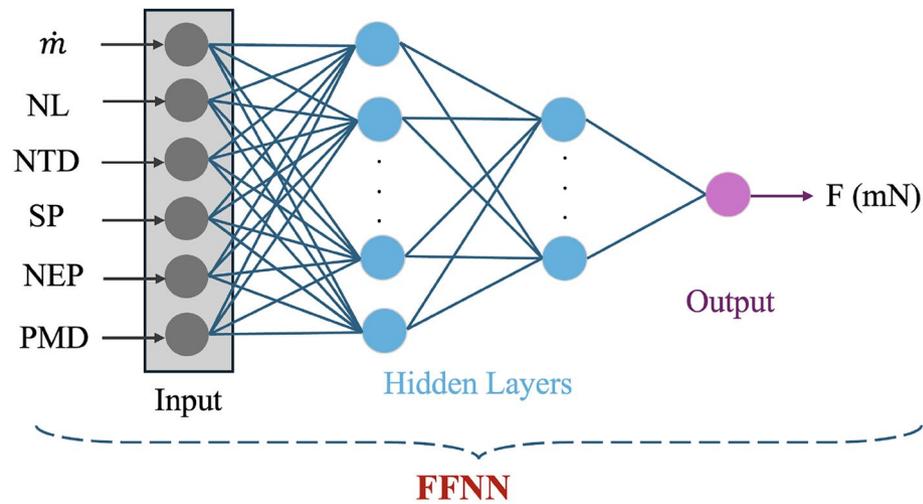
#### Loss function and optimization

To quantify the difference between the predicted and actual thrust values, the mean squared error (MSE) is employed as the loss function:

$$\mathcal{L}_{MSE} = \frac{1}{n} \sum_{i=1}^n (t_i - \hat{t}_i)^2 \quad (1)$$

where  $t_i$  represents the actual thrust value, and  $\hat{t}_i$  denotes the predicted thrust value.

For optimization, the Adam algorithm is utilized to minimize the MSE. Adam adapts the learning rates for each parameter during training, ensuring efficient convergence even with the complexities of the dataset. The weight update rule for Adam is:



**Fig. 1.** Proposed feedforward neural network (FFNN).

$$\theta_{t+1} = \theta_t - \frac{\hat{m}_t}{\sqrt{\hat{v}_t + \epsilon}} \quad (2)$$

where  $\theta_t$  is the parameter at iteration  $t$ ,  $\hat{m}_t = \frac{m_t}{1-\beta_1}$  and  $\hat{v}_t = \frac{v_t}{1-\beta_2}$  are the first and second moment estimates, and  $\epsilon$  is a small constant to avoid division by zero.  $\beta_1$  and  $\beta_2$  are decay rates for the moving averages of the gradient and squared gradient, typically set to  $\beta_1 = 0.9$  and  $\beta_2 = 0.999$ .

The FFNN is trained to accurately model the relationship between operational parameters and thrust generation. The architecture's fully connected layers and choice of activation functions enable it to capture and generalize the underlying patterns in the data effectively. By leveraging the Adam optimizer and MSE loss function, the FFNN achieves robust performance, making it a reliable tool for thrust prediction and cold gas thruster optimization.

#### Training process

We implement the FFNN using MATLAB's neural network toolbox. This paper separates the training and test sets using the holdout method<sup>25</sup>. The holdout method is the most straightforward method for evaluating a classifier. This method chooses  $\rho\%$  of the data as the training data; the rest is test and validation data. Implementing the holdout method is advantageous when dealing with extensive datasets or facing time constraints.

The dataset was split into three sets: 70% for training, 15% for validation, and 15% for testing. The training was conducted using the Levenberg-Marquardt backpropagation algorithm, which is well-suited for smaller datasets with complex relationships. Key performance metrics, including MSE and ( $R^2$ ), were used to evaluate the model. The model was trained using MATLAB's `feedforwardnet` function, with the training parameters set to a maximum of 200 epochs, a minimum gradient of  $1 \times 10^{-6}$ , and a goal of zero MSE.

