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Designing a framework for S.I. engine analysis using Deep Learning Model

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Abstract
This research introduces an innovative approach to modeling Spark Ignition (SI) engines by combining deep learning techniques with the Design of Experiments (DOE) framework. Conventional SI engine models often depend on complex physical equations or empirical correlations, which are computationally demanding and may fall short in fully capturing engine dynamics across diverse operating conditions. To address these challenges, this study develops a data-driven SI engine model designed to accurately predict both performance and emission characteristics. A structured DOE methodology will be applied to generate a comprehensive dataset covering a broad spectrum of input parameters, such as engine speed, load, spark timing, and air–fuel ratio. This carefully designed dataset will serve as the foundation for training and validating advanced deep learning models, including Artificial Neural Networks (ANNs), Recurrent Neural Networks (RNNs), and Convolutional Neural Networks (CNNs), selected based on the nature of the input features.

Keyword: Modelling, Deep Learning, DOE, ANN, RNN, CNN

I. Introduction

It is necessary to have complex control systems and accurate prediction models in order to continue the pursuit of increased fuel efficiency and decreased emissions in internal combustion engines, particularly Spark Ignition (SI) engines. Conventional methods based on physics, despite their importance, frequently fail to adequately capture the complex and non-linear interactions that determine the performance of SI engines in a variety of operating conditions. The fluctuating characteristics of the fuel, the conditions of the environment, and the extended deterioration of the engine all contribute to the development of these problems. As a consequence of this, improving performance and emissions through empirical testing is an activity that is both time-consuming and expensive, and it typically requires full Design of Experiments (DOE) programs.

Deep learning has emerged as a game-changing tool in recent years, making it possible to model complex systems that are characterized by high-dimensional, nonlinear data. Because of its sophisticated pattern recognition and forecasting capabilities, it is ideally suited for the intricate dynamics of SI engines. Based on the findings of this study, a novel SI engine model that is based on deep learning is proposed with the intention of overcoming the deficiencies that are associated with conventional methods. For the purpose of providing accurate forecasts of important performance metrics and emissions, the model makes use of sophisticated neural network topologies. As a result, it achieves both increased precision and greater processing efficiency for its predictions.

The purpose of this study is to emphasize the combination of deep learning with a DOE framework, which makes it possible to conduct a systematic investigation of the operational domain of the engine and to quickly determine the optimal parameter configurations. This method has the potential to significantly speed up calibration and control activities, hence reducing reliance on testing that requires a significant amount of resources.

Despite the growing importance of the global movement for environmentally responsible transportation, SI engines continue to play an essential role in the automotive industry. Accurate modeling of the fundamentally complex and dynamic working of fuel efficiency, power generation, and emissions compliance is required in order to achieve simultaneous advances in these areas. First-principles or empirical models that have been used traditionally typically do not possess the necessary level of precision for this purpose, which subsequently causes calibration and optimization efforts to take longer. This research aims to address these limitations by utilizing the synergy between deep learning and Design of Experiments (DOE), which will ultimately make it easier to build powertrain technologies that are more intelligent, more environmentally friendly, and more efficient.

II. LITERATURE REVIEW

Sok et. al states that physical sensors are commonly used to record performance data of internal combustion engines (ICEs) for online feedback control and calibration, but they are prone to diagnostic and increased development costs. Lookup tables are commonly used in conventional calibration and feedback control; however, the table parameters increase with the advancement of ICE technologies under transient operations. Consequently, the calibration and control systems are time-consuming. This work proposes novel virtual sensors to address these issues by predicting the combustion, performance, and emission of ICEs using neural networks and image processing/ translation. The novel sensors are targeted for onboard feedback control systems under transient driving. Firstly, a virtual diesel engine (VDE) was developed and calibrated against experimental data taken from a production 2.2 L turbocharged diesel engine. The VDE was calibrated under WLTC, JC08, and NEDC transient operations and was used to generate teaching data. Next, the virtual sensors are developed using five machine learning (ML) regressors. The result shows that the coefficient of determination R2 from all ML regressors exceeded 0.94, and the XG-Boost outperforms other ML techniques with R2 > 0.977. XG-Boost parameter estimations were 8 times faster than that on a desktop simulation. Then, an image classification model using a deep convolutional neural network (D-CNN) is constructed, and the dependency of performance parameters and exhaust emissions with the rate of heat release (R.H.R) and in-cylinder pressure profile is confirmed. The performance parameters and emissions dependency was compared individually with R.H.R. and the in-cylinder pressure profile. As a result, a strong correlation between the performance and R.H.R. was observed. Finally, a generative adversarial network (GAN) model was constructed to translate the in-cylinder pressure profile to R.H.R. profile. A novel method to develop virtual sensors for advanced feedback control of any type of ICEs is proposed for the first time. [1]

