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Diesel Engine Modelling with the Use of Artificial Neural Networks to Decrease Simulation Processing Requirements

Nikola S. Manev[a,*], Dame M. Dimitrovski[b], Elenior Nikolov[a]

[a]Military academy "General Mihailo Apostolski" – Skopje, University "Goce Delcev" - Shtip
[b]Faculty of Mechanical Engineering – Skopje, University of "Ss. Cyril and Methodius" - Skopje
nikola.manev@ugd.edu.mk

As the complexities of the internal combustion engine increase, to optimize engine performance and reduce emissions levels, automotive industries look to shorten engine calibration and modeling time. The following paper proposes a diesel engine model that makes use of a pre-built thermodynamic mean-value engine model (MVEM) that integrates novel regression methods and foremost Artificial Neural Networks (ANNs) to capture the inter-dependence of engine control with the output engine operating characteristics and output emission, making it particularly useful in new engine calibration. The primary benefits of such an integration are maintaining sufficient accuracy characteristic of more complex engine models (thermodynamic, wave-action, or even computational fluid dynamics models) while significantly reducing the simulation processing requirements, which adds to the streamlining of the final stages of the new engine design process. The results from this paper point to the fact that ANNs provide the best that fit for engine data compared to older, better-accepted regression methods such as radial basis function (RBF) or polynomial regression while increasing model response time. Since ANNs can be successfully integrated with existing thermodynamic models, this opens the major potential to simplify engine modeling by reducing modeling time and building more efficient and environmentally friendly diesel engines.

1. Introduction

Today's diesel engines contain numerous subsystems that enable better performance, optimal fuel economy, and compliance with strict emissions targets. But with each new subsystem (such as high-pressure fuel injection, exhaust gas recirculation, charge cooling, and turbocharging), the number of input variables in the engine control unit increases (Dowell et al., 2017). This leads to an increase in the dimensions of the control matrix (Isermann, 2014) and poses a challenge for rapid calibration and optimization of the engine (Yu et al., 2022), which in turn is vital in adjusting the engine's performance across its operational range of speeds and loads (Mirakovski, 2018).

Modeling and computer simulations allow for a better understanding of the dynamics of engine operation and lead to the creation of a comprehensive picture of the challenge of controlling their subsystems with the required level of complexity and abstractness (Thompson, 2017). Consequently, an understandable and easily adaptable model provides a much-needed basis for successful engine design and calibration. Traditional Internal Combustion (IC) engine modeling concepts such as thermodynamic models, wave-action models, or computational fluid dynamics (CFD), while offering sufficient accuracy, come at a high computational cost, making this one of their biggest shortcomings (Whitesides, 2019). In comparison, novel regression modeling techniques can also model the combustion mechanisms, albeit less precisely, but they significantly decrease simulation processing requirements (Bhatt and Shrivastava, 2021).

This paper aims to address these modeling weaknesses by offering an integrated model that makes use of a pre-built thermodynamic mean-value engine model (MVEM) of a diesel engine built in Matlab's Simulink as the basis for the subsequent integration of multiple novel regression methods. The focus, in particular, is put on the use of Artificial Neural Networks to successfully capture the inter-dependence of engine control with the output engine operating characteristics and output emission. That being said, this paper promotes and facilitates the use of advanced simulation techniques in the design of new diesel engines, providing more accurate tools leading to the design of more efficient and environmentally friendly diesel engines in the 2027 and 2030 production cycles in line with European Union's Green Deal goals and an important step toward zero emissions from light passenger and commercial vehicles by 2035 (EC, 2023).

