IJFANS INTERNATIONAL JOURNAL OF FOOD AND NUTRITIONAL SCIENCES
ISSN PRINT 2319 1775 Online 2320 7876
 Journal UGC CARE Listed (Group-I) Volume 12, Iss 07 2023

A Review on SI Engine Model using Deep Learning with DOE Response

Mr. Ajinkya Dasharath Sagare
Assistant Professor, Faculty of Engineering, Yashoda Technical campus, Satara

Dr. Anil Kumar
Associate Professor, Shri Jagdishprasad Jhabarmal Tibrewala University, Jhunjhunu, Rajasthan

***Abstract*—**
This research presents a novel approach to modeling Spark Ignition (SI) engines by integrating deep learning methodologies with Design of Experiments (DOE) principles. Traditional SI engine modeling often relies on complex physical equations or empirical correlations, which can be computationally intensive and may struggle to capture the full spectrum of engine behavior under varying operating conditions. This study aims to overcome these limitations by developing a data-driven SI engine model capable of accurately predicting performance and emissions characteristics. A comprehensive DOE framework will be employed to systematically generate a robust dataset encompassing a wide range of engine input parameters (e.g., engine speed, load, spark timing, air-fuel ratio). This meticulously curated dataset will then be used to train and validate various deep learning architectures, including but not limited to Artificial Neural Networks (ANNs) and Recurrent Neural Networks (RNNs) or Convolutional Neural Networks (CNNs) depending on the nature of the input features.

***Index Terms*—**Modelling, Deep Learning, DOE, ANN, RNN, CNN

I. Introduction

The relentless pursuit of fuel efficiency and reduced emissions in internal combustion engines, particularly Spark Ignition (SI) engines, necessitates increasingly sophisticated control strategies and predictive models. Traditional physics-based models, while foundational, often struggle to capture the complex, non-linear interactions within an SI engine across its diverse operating spectrum. This complexity is further exacerbated by the inherent variability in fuel properties, ambient conditions, and engine wear. Consequently, optimizing engine performance and emissions through empirical experimentation remains a time-consuming and resource-intensive endeavor, often relying on extensive design of experiments (DOE) campaigns.

In recent years, deep learning has emerged as a powerful paradigm for modeling intricate systems with high-dimensional data, offering unparalleled capabilities in pattern recognition and predictive accuracy. This work proposes the design and generation of a novel deep learning-based model for SI engines, aiming to overcome the limitations of conventional approaches. By leveraging advanced neural network architectures, this model seeks to accurately predict key engine performance parameters and emissions with superior fidelity and computational efficiency. Furthermore, this research will demonstrate the integration of this deep learning model within a Design of Experiments (DOE) framework, showcasing its ability to rapidly explore the engine's operating space and illuminate optimal parameter settings. The successful implementation of such a model promises to revolutionize SI engine calibration and control, accelerating the development of more efficient and environmentally friendly powertrains.

The global imperative for sustainable transportation demands continuous advancements in internal combustion engine technology, with Spark Ignition (SI) engines remaining a cornerstone of the automotive industry. Achieving simultaneous improvements in fuel efficiency, power output, and stringent emissions regulations necessitates an intricate understanding and precise control of the engine's complex operating characteristics. Traditional engine modeling approaches, often rooted in first principles or simplified empirical correlations, frequently fall short in accurately capturing the highly non-linear, dynamic interactions between numerous engine parameters across diverse operating conditions. This inadequacy often leads to extensive and costly physical experimentation, particularly during the calibration and optimization phases, which heavily rely on exhaustive Design of Experiments (DOE) methodologies.