The training process is summarized in Fig. 2, illustrating the progression of MSE across epochs. The best validation performance was achieved at epoch 13, with an MSE of  $1.0866 \times 10^{-5}$ . The plot highlights the stability and robustness of the training process.

#### GUI development

In this paper, we design a MATLAB-based GUI to facilitate seamless interaction with the trained FFNN model. The GUI enables users to input five operational parameters, processes these inputs in real-time using the trained model, and provides an immediate thrust prediction. The interface allows users to input five key operational parameters: mass flow rate, nozzle length, nozzle throat diameter, storage pressure, nozzle exit pressure, and propellant mass density through intuitive input fields. Once the inputs are provided, the GUI instantly calculates and displays the predicted thrust, offering immediate feedback.

This intuitive and user-friendly interface is a practical tool for optimizing cold gas thruster performance, bridging the gap between advanced computational modeling and real-world engineering applications. By simplifying the prediction process, the GUI empowers engineers and researchers to evaluate multiple design scenarios efficiently, aiding in the rapid development and optimization of spacecraft propulsion systems. Figure 3 illustrates the layout and design of the proposed GUI, showcasing its simplicity and ease of use.

#### Simulation results

In this section, we present the performance of the proposed FFNN model for thrust prediction by MATLAB simulation and discuss the achievements in the investigative model and the design of the GUI. The neural network demonstrated strong predictive performance, as evidenced by several key metrics. These metrics highlight the model's effectiveness in accurately predicting thrust values based on the input parameters. This section uses the dataset based on the holdout method at 70%.

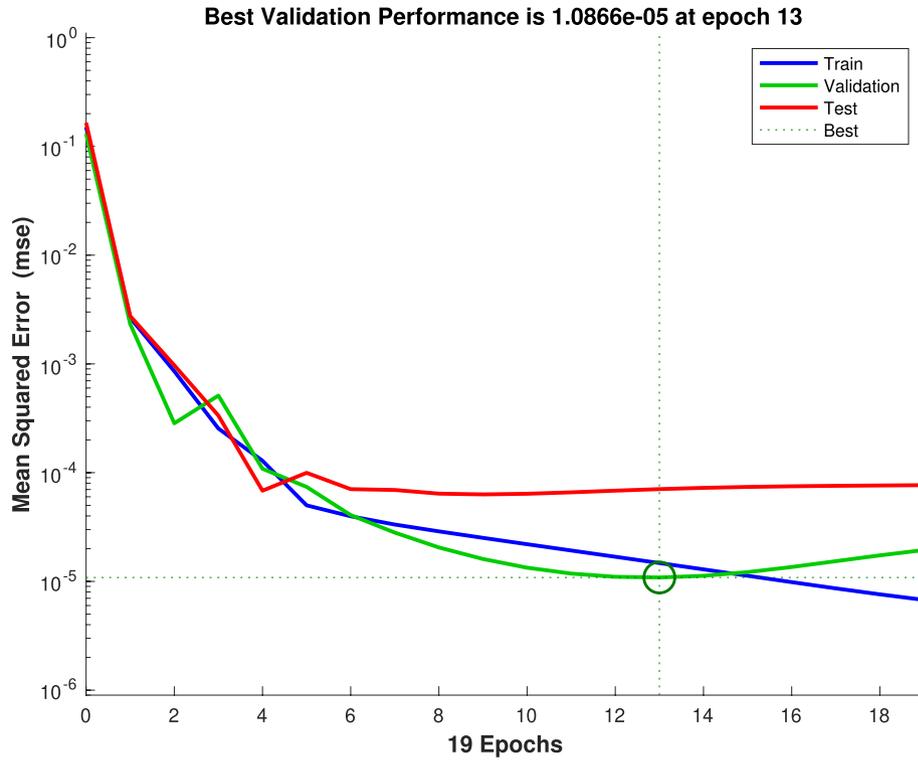


Fig. 2. MSE vs. Epochs.