2. Materials and methods

2.1 Thermodynamic Internal Combustion Engine Models

Three main thermodynamic engine model categories recur in literature, mentioning a trade-off between runtime and complexity. They include Quasi-Steady (QS), Filling-and-Emptying (F&E or 0-Dimensional), and Wave-Action models (WAM or 1-dimensional) (Sjekavica, 2009). Each of them is characterized by increasing complexity, accuracy, and computational cost (Tan, 2015). QS models neglect pressure and temperature gradients and fluctuations, deeming them the simplest model versions. Often to compensate for the lack of accuracy of these models, empirical data is used to provide better results at little computational cost. F&E models provide more accuracy than the QS models, treating the engine as separate volumes (for the intake manifold, cylinders, and exhaust manifold) (Horlock and Winterbone, 1986). The filling and emptying method balances mass and energy equations in the engine's control volumes. The different volumes exchange mass, heat, and work. Their only limitation is that they do not capture pressure and temperature gradients inside the control volumes (Rakopoulos and Giakoumis, 2006).
These two engine modeling methods are further implemented in the mean-value engine model (MVEM), which is a type of F&E model where the combustion volume is defined using simple, empirically derived equations, with thorough consideration of the thermodynamics laws (Sjekavica, 2009). MVEM models capture all the fundamental characteristics of engine transient operation, and further, they can successfully represent airflow dynamics. Their only disadvantage is that they do not represent the changes in pressure and temperature in the control volumes (Rakopoulos and Giakoumis, 2006). Should higher accuracy and complexity be desired, possibly for the need to simulate transient conditions accurately, a wave-action model would be more suitable, assuming computational cost is not an issue (Horlock and Winterbone, 1986). Also, multi-dimensional models or as they are often referred to – Computational Fluid Dynamics (CFD) models, can be used to generate highly detailed models of combustion, but they come at an enormous computational cost. Precisely because of their comparatively small processing requirements and the satisfactory level of precision, MVEM models are the most suitable solution for model-based control, which is the main reason why this paper's proposed model is based on their principles of operation (Tan, 2015).

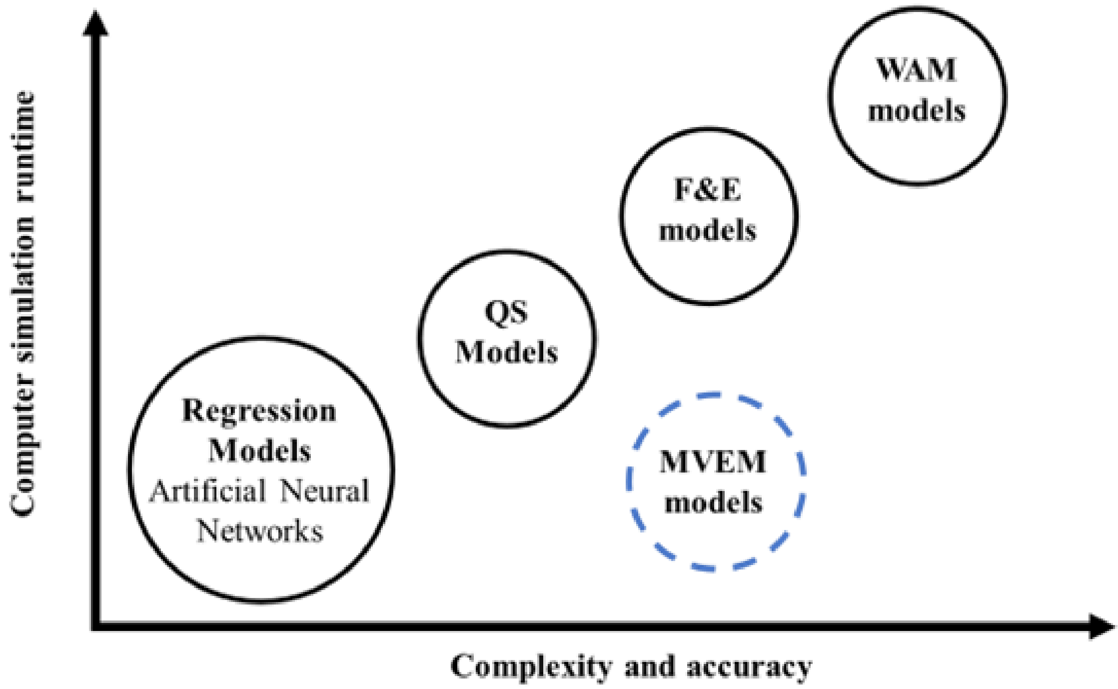

Figure 1: The trade-off between runtime and accuracy offered by different engine model types

