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EXPLORING THE POTENTIAL OF MACHINE LEARNING IN COMBUSTION ENGINE OPTIMIZATION

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1. ABSTRACT

This study integrates machine learning (ML) with computational fluid dynamics (CFD) to optimize the performance of engine combustion process. Three ML models are compared: Random Forest Regression (RFR), Gaussian Process Regression (GPR), and Neural Networks (NN). The findings show that the GPR model outperforms the others in terms of accuracy, as indicated by metrics like Mean Absolute Error (MAE), Mean Squared Error (MSE), Pearson Coefficient (PC), R-squared (R^2), and lower uncertainty values. Additionally, the selected ML model significantly speeds up the computational process, around 21.6 times faster than traditional CFD solvers, while accurately capturing momentum and thermal characteristics. The optimization results highlight the importance of critical parameters, such as turbulence kinetic energy (TKE) and tumble-y, in enhancing engine efficiency by improving fuel-air mixing and reducing emissions.

2. INTRODUCTION

The integration of artificial intelligence (AI) with machine learning (ML) has revolutionized combustion science and engineering, addressing challenges relevant to fuel efficiency, emission control and NOx emissions [1]. Understanding the complex mechanism of the combustion process, particularly the phenomena of fuel droplet heating and evaporation in combustion, is crucial [2]. By leveraging AI-ML algorithms, we can analyse extensive datasets and uncover the hidden patterns, leading to insights that can help to optimize the combustion efficiency and advance sustainable energy solutions [3]. AI-ML overcomes the limitations of conventional modelling approaches, enhancing accuracy, comprehensiveness, and capturing intricate dynamics.

3. METHDOLOGY

This research explores the use of machine learning (ML) models to predict key combustion parameters in internal combustion engines (ICEs), aiming to replace computationally expensive CFD simulations. The study evaluates various ML models, including Random Forest Regression (RFR), Gaussian Process Regression (GPR), and Neural Networks (NN), to predict parameters like cylinder pressure, swirl, and turbulence kinetic energy (TKE). Using Simcenter Star CCM+ for in-cylinder simulations, the data is partitioned into training and testing sets. The models are assessed based on metrics such as Mean Absolute Error (MAE), Mean Squared Error (MSE), Pearson Coefficient (PC), and R-squared (R2). The best-performing model is used for design optimization to achieve targeted TKE and tumble-Y values, potentially speeding up the design process significantly. (see Fig. 1).

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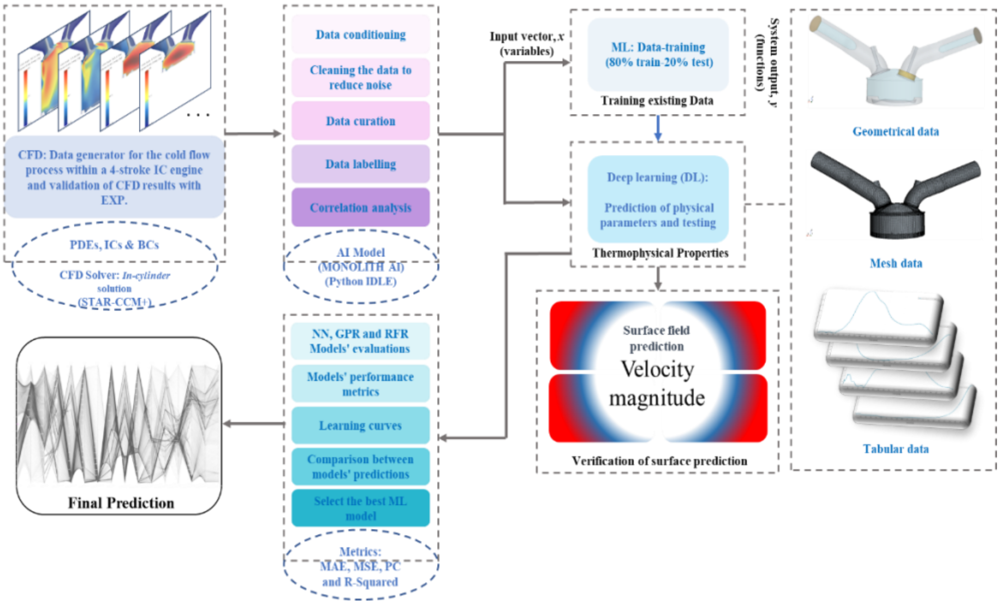
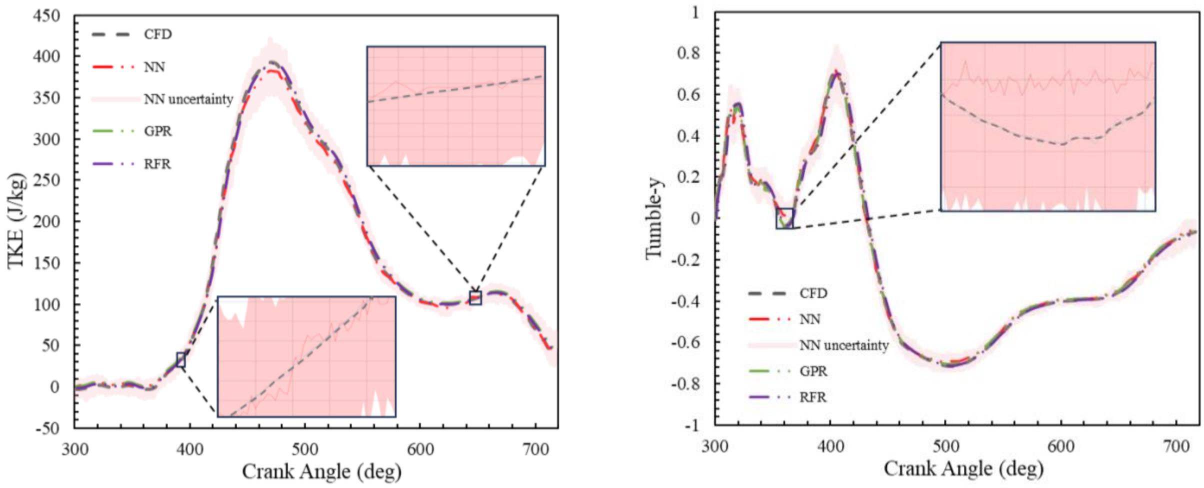