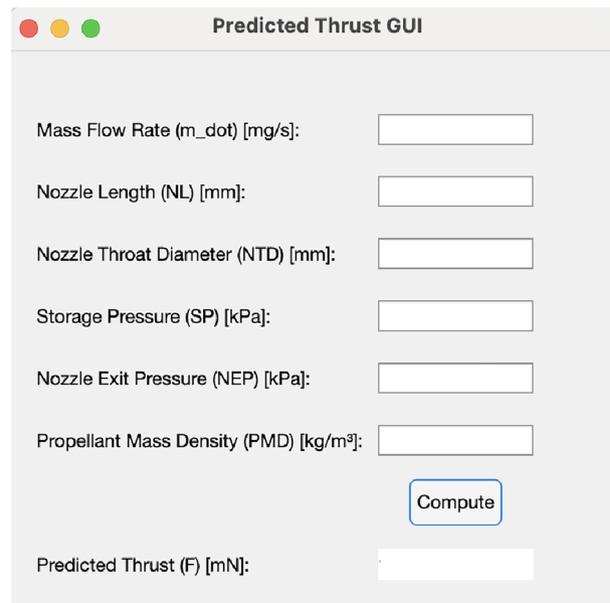
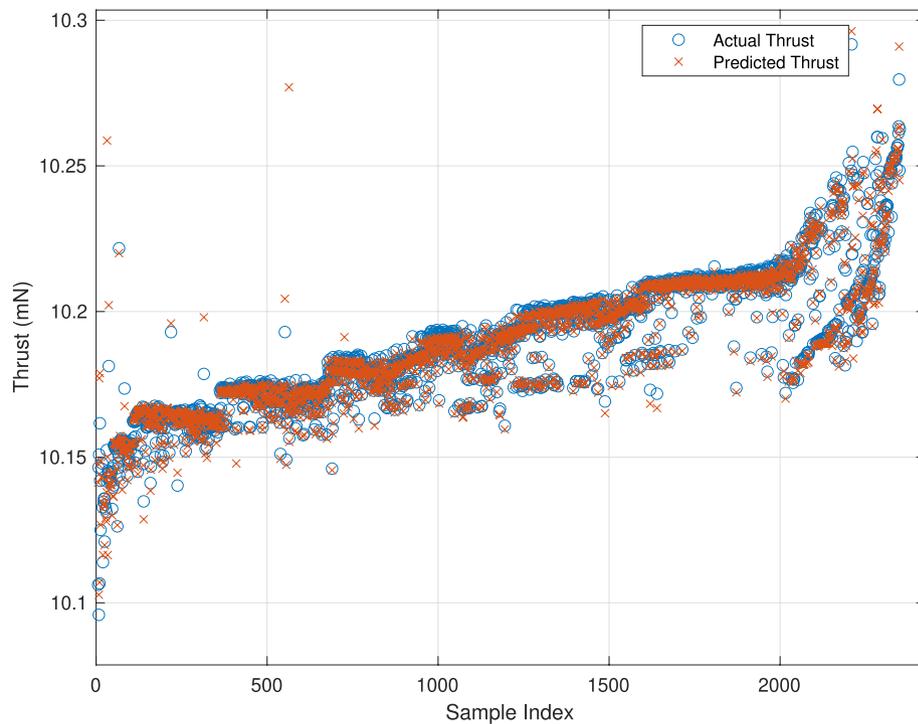