2.2 Engine regression modeling

Regression models can be used to create predictions based on trends observed within a set of data (Frost, 2013). Once the required amount of data has been collected, MATLAB's Model-Based Calibration (MBC) toolbox provides a methodical approach to the engine regression modeling process (Burggraf et al., 2020). The model types available in the MBC toolbox include polynomials, radial basis functions, hybrid models, and neural networks (MathWorks, 2023).
An analysis of engine regression modeling literature makes it evident that the ANN method, although promising, is under-researched and underutilized (Tosun et al., 2016). Out of the identified works, (Guhmann and Riedel, 2011) compare different non-linear dynamic modeling methods of HC and NOx, where the multi-layer perceptron (MLP) Neural Network showed to have some of the lowest errors. The MLP Neural Network has further been praised for its accurate modeling of transient calibration in comparison to RBFs by (Martinez-Morales et al., 2017). Other sources (Brahma and Chi, 2012) seem to prefer simpler regression methods over the neural network method. However, this could possibly be caused by a number of things, such as a large amount of input parameters, over-fitting the data, or not having enough data points, as suggested by (MathWorks, 2023). The MLP method is based on how neurons pass information within the human brain. ANNs are divided into a number of layers, where each neuron has a number of inputs, along which a certain weighting is applied. The summation is output if and when a certain "firing rule" input condition is met, where the signal is passed onto the neurons in the next layer or the output of the network (Nielsen, 2016). Biases can also be introduced to improve the performance on the network which are constants with a certain weighting (Leverington, 2009). Additionally, perceptrons are the simplest feed-forward network type, most commonly used in engine modeling (Bhatt and Shrivastava, 2021).

2.3 Model generation

As this paper aims to produce a model which can be used in several automotive modules, it was important to set clear requirements for it to run efficiently. The requirements are as follows, the model must:

- Provide the user with a stable interface that allows for data inputs and displays the consequent outputs, being suitable and facilitating the process of engine calibration;
- Run at a speed similar to real-time, or faster if possible;
- The complexity of the model must be of enough relevance for today's and future diesel engines.