Badra et. al. states that gasoline compression ignition (GCI) engines are considered an attractive alternative to traditional spark-ignition and diesel engines. In this work, a Machine Learning-Grid Gradient Ascent (ML-GGA) approach was developed to optimize the performance of internal combustion engines. ML offers a pathway to transform complex physical processes that occur in a combustion engine into compact informational processes. The developed ML-GGA model was compared with a recently developed Machine Learning-Genetic Algorithm (ML-GA). Detailed investigations of optimization solver parameters and variable limit extension were performed in the present ML-GGA model to improve the accuracy and robustness of the optimization process. Detailed descriptions of the different procedures, optimization tools, and criteria that must be followed for a successful output are provided here. The developed ML-GGA approach was used to optimize the operating conditions (case 1) and the piston bowl design (case 2) of a heavy-duty diesel engine running on a gasoline fuel with a research octane number (RON) of 80. The ML-GGA approach yielded >2% improvements in the merit function, compared with the optimum obtained from a thorough computational fluid dynamics (CFD) guided system optimization. The predictions from the ML-GGA approach were validated with engine CFD simulations. This study demonstrates the potential of ML-GGA to significantly reduce the time needed for optimization problems, without loss in accuracy compared with traditional approaches. The global demand for energy used in the transportation sector is expected to continue rising at an annual rate of 1–1.5% by 2040 according to recent projections. This increase is mainly driven by the expected rise in population, gross domestic product (GDP), and living standards. Currently, internal combustion (IC) engines, fueled by petroleum-derived liquid hydrocarbons (gasoline and diesel), dominate the passenger and commercial transportation sectors with over 99% market share. IC engines are expected to remain the major source of the transportation energy demand in the interim future, despite significant growth in alternative energy and competing technologies (e.g., electric and fuel cells). [2]

Osman et. al. states that the demand for clean and sustainable energy solutions is escalating as the global population grows and economies develop. Fossil fuels, which currently dominate the energy sector, contribute to greenhouse gas emissions and environmental degradation. In response to these challenges, hydrogen storage technologies have emerged as a promising avenue for achieving energy sustainability. This review provides an overview of recent advancements in hydrogen storage materials and technologies, emphasizing the importance of efficient storage for maximizing hydrogen's potential. The review highlights physical storage methods such as compressed hydrogen (reaching pressures of up to 70 MPa) and material-based approaches utilizing metal hydrides and carboncontaining substances. It also explores design considerations, computational chemistry, high-throughput screening, and machine-learning techniques employed in developing efficient hydrogen storage materials. This comprehensive analysis showcases the potential of hydrogen storage in addressing energy demands, reducing greenhouse gas emissions, and driving clean energy innovation. Global energy demand has been steadily increasing due to factors like population growth, economic development, and urbanization. Predictions suggest the world population will reach around 9.7 billion by 2050, consequently continuing the rise in energy demand. Presently, fossil fuels, encompassing coal, oil, and natural gas, account for approximately 80% of the world's energy consumption. [3]

Fleitmann et. al. states that co-design of alternative fuels and future spark-ignition (SI) engines allows very high engine efficiencies to be achieved. To tailor the fuel's molecular structure to the needs of SI engines with very high compression ratios, computer-aided molecular design (CAMD) of renewable fuels has received considerable attention over the past decade. To date, CAMD for fuels is typically performed by computationally screening the physicochemical properties of single molecules against property targets. However, achievable SI engine efficiency is the result of the combined effect of various fuel properties, and molecules should not be discarded because of individual unfavorable properties that can be compensated for. Therefore, we present an optimization-based fuel design method directly targeting SI engine efficiency as the objective function. Specifically, we employ an empirical model to assess the achievable relative engine efficiency increase compared to conventional RON95 gasoline for each candidate fuel as a function of fuel properties. For this purpose, we integrate the automated prediction of various fuel properties into the fuel design method: Thermodynamic properties are calculated by COSMO-RS; combustion properties, indicators for environment, health and safety, and synthesizability are predicted using machine learning models. The method is applied to design pure-component fuels and binary ethanol-containing fuel blends. The optimal pure-component fuel tert-butyl formate is predicted to yield a relative efficiency increase of approximately 8% and the optimal fuel blend with ethanol and 3,4-dimethyl-3-propan-2-yl-1-pentene of 19%. The molecular structure of a fuel is a crucial degree of freedom for sustainable mobility. [4]