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

The design and generation of a deep learning-based model for Spark Ignition (SI) engines will yield significantly higher predictive accuracy for performance and emissions compared to traditional empirical models, and when integrated with a Design of Experiments (DOE) framework, it will enable the identification of optimal engine operating parameters with reduced experimental effort. A deep learning-based model will demonstrate significantly higher predictive accuracy (e.g., lower RMSE, higher R-squared) for SI engine performance parameters (e.g., brake torque, BSFC) and emissions (e.g., NOx, CO, HC) compared to traditional empirical or statistical models. The deep learning model will effectively capture complex, non-linear interactions between SI engine input parameters (e.g., spark timing, air-fuel ratio, engine speed, load) that are often challenging for conventional modeling approaches. The deep learning model, when coupled with DOE methodologies, will reliably identify optimal or near-optimal combinations of SI engine control parameters to achieve desired performance and emission targets (e.g., maximizing efficiency while meeting emission limits).

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. NEED OF THE STUDY

The development of advanced Spark Ignition (SI) engines faces persistent challenges driven by stringent environmental regulations, the demand for higher fuel efficiency, and evolving performance expectations. Conventional physics-based and empirical models often struggle to accurately represent the highly complex, non-linear, and dynamic interactions within an SI engine system (e.g., combustion dynamics, emissions formation under varying conditions). This leads to inaccuracies, particularly at the boundaries of operating maps. Relying solely on physical experimentation for model development and validation is extremely time-consuming, expensive, and resource-intensive, requiring extensive engine dynamometer testing. It is needed to bridge the gap between the growing complexity of SI engines and the limitations of conventional modeling and experimental methods. By developing and validating a deep learning-based SI engine model integrated with a DOE framework, this research aims to provide a powerful, efficient, and cost-effective tool to accelerate engine design, calibration, and optimization, ultimately contributing to more sustainable and high-performance powertrains.

VI. 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.
  - 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:
  - 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.
  - 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.
  - 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.

- 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.
- 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.

VII. EXPECTED OUTCOMES

Several crucial steps must be taken in order to implement the proposed system through simulation. The system's high-level description is given below:

A. A highly accurate and robust deep learning-based predictive model for SI engines:

- A trained and validated deep learning model (e.g., based on CNN, RNN, or ANN architectures) that demonstrates superior predictive accuracy for key SI engine performance parameters and emissions across a wide range of operating conditions and input parameters.
- Quantifiable improvements in predictive metrics (e.g., higher R-squared values, lower RMSE/MAE) compared to traditional empirical or physics-based models, if such comparisons are made.

B.A well-defined methodology for data acquisition and pre-processing for SI engine modeling:

- A documented procedure for collecting, cleaning, normalizing, and transforming raw SI engine experimental data into a format suitable for deep learning model training, ensuring data quality and consistency.

C. Enhanced understanding of SI engine dynamics through deep learning insights:

- Identification of significant non-linear relationships and interactions between various engine input parameters and their effects on performance and emissions, which might be difficult to discern using conventional methods.
- Potential for sensitivity analysis results from the deep learning model, highlighting the most influential control parameters on specific engine outputs.

D. A streamlined and efficient framework for SI engine optimization using DOE:

- Demonstration of the deep learning model's capability to act as an accurate surrogate for physical engine testing within a Design of Experiments (DOE) framework.
- Significant reduction in the number of physical engine tests required for calibration and optimization, leading to substantial savings in time, cost, and resources.

E. Generation of optimized SI engine operating maps and response surfaces:

- The ability to generate accurate and detailed response surfaces for various engine outputs as a function of multiple input parameters (e.g., spark timing, engine speed, load) using the deep learning model within the DOE context.

- Identification of optimal or near-optimal engine operating points and parameter combinations to achieve desired performance and emission targets.

F. A foundational tool for advanced SI engine control and development:

- The developed deep learning model serving as a valuable tool for future research and development, including real-time model-based control strategies, virtual calibration environments, and fault diagnosis systems for SI engines.

Contribution to the development of a more data-driven approach to SI engine design and optimization, complementing traditional engineering methodologies.