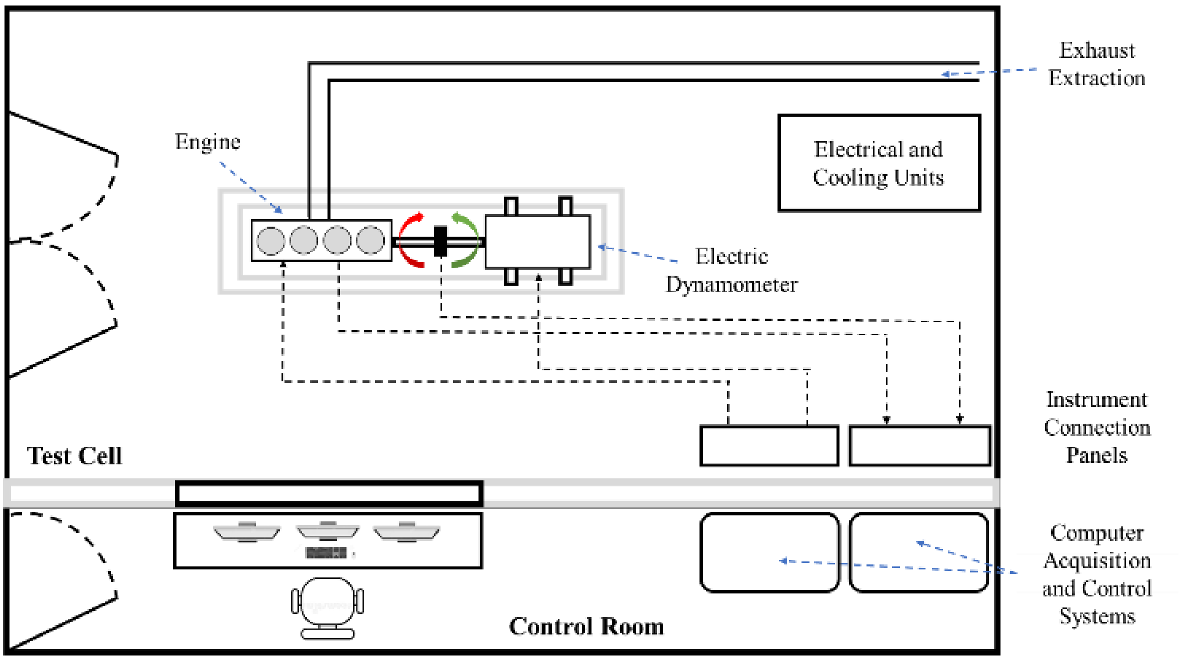

Figure 2: The Ford Duratorg 2.4l 4-cylinder diesel engine test cell

An engine test cell (Figure 2) was set up with a 2.4l 4-cylinder Ford Duratorq engine. The test cell's Sierra-cp control software, supporting infrastructure (cooling, air intake, fuel metering, exhaust extraction, etc.), an electric

dynamometer (with a 135 kW maximum power output), and a variety of sensing devices allowed the capture of the engine's dynamic performance. Traditionally, the study of engine efficiency and emission behavior has focused on steady-state performance. However, most driving consists of engine transient operation, and the fuel economy and exhaust emissions during transient conditions are much worse compared with those in the steady state (Rakopoulos and Giakoumis, 2009). The test cell is capable of full simulation of the transient duty cycle, such as the new European driving cycle (NEDC). The decision was made to collect 10,000 data points since the regression models will become more accurate with a high number of data points, as well as the fact that the data itself will not be input to the final model and will not affect the runtime. The number 10,000 was selected based on the realistic amount of time that could be afforded to spend on data collection.
The pre-built MVEM model (whose modeling is beyond the scope of this paper) was produced in Matlab's R2022b Simulink and includes multiple components required to imitate the behavior of a modern diesel engine (intake manifold with charge cooler, exhaust manifold, cylinders block, variable geometry turbocharger, and models the effects of exhaust gas recirculation and pilot injection). The modeling of the combustion processes within the cylinders block, however, is much the focus of the paper, and this is where the regression methods were implemented (Figure 3). The Neural Networks block was produced using Matlab's Neural Networks Fitting Tool.