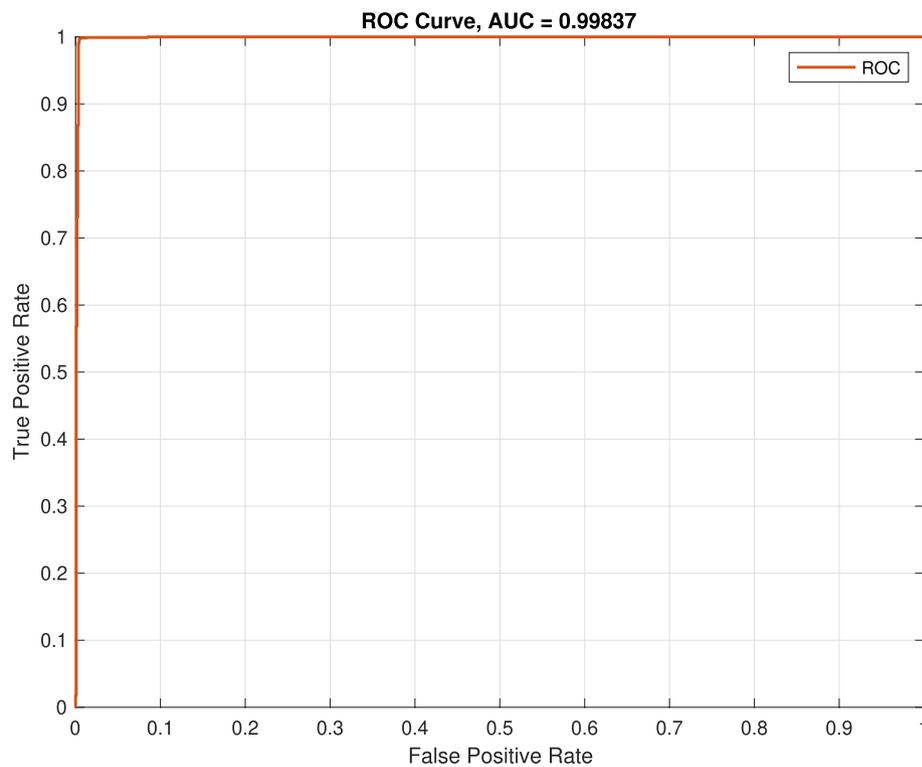
Fig. 3. The proposed GUI model.

The performance metrics are as follows: the MSE is  $2.2554 \times 10^{-5} \text{ mN}^2$ , indicating a remarkably low average squared deviation between predicted and actual thrust values. The coefficient of determination ( $R^2$ ) is 0.99102, reflecting an excellent fit of the model to the data, with over 99% of the variance in thrust values explained by the network. Finally, the root mean squared error (RMSE) is 0.0047491 mN, demonstrating a very low typical prediction error in absolute terms.

Figure 4 visually compares the actual versus predicted thrust values, illustrating the close alignment between the two. The network's capacity to accurately model complex relationships is evident in its ability to generalize



**Fig. 4.** Comparison of actual and predicted thrust values.



**Fig. 5.** ROC curve for binary classification of high/low thrust.

effectively across unseen test data. This consistency highlights the neural network's robustness in capturing the system's underlying dynamics and minimizing prediction errors.

Figure 5 illustrates the receiver operating characteristic (ROC) curve obtained for the thrust prediction task. Although typically associated with binary classification, the ROC curve evaluates the model's performance,

distinguishing between different threshold levels of predicted thrust values. The curve plots the true positive rate (sensitivity) against the false positive rate (1-specificity) across various thresholds, effectively assessing the model's ability to predict thrust accurately. The area under the curve (AUC) is calculated as 0.99, indicating an outstanding predictive capability. This high AUC value confirms the model's reliability in capturing the underlying dynamics of thrust predictions, demonstrating its precision in identifying accurate thrust levels while minimizing prediction errors across the range of thresholds.

Figure 6 displays the confusion matrix for the proposed FFNN model applied to thrust prediction, where the matrix compares the model's true positive (TP), true negative (TN), false positive (FP), and false negative (FN) predictions. The confusion matrix provides a detailed view of the model's performance in classifying predicted thrust values into correct or incorrect categories. The results indicate the FFNN model's high accuracy, with a significant number of true positives and true negatives, demonstrating the model's effectiveness in correctly predicting thrust under various operational conditions. This strong classification performance is essential for spacecraft propulsion systems, where minimizing misclassification is critical for mission success and system reliability.

