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OPTIMAL CONTROL SIMULATION OF DIESEL INJECTION SYSTEM USING NEURO MODEL PREDICTIVE-BASED ELECTRONIC CONTROL UNIT

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Abstract

This paper presents an optimal control simulation of a diesel injection system using a Neuro model predictive-based Electronic Control Unit (ECU). The research aimsto improve diesel engine efficiency while maintaining fuel economy. This was achieved using a model predictive control system and a neural network trained with data collected from diesel engine vehicles online during a 54km to model a Neuro-MPC algorithm which was used to improve the ECU. The Neuro-MPC-based ECU was implemented on a Diesel Control System (DCS) using Simulink. The resultof the Neuro-MPC when evaluated with mean square error is 0.047964Mu and Regression of 0.9773. The results implied good training performance at tolerable error and the ability to predict engine behaviour and supply desired fuel. The result of DCS when tested at a distance of 54Km showed that the Air to Fuel Ratio (AFR) is 14.53: 1 which gives a tolerable error of $\pm$ (0.03) error when compared with the ideal Stoichiometric standard for DCS which is 14.5: 1, thus giving a mechanical efficiency of 94.3%.

Keywords: NECU, DSC, FFNN, injector actuator, Stoichiometric, Training, Regression

1. INTRODUCTION

Over the years, the use of Heavy-Duty Vehicles (HDV) has evolved with great technological advancements which seek to enhance their performance efficiency and fuel consumption rate. One major area of the vehicle which has experienced major attention is the engine, due to the high demand for more energy management to reduce fuel consumption and also reduced environmental pollution (Guzzella and Sciarretta, 2007). According to Bosch (2011) engines are of two major categories which are gasoline-based engines and diesel-based engines. The former is associated with smaller cars, while the latter is for heavy-duty vehicles. This diesel engine is popular today due to its ability to manage fuel better than the traditional gasoline engine; however, the rate at which this fuel is conserved can be better managed to achieve optimal efficiency and better fuel economy. This triggered many research publications over time immemorial, proposing the use of many approaches which are capable of improving fuel economy and better engine efficiency.

Traditionally, requirements such as driving at a constant speed, good tyre pressure, slow and steady gearing, and cruise control among others, are capable to achieve the aim of fuel economy and have been established as procedures to manage the use of fuel in HDV (James, 2021). Furthermore, the use of air-fuel mixture, ignition timing, and idle speed were mechanically set and dynamically controlled by pneumatic and mechanical means to improve Engine Management System (EMS); however, the need for an EMS which is more efficient, intelligent, and autonomous triggered the evolution of Electronic Engine Management System (EEMS) (Hellstrom et al., 2013).This EEMS makes use of Engine Control Unit (ECU) technology which employed a series of sensors and actuators to control the performance of the engine. This ECU employ techniques such as high-pressure injection control, compression and induction air cooling, and exhaust gas recirculation for the management of engines. These techniques all have their pros and cons (Chartier et al., 2011). However, the use of high-pressure injection control has remained the most effective for fuel economy (Hellstrom et al., 2013).The injection system is responsible for the supply of fuel directly to the engine based on the real-time data collected from its online during the vehicle translation. The pattern of this data is determined by many factors such as how well the vehicle is maintained, driving behaviour, and road condition among others, and is feedback to the ECU for processing and control of the injection system.

This has been achieved using many approaches which involve Programmable logic controller (PID), dynamic programming (Olanrele et al., 2014), optimization-based Genetic algorithm (Dai Duong et al., 2018), Local based speed control, Model Predictive Control (MPC); Pontryagin Minimum principle (Van, 2018) among others. However, they all have their advantages and disadvantages. Nevertheless, the use of MPC provided better performance when compared to the rest, due to their ability to control multi-nonlinear input systems. However, when these multi-nonlinear parameters change with time, the MPC cannot update with the changing condition of the parameters of the constraint and this has limited its efficiency as a reliable system for ECU management. To address this problem, most of the state-of-the-art algorithms employed a dynamic programming approach to make the MPC adaptive; however, despite the success achieved, there is still great room for improvement. This research, therefore, proposes to help achieve it using Machine Learning (ML) to improve the MPC.

ML is a set of algorithms that can learn from the training dataset and make accurate decisions. The ML will be trained with the engine data and generate a reference model which the MPC will be used to update the injection system for precise control supply of fuel to the engine. This, when achieved, will guarantee highly efficient engine performance, and low fuel consumption rate, and save the cost of maintenance to mention a few of the merits it will provide.