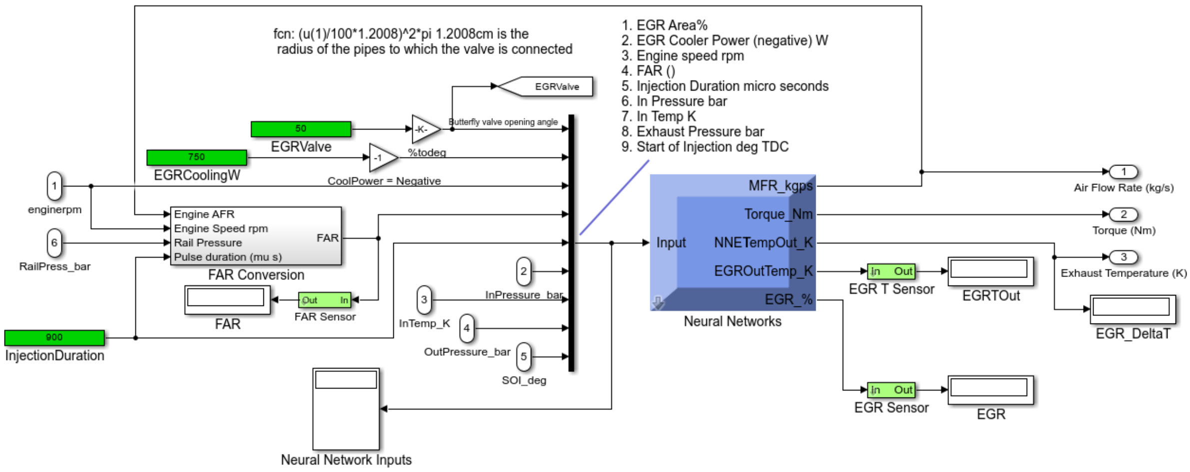

Figure 3: The Simulink's model Cylinder subsystem with the Neural Networks Block

3. Results and discussion

Several regression methods were tested using Matlab's MBC Toolbox using the 10,000 data points collected through the data acquisition setup against a validation sample of 100 randomly selected data points through the MBC Toolbox's design of experiment (DoE) setup against which the absolute error was calculated. It should be noted that since Matlab uses its own randomization algorithm in the DoE, its unclear if the random sample variation has any effect on the results. The results are shown in Figure 4.
It is evident that the cubic polynomial fit has been proven to be the most accurate, as the normalized average absolute error is the lowest for the combined input variables. Additionally, it showed favorable runtime compared to both the Gaussian and Multiquadric RBF. It should be noted that over-fitting of the data occurs when the polynomial orders are increased. The MBC Toolbox offered the option of minimizing the Predicted REsidual Sum of Squares (PRESS) statistic by excluding certain data points, but minimizing the PRESS had no consistent effect on improving the models.
Matlab's Neural Network Fitting Tool allowed the generation of an ANN-based on a selected number of hidden layers and one of three training algorithms. Figure 5 compares the absolute error on the torque, which is taken to represent the accuracy of the models for 1,000 samples. This absolute error is taken by calculating the actual versus predicted torques of 100 random data points (unrelated to the training data).
The networks were trained on 1,000 data points, slightly randomizing the areas where the network was trained well. Unlike the polynomial models, as the number of hidden neurons increases, no signs of overfitting are shown. The number of hidden layers continues to improve the accuracy of the model. Tests were stopped at 100 neurons as the training time per model largely increased, approaching the 3 h mark for one model. As the average absolute errors on the above output variables were still high when random data points were tested,

further regression models were tested with a larger sample pool (up to 10 000 samples). The results are shown in figure Figure 6, which shows the normalized average absolute error for the same variables.