Fig. 1 Flowchart of CFD simulation, data extraction, model training, and evaluation.

4. RESULTS

Figs. 2 (a-b) show the uncertainty and predictions from the NN, GPR, and RFR models compared with measured data from validated CFD results. Fig. 2 (a) presents TKE predictions, and Fig. 2 (b) shows tumble-y predictions at various crank angles. The GPR model performs exceptionally well, and the RFR model also shows notable performance with low absolute error values, indicating their accuracy. These results highlight the importance of advanced modelling techniques like GPR and RFR for accurate predictions in scientific and engineering fields. Fig. 3 presents the velocity magnitude at the cylinder centre on a Y plane for both ML prediction and CFD simulation at 428 and 517 degrees of crank angle. The error distribution contour shows the similarity between ML predictions and CFD results, with consistent flow patterns and comparable velocity magnitudes, despite significant differences in running time and processing resources.



(a) (b)

Fig. 2 (a) TKE and (b) tumble-y predicted by NN, RFR and GPR models at different crank angles.

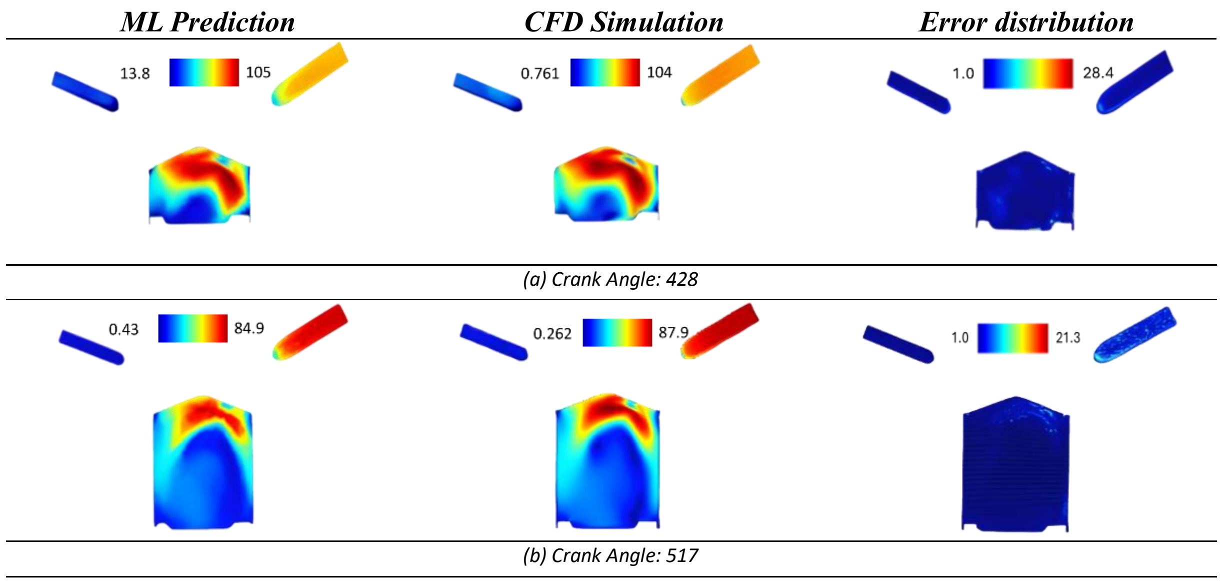


Fig. 3 Velocity magnitude for both ML prediction and CFD simulation at (a) 428 and (b) 517 crank angles.

5. CONCLUSION

This study has comprehensively investigated the optimisation process of combustion engines by integrating the machine learning (ML) techniques with computational fluid dynamics (CFD). The comparative analysis of three ML models, i.e., Random Forest Regression (RFR), Gaussian Process Regression (GPR), and Neural Networks (NN), has provided insights into their predictive capabilities for engine performance. The superior accuracy and reduced uncertainty of the GPR model, as demonstrated by metrics such as Mean Absolute Error (MAE), Mean Squared Error (MSE), Pearson Coefficient (PC), and R-squared (R^2), position it as the optimal choice for predicting critical engine parameters. Furthermore, the remarkable speedup of 21.6 times faster in the ML model compared with traditional CFD solvers, along with its ability to effectively capture momentum and thermal characteristics in surface field prediction, signifies a significant leap in computational efficiency.

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