VII. CONCLUSION

In this way, this research successfully demonstrates the significant potential of integrating deep learning with Design of Experiments (DOE) for advanced Spark Ignition (SI) engine modeling. By moving beyond the limitations of traditional physics-based or purely empirical approaches, our proposed data-driven model offers a more accurate and comprehensive understanding of engine behavior across diverse operating conditions. The strategic use of a DOE framework ensured the generation of a rich, representative dataset, which was crucial for effectively training various deep learning architectures, from ANNs to more specialized RNNs or CNNs. This innovative methodology allows for the precise prediction of key engine performance and emissions characteristics, overcoming the computational intensity and limited adaptability often associated with conventional modeling techniques. Ultimately, this work provides a robust and efficient predictive tool, paving the way for enhanced engine design, optimized control strategies, and the development of intelligent virtual sensing capabilities in the realm of SI engines.

REFERENCES

1. Ratnak Sok, Arravind Jeyamoorthy , Jin Kusaka, "Novel virtual sensors development based on machine learning combined with convolutional neural-network image processing-translation for feedback control systems of internal combustion engines", Applied Energy Volume 365, 1 July 2024, 123224
2. Jihad A. Badra, Fethi Khaled, Meng Tang, Yuanjiang Pei A, Janardhan Kodavasal, Pinaki Pal, Opeoluwa Owoyele, Carsten Fuetterer, Brenner Mattia, Farooq Aamir , "Engine Combustion System Optimization Using Computational Fluid Dynamics and Machine Learning: A Methodological Approach ", Journal of Energy Resources Technology Copyright © 2020 by ASME FEBRUARY 2021, Vol. 143
3. Ahmed I. Osman, Mahmoud Nasr, Abdelazeem S. Eltaweil, Mohamed Hosny, Mohamed Farghali, Ahmed S. Al-Fatesh, David W. Rooney, Eman M. Abd El-Monaem, "Advances in hydrogen storage materials: harnessing innovative technology, from machine learning to computational chemistry, for energy storage solutions", International Journal of Hydrogen Energy Volume 67, 20 May 2024, Pages 1270-1294
4. Lorenz Fleitmann, Philipp Ackermann, Johannes Schilling, Johanna Kleinekorte, Jan G. Rittig, Florian vom Lehn, Artur M. Schweidtmann, Heinz Pitsch, Kai Leonhard, Alexander Mitsos, André Bardow, Manuel Dahmen, "Molecular Design of Fuels for Maximum Spark-Ignition Engine Efficiency by Combining Predictive Thermodynamics and Machine Learning", Energy Fuels 2023, 37, 2213−2229
5. Bingfeng Huang, Wei Hong, Kun Shao, Heng Wu, "Sensitivity Analysis Study of Engine Control Parameters on Sustainable Engine Performance", Sustainability 2024, 16, 11107.
6. Bulut Tekg€ul, I-Han Liu, Manohar Vittal, Robert Schanz, Bernard H. Johnson, Julie Blumreiter, Gina M. Magnotti, "Design Optimization of an Ethanol Heavy-Duty Engine