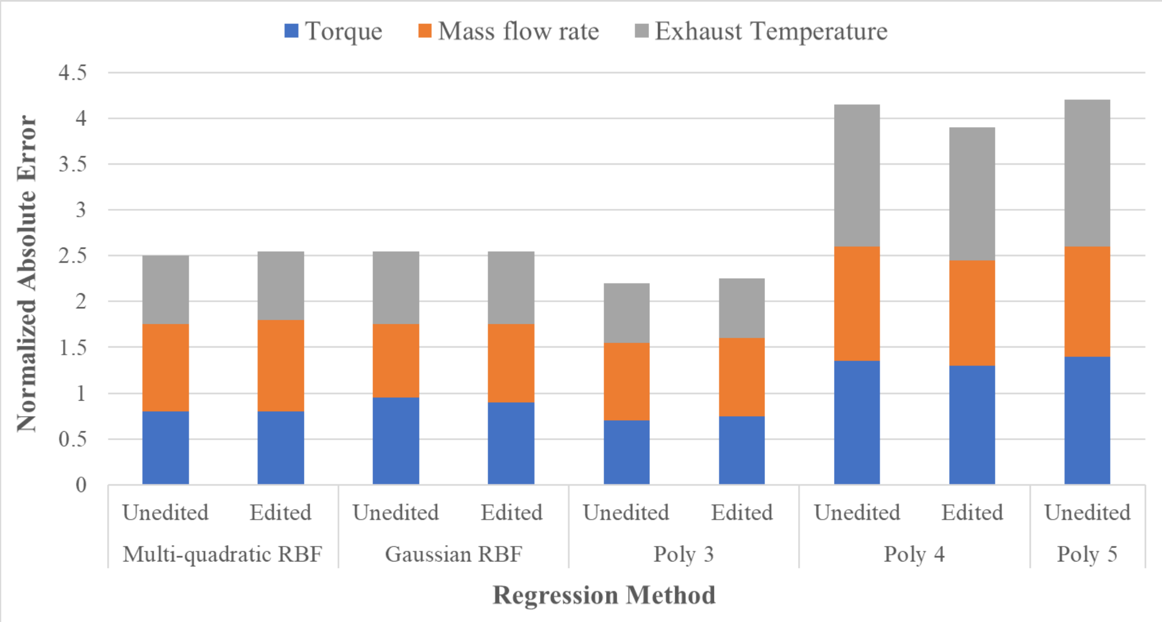

Figure 4: The average normalized errors of older regression methods (Poly X refers to a polynomial fit of the Xth order)

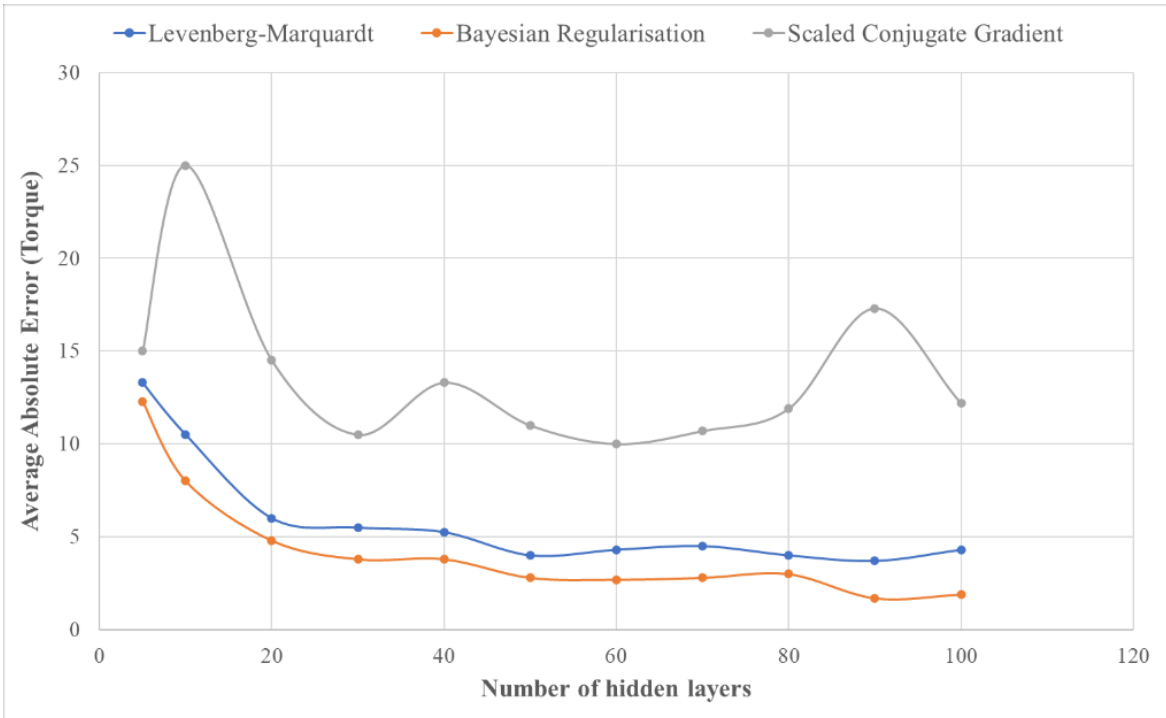

Figure 5: The ANNs' accuracy using different training algorithms and layer size against 100 random samples

Figure 6 compares the MBC Toolbox' regression methods and two Neural Networks trained with the Bayesian Regularization algorithm for both 1,000 and 10,000 test points. Based on Figure 6, a neural network with 25 hidden layers is chosen. The number of hidden layers can be changed later if more accuracy or better runtime is demanded. Similar conclusions can be drawn from Figure 7, which shows the coefficient of determination (R^2) for the aforementioned plots. The best fits are shown by the ANN models for both data groups.