Huang et. al. states that with the increasing global concern for environmental protection and sustainable resource utilization, sustainable engine performance has become the focus of research. This study conducts a sensitivity analysis of the key parameters affecting the performance of sustainable engines, aiming to provide a scientific basis for the optimal design and operation of engines to promote the sustainable development of the transportation industry. The performance of an engine is essentially determined by the combustion process, which in turn depends on the fuel characteristics and the work cycle mode suitability of the technical architecture of the engine itself (oil-engine synergy). Currently, there is a lack of theoretical support and means of reference for the sensitivity analysis of the core parameters of oil–engine synergy. Recognizing the problems of unclear methods of defining sensitivity parameters, unclear influence mechanisms, and imperfect model construction, this paper proposes an evaluation method system composed of oil–engine synergistic sensitivity factor determination and quantitative analysis of contribution. [5]

III. PROPOSED SYSTEM

It is anticipated that the construction of a model for Spark Ignition (SI) engines that is based on deep learning will significantly enhance the accuracy of the predicted performance and emissions when compared to standard empirical or statistical approaches. This is because deep learning is one of the most advanced technologies currently available. The reason for this is because deep learning produces results that are significantly more accurate than those obtained through more traditional methods. By utilizing this methodology, the process of determining the optimal operating parameters will be simplified. Additionally, when this methodology is integrated with a Design of Experiments (DOE) framework, the amount of comprehensive experimental testing that is required will be reduced. In the grand scheme of things, this will provide a useful advantage. The proposed deep learning model would achieve improved prediction accuracy, as demonstrated by decreased root mean square error (RMSE) values and increased R-squared metrics, for essential SI engine performance indicators such as brake torque and brake-specific fuel consumption (BSFC), as well as pollutants such as nitrogen oxides, carbon monoxide, and hydrocarbons. This success would be demonstrated by the fact that the R-squared metrics would increase. The emissions and the amount of fuel that is consumed will both be impacted in this scenario. To the contrary, in contrast to conventional models, which are incapable of fully reflecting the intricate and nonlinear interactions that take place between essential input elements such as spark timing, air–fuel ratio, engine speed, and load, our model will accurately characterize these interactions. Additionally, the incorporation of the model with Design of Experiments (DOE) methodologies will make it possible to determine optimal or near-optimal parameter values in a logical and reliable manner. This will be achievable since the model will be integrated with DOE procedures. This will be feasible as a result of the fact that the model will integrate both of the components. By making these adjustments, you will be able to strike a balance between complying with severe emission requirements and increasing operational efficiency. This will allow you to reach a balance.

IV. OBJECTIVES OF PROPOSED SYSTEM

Following are the objectives in which the work will be achieved

- To design, generate, and validate a robust deep learning-based model for Spark Ignition (SI) engines, capable of accurately predicting performance and emissions
- To demonstrate its utility within a Design of Experiments (DOE) framework for optimized engine parameter selection.
- To design and train a deep learning model capable of accurately predicting key SI engine performance parameters (e.g., brake torque, brake specific fuel consumption, indicated mean effective pressure) and emission constituents.
- To analyze the response surfaces generated by the deep learning model within the DOE context, providing insights into the sensitivities and interactions of various engine control parameters.

V. Research Methodology

A. Data Acquisition and Pre-processing

- To obtain a comprehensive, high-quality dataset representing diverse SI engine operating conditions for deep learning model training and validation.

o Utilize an instrumented SI engine test bench (e.g., single-cylinder research engine or multi-cylinder production engine). The setup will include sensors for measuring:

o Data Collection Strategy:

▪ DOE-guided Data Collection: Employ a preliminary DOE approach (e.g., fractional factorial design or D-optimal design) to systematically vary key input parameters (e.g., engine speed, load, spark timing, AFR) and ensure comprehensive coverage of the engine's operating map. This ensures that the collected data is maximally informative for model training.