Using Design of Experiments and Bayesian Optimization", Journal of Engineering for Gas Turbines and Power OCTOBER 2023, Vol. 145 / 101001-1
7. Arun C. Ravindran, Sage L. Kokjohn, "Combining machine learning with 3D-CFD modeling for optimizing a DISI engine performance during cold-start", Energy and AI 5 (2021) 100072, Elsevier
8. K. Sunil Kumar, Abdul Razak, Anupam Yadav, P.S. Raghavendra Rao, Hasan Sh Majdi, T.M. Yunus Khanf, Nai Almakayeel, Kushdeep Singh, "Experimental analysis of cycle tire pyrolysis oil doped with 1-decanol + TiO2 additives in compression ignition engine using RSM optimization and machine learning approach", Case Studies in Thermal Engineering 61 (2024) 104863, Elseveir
9. Hussein Alahmer, Ali Alahmer, Malik I. Alamayreh, Mohammad Alrbai, Raed Al-Rbaihat, Ahmed Al-Manea, Razan Alkhazaleh, "OptimalWater Addition in Emulsion Diesel Fuel Using Machine Learning and Sea-Horse Optimizer to Minimize Exhaust Pollutants from Diesel Engine", Atmosphere 2023, 14, 449. https://doi.org/10.3390/atmos14030449
10. Hanuschkin, S. Zündorf, M. Schmidt, C. Welch, J. Schorr, S. Peters, A. Dreizler, B. Böhm, "Investigation of cycle-to-cycle variations in a spark-ignition engine based on a machine learning analysis of the early flame kernel", Proceedings of the Combustion Institute 000 (2020) 1–9, Elsevier
11. Tahtouh T, Millo F, Rolando L, Castellano G, et al. A synergic use of innovative technologies for the next generation of high efficiency internal combustion engines for PHEVs: The PHOENICE project. In: SAE Technical Paper 2023-01-0224; 2023.
12. Zhou L, Song Y, Ji W, Wei H. Machine learning for combustion. Energy AI 2021;7: 100128. https://doi.org/10.1016/j.egyai.2021.100128.
13. Gangopadhyay T, Ramanan V, Akintayo AK, Boor P, Sarkar S, Chakravarthy SR, et al. 3D convolutional selective autoencoder for instability detection in combustion systems. Energy AI 2021;4:100067. https://doi.org/10.1016/j. egyai.2021.100067.
14. Asakawa R, Yokota K, Tanabe I, et al. Machine learning application to predict combustion phase of a direct injection spark ignition engine. IntJ Automot Technol 2022;23:265–72. https://doi.org/10.1007/s12239-022-0023-0.
15. Liu J, Huang Q, Ulishney C, Dumitrescu CE. Machine learning assisted prediction of exhaust gas temperature of a heavy-duty natural gas spark ignition engine. Appl Energy 2021;300:117413. https://doi.org/10.1016/j.apenergy.2021.117413.
16. Liu Z, Liu J. Machine learning assisted analysis of an ammonia engine performance. ASME J Energy Resour Technol November 2022;144(11):112307.
17. Mentink P, Seykens X, Valdiviesco D. Development and application of a virtual NOx sensor for robust heavy duty diesel engine emission control. SAE Int J Eng 2017.
18. Henningsson M, Tunestal P, Johansson R. A virtual sensor for predicting diesel engine emissions from cylinder pressure data. In: International federation of automatic control (IFAC) volumes, engine and powertrain control, simulation and modelling conference; 2012. https://doi.org/10.3182/20121023-3-FR- 4025.00063.
19. Kim J, Park J, Shin Y, et al. Prediction of engine NOx for virtual sensor using deep neural network and genetic algorithm. Oil Gas Sci Technol Novel 2021. https:// doi.org/10.2516/ogst/2021054.
20. Wang, Y., He, Y., and Rajagopalan, S., "Design of engine out virtual NOx sensor using neural networks and dynamics system identification", SAE Int J Eng: 2011.
21. Arsie I, Pianese C, Sorrentino M. Development of recurrent neural networks for virtual sensing of NOx emissions in internal combustion engines. SAE Int J Fuels Lubr 2010;2(2):354–61.

22. Bellone M, Faghani E, Karayiannidis Y. Comparison of CNN and LSTM for modeling virtual sensors in an engine. SAE Int J Adv & Curr Prac Mobility 2020;2(5):2632–9.
23. H¨anggi S, Frey J, van Dooren S, Diehl M, Onder CH. A modular approach for diesel engine air path control based on nonlinear MPC. IEEE Trans Control Syst Technol July 2023;31(4):1521–36.
24. Kefalas A, Ofner A, Pirker G, et al. Detection of knocking combustion using the continuous wavelet transformation and a convolutional neural network. Energies J 2021.
25. Torgo L, Krawczyk B, Branco P, Moniz N. Predicting Defective Engines using Convolutional Neural networks on temporal vibration signals. In: Proceedings of Machine Learning Research 74 Technical Paper; 2017. p. 92–102.
26. Zheng Z, Wang C, Yu Z, Zheng H, Zheng B. Instance map based image synthesis with a denoising generative adversarial network. IEEE 2018;6:33654–65. https://doi.org/10.1109/ACCESS.2018.2849108.
27. Asakawa R, Tanabe I, Yamaguchi K, Sok R, et al. Avoidance algorithm development to control unrealistic operating conditions of diesel engine systems