Comparing the different regression methods offered by Matlab's MBC Toolbox, the final model using neural networks with 25 hidden layers to predict the engine torque, exhaust temperature, MFR, EGR (%) and EGR exit temperature runs at approximately real time. The model uses regression methods and simplified flow dynamics to predict engine performance. At this stage emphasis was mostly placed on maintaining correct relationships among the variables, and less so on the actual accuracy of the numbers it outputs. Generally, it has been proved difficult to build models which accurately predict all its output parameters whilst maintaining a real-time simulation speed, and empirical methods such as regression modeling have been substituted in, at the cost of precision. Nevertheless, the results indicate that using ANNs offers the highest quality of regression for engine modelling at the lowest runtime.

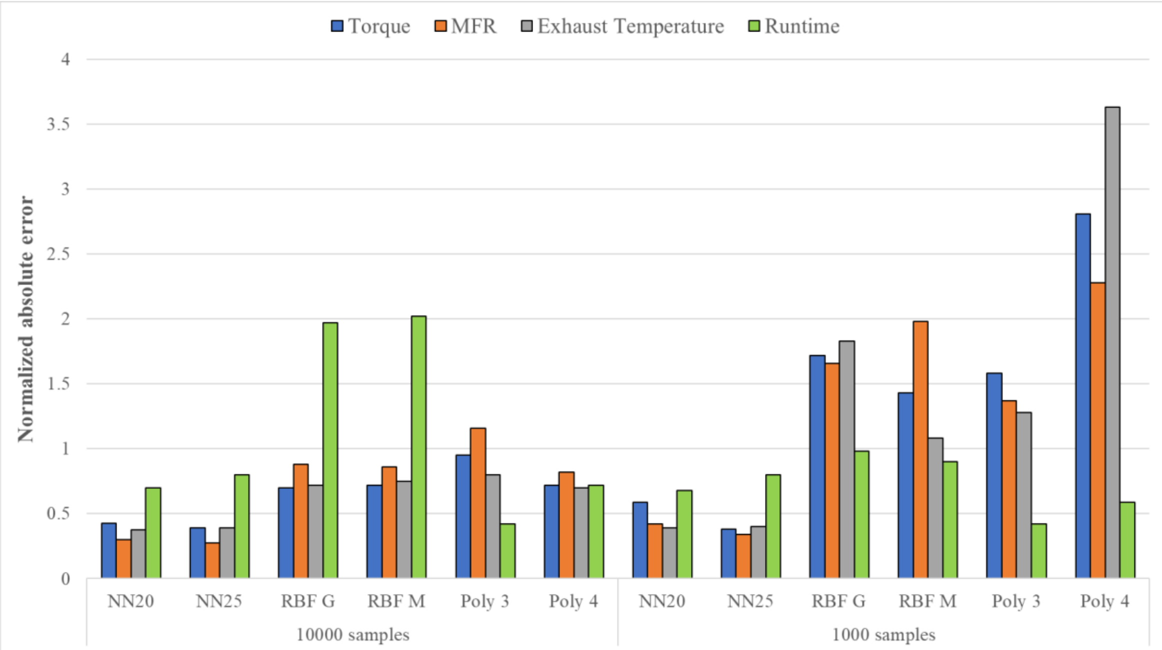

Figure 6: Different regression methods tested, displaying normalized average absolute error and runtime per method