▪ Collect data at steady-state and potentially transient conditions (if time-series modeling is pursued).

▪ Ensure multiple repetitions at selected points to assess repeatability and quantify measurement noise.

o Data Pre-processing:

▪ Cleaning: Identify and remove outliers, sensor noise, and erroneous readings.

▪ Normalization/Scaling: Apply appropriate scaling techniques (e.g., Min-Max scaling, Standardization) to input and output features to optimize deep learning model training stability and performance.

▪ Feature Engineering (if applicable): Create new features from existing ones if they enhance model performance (e.g., pressure rise rate from cylinder pressure, exhaust gas recirculation (EGR) if applicable).

▪ Data Splitting: Divide the pre-processed dataset into training (e.g., 70-80%), validation (e.g., 10-15%), and testing (e.g., 10-15%) sets to ensure unbiased model evaluation.

B. Deep Learning Model Design and Development

- To design, train, and optimize a deep learning model capable of accurately predicting SI engine performance and emissions.

o Architecture Selection: Explore and select candidate deep learning architectures based on the nature of the data and problem complexity. This may include:

▪ Feedforward Neural Networks (FNN/MLP): For static mapping of inputs to outputs.

▪ Recurrent Neural Networks (RNNs) / LSTMs / GRUs: If transient engine behavior and time-series data are considered.

▪ Convolutional Neural Networks (CNNs): Potentially for feature extraction from raw sensor signals or for image-based combustion analysis (if applicable).

▪ Ensemble Models: Combining multiple deep learning models for improved robustness.

o Model Training:

▪ Initialize model weights and biases.

▪ Select appropriate loss functions (e.g., Mean Squared Error for regression tasks).

▪ Choose an optimizer (e.g., Adam, RMSprop).

▪ Train the model using the training dataset, monitoring performance on the validation set to prevent overfitting.

o Hyperparameter Tuning: Systematically optimize hyperparameters (e.g., number of layers, neurons per layer, learning rate, batch size, activation functions, regularization techniques like dropout) using techniques such as:

▪ Grid Search or Randomized Search.

▪ Bayesian Optimization for more efficient tuning.

C. Model Validation and Performance Evaluation

- To rigorously assess the predictive accuracy, generalization capability, and robustness of the developed deep learning model.

○ Performance Metrics: Evaluate the model's performance on the unseen test dataset using standard regression metrics:

▪ R2 (Coefficient of Determination)

▪ RMSE (Root Mean Squared Error)

▪ MAE (Mean Absolute Error)

▪ MAPE (Mean Absolute Percentage Error)

○ Comparative Analysis: Compare the performance of the deep learning model against established empirical or statistical models (e.g., polynomial regression, traditional engine maps) developed from the same dataset to highlight its advantages.

○ Sensitivity Analysis: Conduct sensitivity analysis on the trained deep learning model to understand the relative importance of different input parameters on engine outputs. Techniques like SHAP (SHapley Additive exPlanations) or LIME (Local Interpretable Model-agnostic Explanations) can be employed for interpretability.

D. Integration with Design of Experiments (DOE)

- To demonstrate the deep learning model's utility as a surrogate for physical experimentation within a DOE framework, enabling efficient optimization.

○ DOE Design using DL Model:

▪ Define the experimental factors (engine control parameters) and their ranges.

▪ Choose a suitable DOE design (e.g., Central Composite Design, Box-Behnken Design) to construct virtual experimental points using the trained deep learning model.

▪ Use the deep learning model to predict the responses (performance and emissions) for these virtual design points.

○ Response Surface Modelling:

▪ Develop response surface models (e.g., polynomial regression models) based on the deep learning model's predictions from the DOE.

▪ Analyse the response surfaces to identify optimal operating conditions and visualize the interactions between parameters.

○ Optimization:

▪ Apply optimization algorithms (e.g., desirability function approach, genetic algorithms) to the response surface models to find optimal engine settings that meet multiple performance and emission targets simultaneously.

▪ Compare the results (optimized parameters and predicted outcomes) with traditional DOE outcomes from physical experimentation, if available, or with literature.