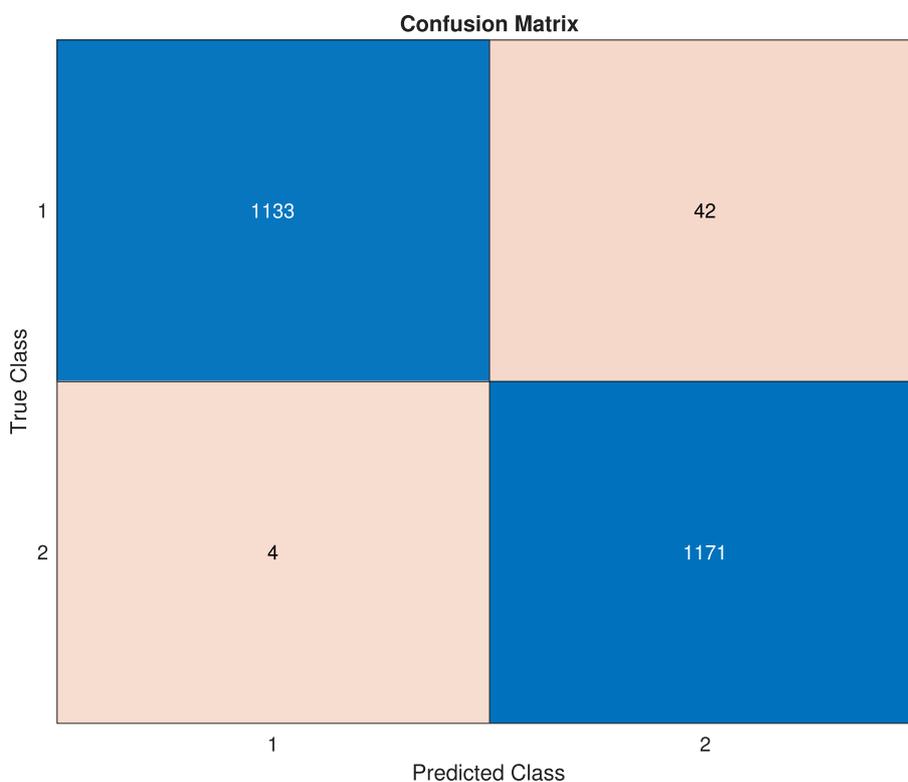
### Performance comparison

Numerous meta-modeling techniques are available for capturing the nonlinear relationships between operational parameters and thrust output in propulsion systems. Traditional models such as SVM, logistic regression (LR), and Gaussian process regression (GPR) have been successfully applied in various aerospace applications due to their robustness and generalization capabilities.

The LR is a widely used linear classification model that estimates the probability of a binary outcome based on input features. It is popular due to its simplicity, interpretability, and efficiency, making it a common baseline in classification tasks. SVM is a powerful classifier that finds an optimal hyperplane to separate classes by maximizing the margin between data points of different categories. SVMs are effective for both linear and nonlinear classification, especially with kernel functions, and are known for their robust performance in various domains. These models were selected as baselines due to their established use and strong performance in classification problems, providing meaningful points of comparison for evaluating the effectiveness of the proposed approach.

Despite these alternatives, FFNN offers a particularly attractive balance of flexibility and computational efficiency. FFNNs are well-suited for modeling complex, nonlinear, and high-dimensional datasets, as they can approximate any continuous function given sufficient network complexity. Their layered structure enables the learning of hierarchical feature representations, which is critical for capturing subtle interactions among input parameters such as mass flow rate, nozzle geometry, and storage pressure.

The performance of the neural network model was compared with two other methods, which include the LR<sup>26</sup> and SVM<sup>27</sup> methods. The comparison is based on key performance metrics, including accuracy and F1 Score.