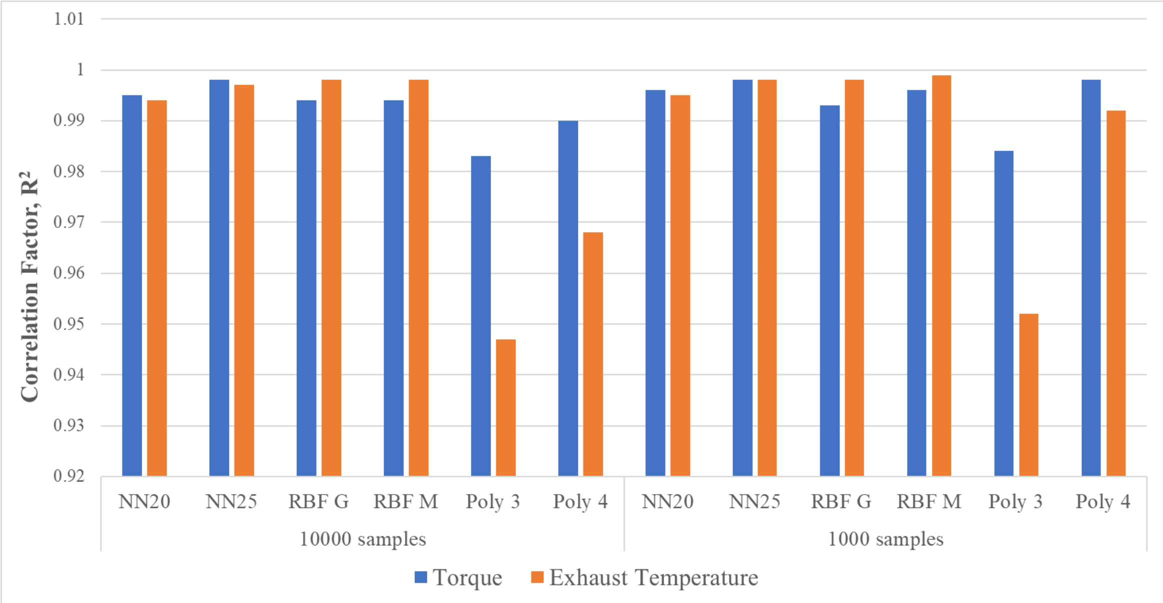

Figure 7: The correlation factor (R^2) for different regression methods and training dataset sizes

4. Conclusion and future work

The aim of this paper was to produce a model of a diesel engine that makes use of ANNs to increase simulation speed while maintaining sufficient model complexity and precision. To obtain reasonable accuracy with quick runtime, regression models have been used and compared against each other to avoid processing the complex and computationally intensive calculations of combustion dynamics. As suggested by referent literature, ANNs are still a rather new and not thoroughly investigated method used in modern engine models, and have been selected as the focus of this paper.

The ANNs were trained using engine data from a Ford Duratorq 2.4l 4-cylinder diesel engine. The networks were shown to have excellent fit with the 10,000 data samples taken, having R^2 values ranging from 0.988 to 1. Subsequently, a model was developed in Simulink which allowed us to compare different regression methods (such as RBF or polynomial regression) available through Matlab's MBC Toolbox. The results show that ANNs provide the best fit for the engine data than the older, better accepted regression methods and hold potential to simplify engine modelling and reduce modelling time while improving the model's accuracy and reducing simulation computational cost and running time.

The resulting model makes use of a thermodynamic MVEM model and ANNs to portray the combustions mechanisms within the engine and delivers on the principal objective of capturing the inter-dependence of engine control with the output engine operating characteristics. The model itself could very successfully facilitate an engine's calibration process, allowing for the testing and comparison of different optimization settings. A direction for future work would include integrating multiple regression methods as part of a single engine model. Volterra series-based models have been known to accurately capture gaseous emission-creating mechanisms (Tsai et al., 2016), while B-spline regression has been used to depict exhaust soot emission levels (Grahn et al., 2014). Such an approach has the potential to further reduce simulation processing requirements while improving the model's accuracy.

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