Summary:

- Data Acquisition: Instead of random testing, you are using DOE (Design of Experiments) to ensure every data point collected from the test bench is statistically significant, covering the full map of speed, load, and AFR.
- Model Design: The framework is flexible, allowing for FNNs (for quick mapping) or LSTMs (if you decide to capture the "memory" of transient engine behavior).
- Validation: Beyond just looking at error codes like R^2 you've included SHAP/LIME, which is crucial for engineering. It moves the model from a "black box" to a tool where you can actually see why the model thinks a certain spark timing reduces NOx.
- Optimization: The final stage uses the Deep Learning model as a Digital Twin. This allows you to run thousands of "virtual experiments" in seconds to find the sweet spot for performance vs. emissions without burning a single drop of fuel in the lab.
-

VI. GENERATE THE DEEP LEARNING ENGINE MODEL FOR YOUR VIRTUAL VEHICLE:

- Start the Virtual Vehicle Composer application. Enter this command in the MATLAB® Command Window.
- virtualVehicleComposer
- On the Composer tab, click New
- On the Setup pane, select Vehicle class to be Passenger car and select a Powertrain architecture having an SI engine, such as Conventional Vehicle. Set Model template and Vehicle dynamics as desired.
- Click Configure. The app will prepare the vehicle data.
- On the left side of the Data and Calibration pane, select Powertrain > Engine.
- On the Engine tab, select SI Deep Learning Engine.

- Click the Calibrate from Data tab.
- Select the data source file to use to train your engine model. You can use data acquired by physical testing, or generated by Powertrain Blockset from Gamma Technologies LLC engine models or other high-fidelity engine models.
- Click Calibrate to initiate the training. Model generation can take several hours.

During model generation, the training progress window shows how the deep learning loss function (cost function) varies vs. iterations. You can also stop the training process from this window. When processing is complete, the Stop button turns green. Note that the training may stop before reaching its scheduled number of iterations if it reaches its loss tolerance first.