2. Modelling of the Electronic Diesel Control (EDC) System

The EDC is a hybrid electro-mechanical control system architecture that is made up of four main sections which are the actuator sensors, the electronic control unit, the engine and then the injection system (Riggs, 2015). The actuator sensors are the torque position sensor which monitors the position of the engine, the vehicle speed sensor to determine the engine speed, the clutch and brake sensor to determine the throttle performance, the oxygen sensor to monitors the air-to-fuel ratio, temperature sensor to monitor the engine temperature, pulse sensor to monitor the timing of the injection systems. All these actuator sensors are connected to the electronic control system to monitor the engine performance as shown in the modelling diagram of figure 1;

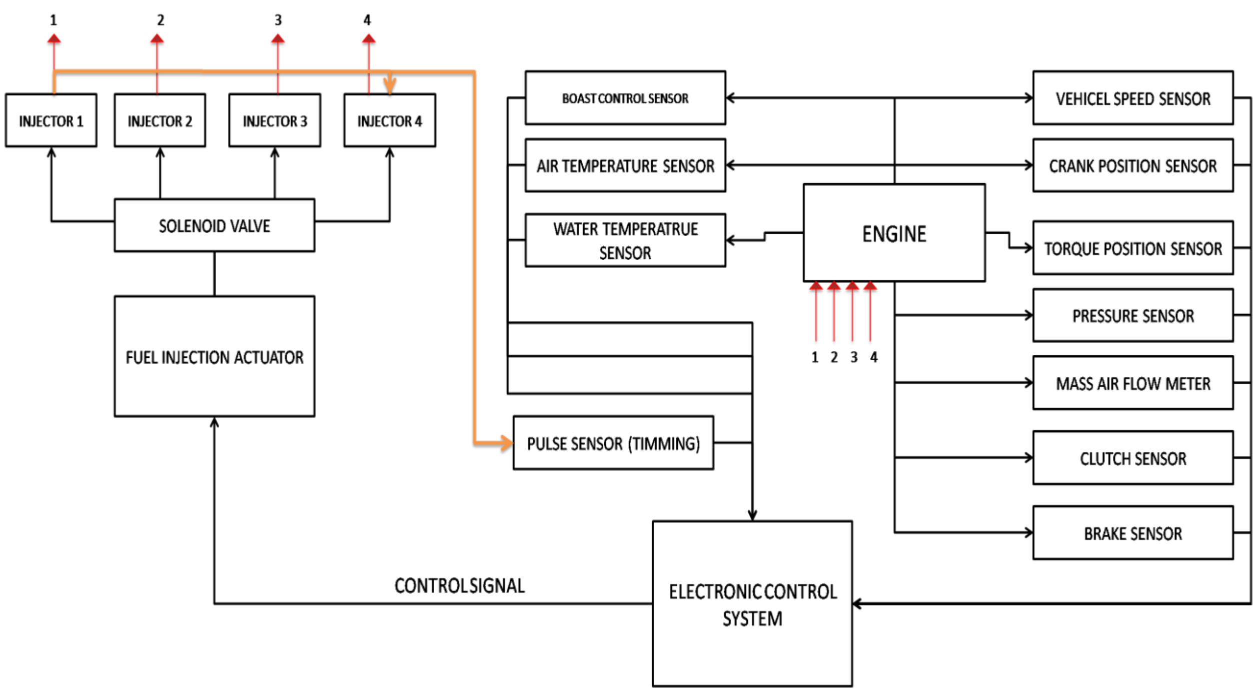

Figure 1: Modeling diagram of the Electronic Diesel Control System (Riggs, 2015).

The modelling diagram of the EDC shows the relationship between the control system actuator, injectors and the diesel engine. After data from the engine was collected by the actuator sensors, they are fed to the ECU control system for processing and then control the timing of the injection actuator which then supplies controlled fuel to the engine.

2.1 Mathematical Modeling

The models for these measurements are the torque model in equation 1, the angular speed in equation 3; the mass flow rate for the fuel consumption rate is modelled in equation 4 and the air-to-fuel ratio in equation 5. The data were analyzed using the Phoenix combustion analysis software and stored in the Zenix Log file. The results of the characterization are reported in the next chapter. To measure the torque performance of the engine, angular speed function and mass of fuel in the cylinders were used to determine the torque as shown in equation 1 (Tri et al. (2014);

$$T_{e_{w_e}} = u_3 T_{e,max}\,(w_e) \quad 1$$

Where u_3 is the normalized fuel mass in the cylinders, when this value (u) is zero, when no fuel was injected on the cylinder, but when once, then there is fuel injection, which is when the engine delivers optimal torque concerning angular speed. The model of the torque at a controlled angular speed using a second-order polynomialpresented by equation 2 (Tri et al. (2014);is

$$T_{e,max}(w_e) = k_1 + k_2 w_e + k_3 w_e^2 \quad 2$$

Where k is the fitting coefficient, but to determine the angular speed of the engine when connected directly to the fuel injection pump, the relationship between the pump inertia and load torque was used to present the model in equation 3 (Tri et al. (2014);

$$\dot{w} = \frac{1}{J_e + J_{pi}}\,(T_e - T_1) \quad 3$$

Where $\dot{w}$ is the engine speed of the engine, J_e is the engine inertia; J_{pi} is the injection pump inertia. The fuel flow rate is therefore determined using the relationship between the maximum engine torque in equation 1 and engine speed in equation 3 to determine the fuel consumption model below (Rolf, 2005);

$$m_f = k_{00} + k_{10}\dot{w} + k_{20}\dot{w}^2 + k_{11}\dot{w}T_e + k_{01}T_e + k_{o2}T_e^2 4$$