**Fig. 6.** Confusion matrix in classification.

Method	Accuracy	F1 Score
Proposed Method 80%	0.987	0.987
Proposed Method 70%	0.98	0.981
Proposed Method 50%	0.96	0.96
LR <sup>26</sup>	0.85	0.85
SVM <sup>27</sup>	0.93	0.93

**Table 1.** Performance comparison of thrust prediction values.

The screenshot shows a window titled "Predicted Thrust GUI". It contains several input fields with their corresponding values: Mass Flow Rate (m\_dot) [mg/s] is 14.3, Nozzle Length (NL) [mm] is 2.1, Nozzle Throat Diameter (NTD) [mm] is 0.18, Storage Pressure (SP) [kPa] is 202, Nozzle Exit Pressure (NEP) [kPa] is 0.5, and Propellant Mass Density (PMD) [kg/m<sup>3</sup>] is 578. A "Compute" button is located below these fields. At the bottom, the "Predicted Thrust (F) [mN]" is displayed as 10.15.

**Fig. 7.** Tested GUI.

We scrutinized the model's efficacy using the holdout method with various proportions of training data (80%, 70%, and 50%). As shown in Table 1, the proposed FFNN outperforms the LR and SVM methods, achieving an accuracy of 0.98 and an F1 score of 0.981 based on the holdout method at 70%. This demonstrates the superiority of the FFNN method in predicting thrust value in cold gas thrusters.

While traditional isentropic flow and computational fluid dynamics (CFD) models offer high-fidelity predictions based on physical principles, they are computationally intensive and often impractical for large-scale screening of candidate propellants<sup>28</sup>. In contrast, the proposed meta-model provides rapid estimations across a constrained design space, making it suitable for early-phase decision-making. However, we acknowledge that our approach does not currently include a direct numerical comparison with CFD or analytical benchmarks, which remains a valuable avenue for future validation and calibration efforts.

## GUI

The GUI developed for this paper provides a user-friendly platform to interact with the neural network model for real-time thrust prediction. This tool is designed to facilitate the application of the neural network model in practical scenarios, enabling engineers and researchers to quickly assess the effects of various operational conditions on thrust generation.

The GUI was tested with various input scenarios to evaluate its performance and accuracy. One such scenario included the following input parameters: a mass flow rate of 14.3 mg/s, a nozzle length of 2.1 mm, a nozzle throat diameter of 0.18 mm, a storage pressure of 202 kPa, a nozzle exit pressure of 0.5 kPa, and a propellant mass density of 578 kg/m<sup>3</sup>. For this set of parameters, the predicted thrust was 10.15 mN, which closely matched the experimental value, demonstrating the accuracy and reliability of the model in real-world applications. Figure 7 illustrates the GUI result for this scenario.

## Conclusion

In this paper, we developed the FFNN method for predicting thrust in cold gas thrusters, leveraging the power of machine learning to capture the complex, nonlinear relationships between operational parameters. Our proposed method used two hidden layers and demonstrated excellent predictive accuracy, outperforming traditional methods like linear regression and support vector machines. The model achieved an accuracy of 0.98 and an F1 score of 0.981, showcasing its robustness and generalizability across various test cases. To enhance

accessibility, we designed a GUI based on MATLAB that allows engineers and researchers to input operational conditions and obtain thrust predictions in real-time systems. Our proposed method represents a significant advancement in the design and practical application of cold gas thrusters, enabling more efficient mission planning and execution.

### Data availability

The datasets analysed during this study are publicly available on Zenodo via the following DOI: <http://dx.doi.org/10.5281/zenodo.7765215>.

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### Author contributions

M. Farhid, M.R.Ghavidel and M.shameli wrote the main manuscript text and prepared figures 1-6. All authors reviewed the manuscript.

### Competing interests

The authors declare no competing interests.

### Additional information

**Correspondence** and requests for materials should be addressed to M.F.

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