VII. Result

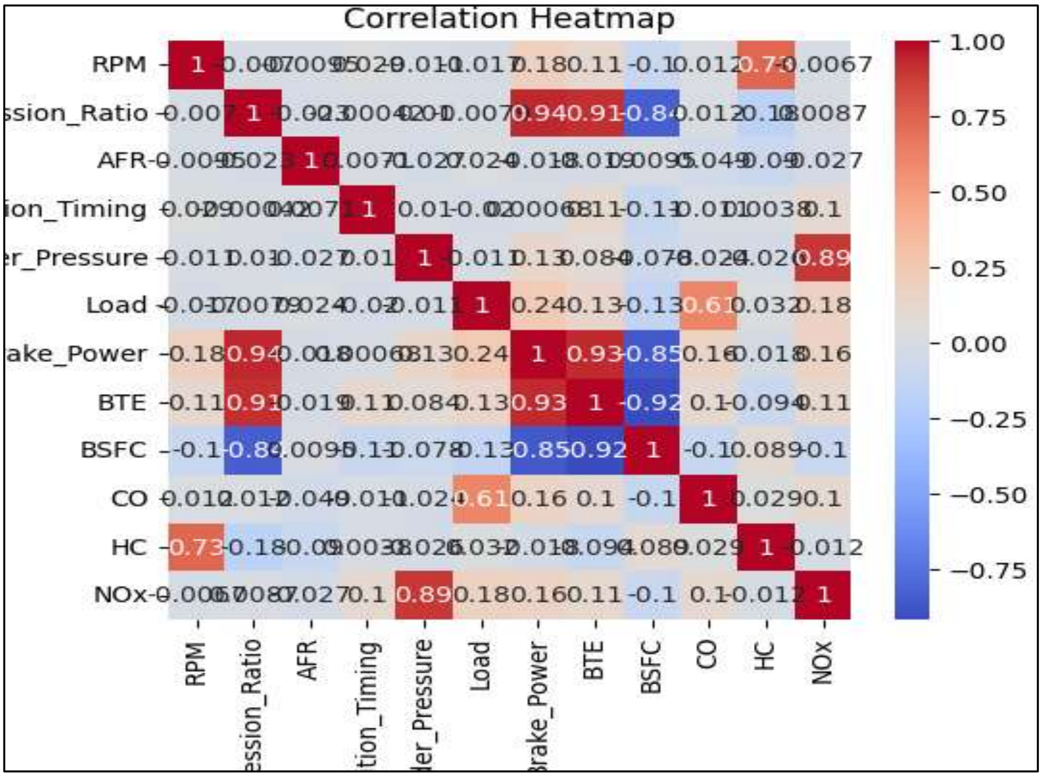

Fig.1 Graph1_CorrelationHeatmap

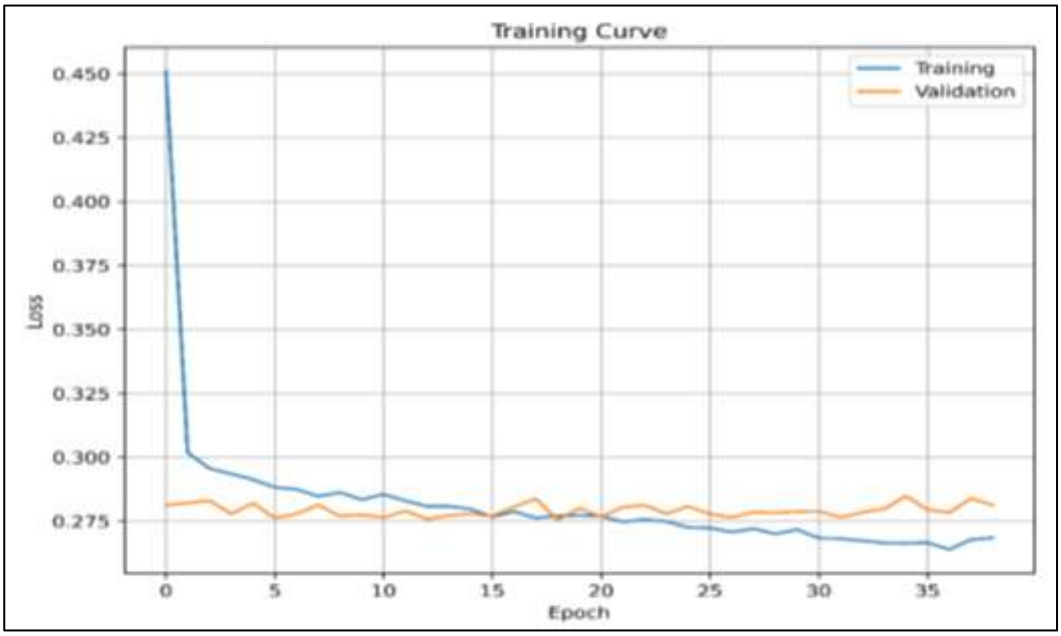

Fig. 2 Graph2_TrainingCurve

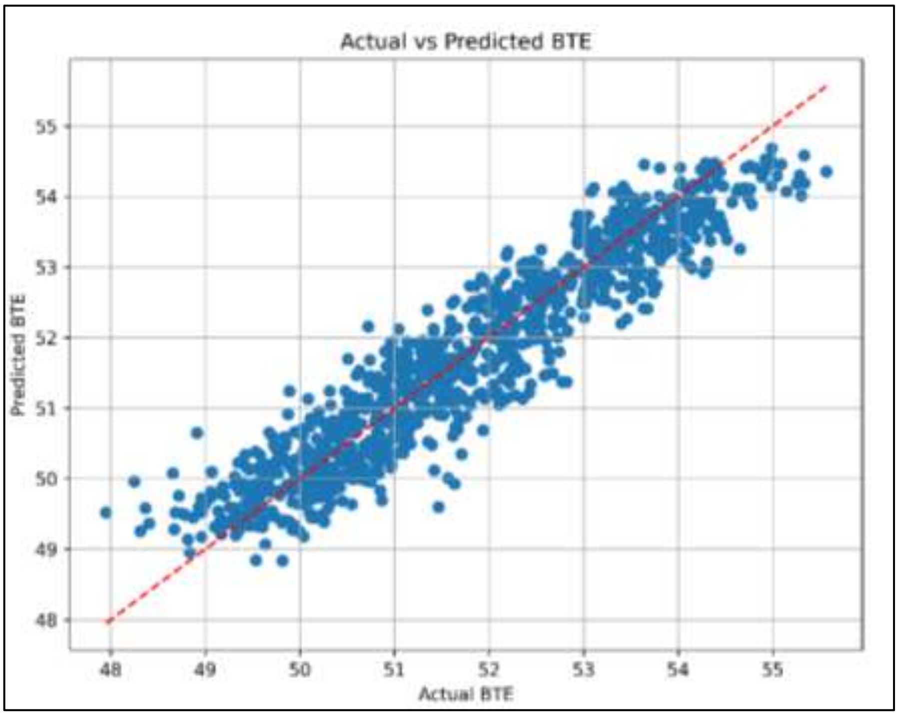

Fig. 3 Graph3_BTEPrediction

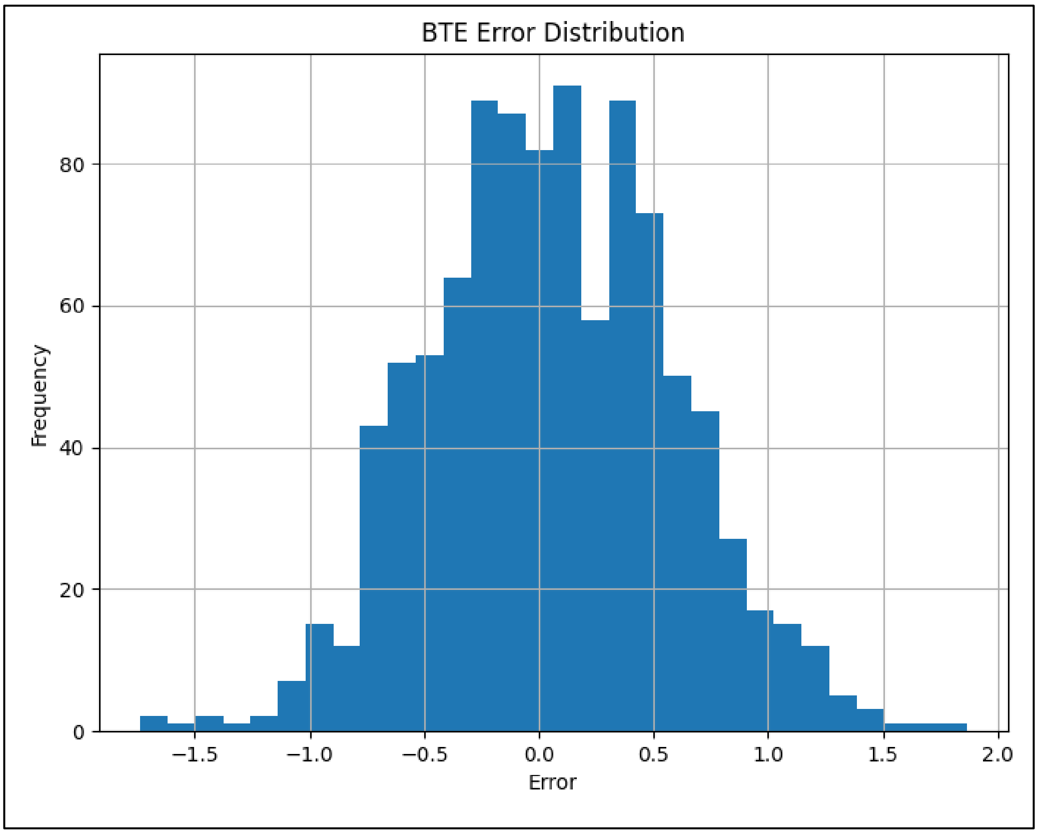

Fig. 4 Graph4_ErrorDistribution

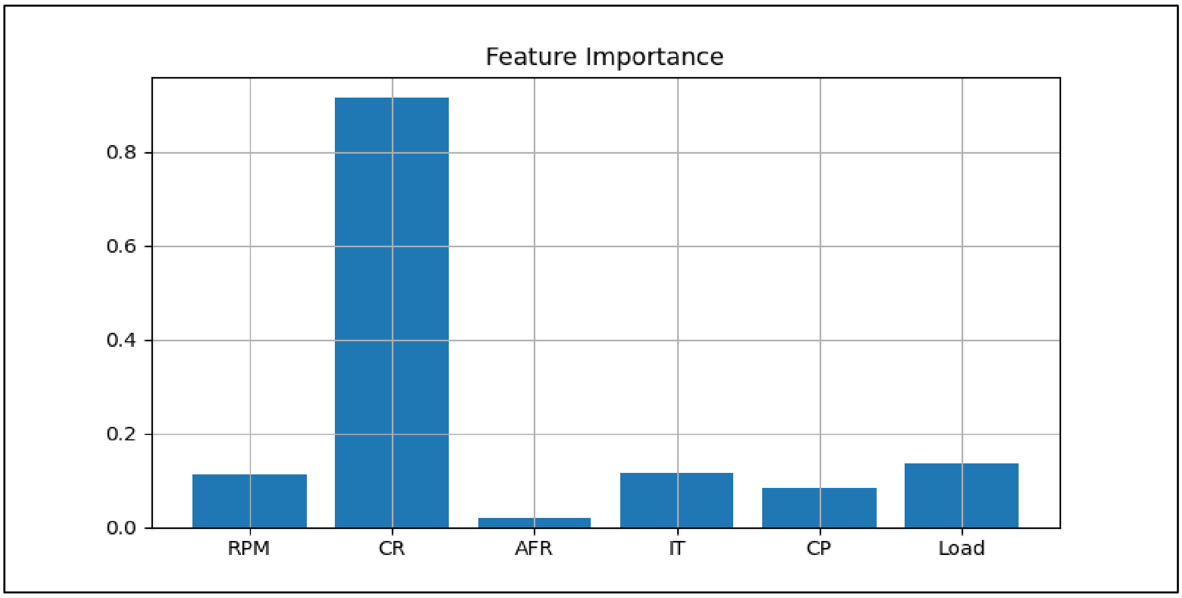

Fig. 5 Graph5_FeatureImportance

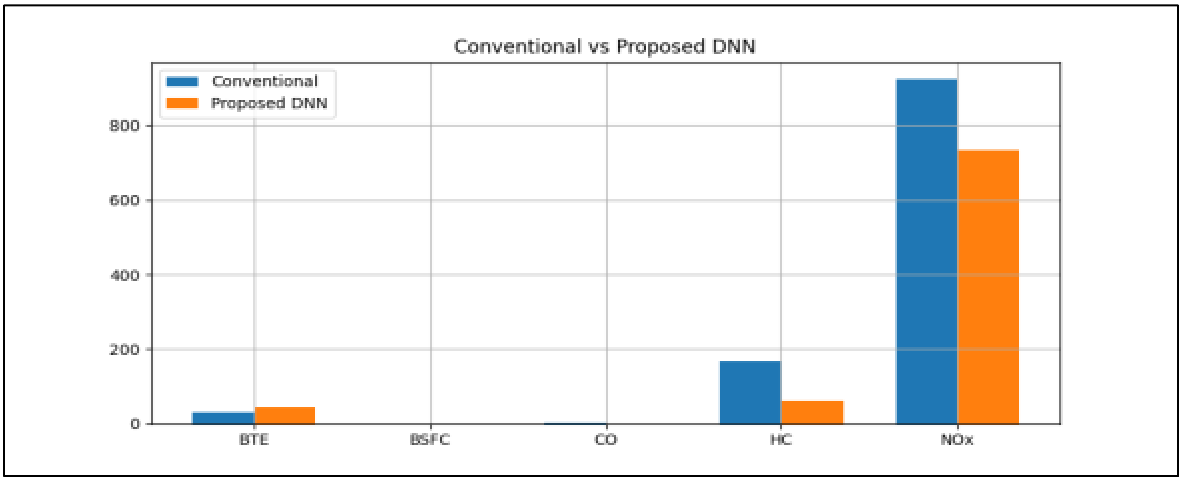

Fig. 6 Graph6_PerformanceComparison

VIII. Conclusion

This research highlights the strong potential of combining deep learning with Design of Experiments (DOE) for advanced Spark Ignition (SI) engine modeling. By surpassing the constraints of conventional physics-based and empirical methods, the proposed data-driven framework delivers a more accurate and holistic representation of engine behavior under diverse operating conditions. The strategic application of DOE facilitated the creation of a comprehensive and representative dataset, essential for training a range of deep learning architectures—from Artificial Neural Networks (ANNs) to specialized models such as Recurrent Neural Networks (RNNs) and Convolutional Neural Networks (CNNs). This integrated methodology enables precise prediction of critical performance and emissions parameters while mitigating the computational burden and limited flexibility often encountered in traditional approaches. Ultimately, the study introduces a robust and efficient predictive tool that supports improved engine design, optimized control strategies, and the advancement of intelligent virtual sensing technologies for SI engines.

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