Where K_n represents the varying engine speed function determined experimentally by Ford Technical centre as shown in Tri et al. (2014). To measure the Air to Fuel Ratio (AFR), the relationship between the mass of air (oxygen) in the atmosphere and then the mass flow rate of fuel consumed in the online engine in equation 4 was used to develop the model as shown in equation 5 (Tri et al. (2014);

$$\text{AFR} = \frac{m_a}{m_f} 5$$

The ideal air-to-fuel ratio for a complete combustion process is called stoichiometric air-to-fuel ratio and is used to measure the quality of the fuel combustion process. When the air-to-fuel ratio is lower than the stoichiometric standard, the AFR is rich, when it is equal it is ideal and when it is more than the stoichiometric standard, it is called lean. The stoichiometric standard for diesel fuel is 14.5: 1 which means that to burn 1kg of diesel, 14.5kg of air is required (Rolf, 2005).To measure the engine displacements, the position sensor model in equation 6 was used;

$$\text{PD} = \pi * r^2 * L * N 6$$

Where r is the radius of the cylinders, L is the stroke, and N is the number of cylinders.

2.2 Modeling of the Diesel Fuel Injection Actuator System

The fuel injection system is part of the DCS which supplies regulated fuel to the engine for operation. This was achieved via the injection of compressed air and pressure into the combustion chamber. The diesel fuel injection system was modelled using the fuel injection pump, high-pressure lines, injection nozzles, feed pump and fuel filter as shown in the modelling architectural diagram in figure 2;

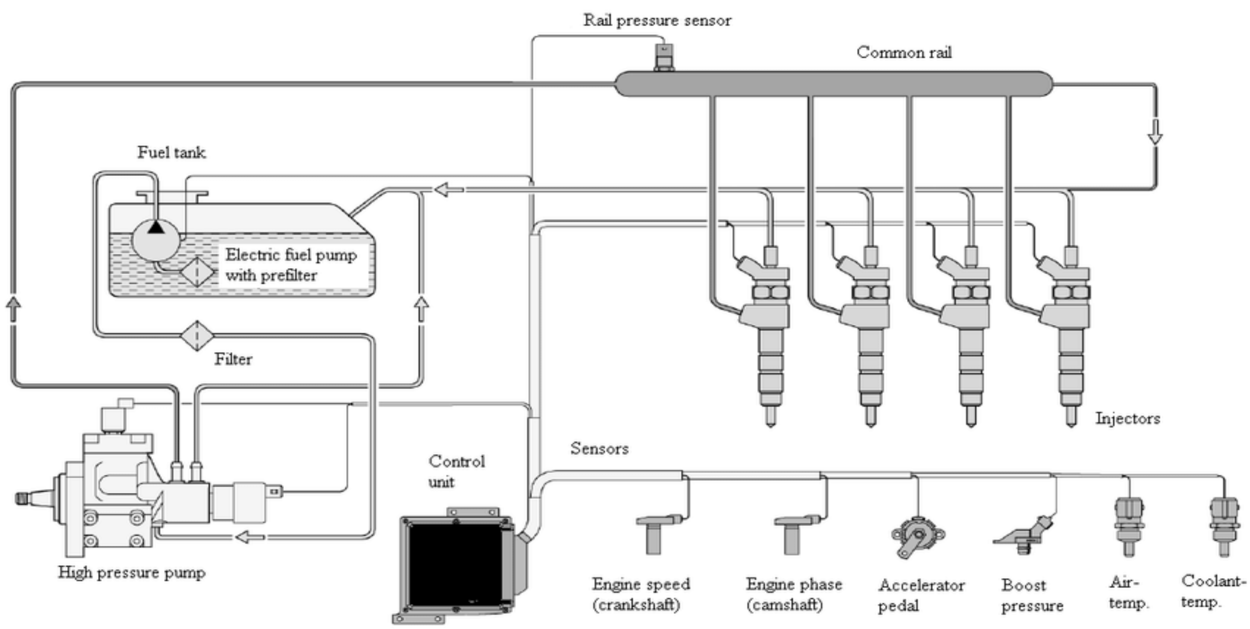

Figure 2: Architectural model of the diesel injection system (Liu et al., 2008)

The model was developed of a four-stroke cycle injectors system that accumulated high-pressure fuel and injectedit into the engine cylinder at timing control based on the engine angular speed, torque and other engine parameters processed by ECU. The fuel from the fuel tank is filtered and fed through to the injector pump via the feed pump. This fuel is then pressured at the injector and delivered to the combustion chamber in an atomized system where combustion occurs. The excess fuel is returned to the fuel tank via the leak-off pipe. The injector model developed suffers many limitations as it supplies constant fuel to the engine despite the multivariable constraints attributed to it. This as a result leads to excess fuel consumption and also poor efficiency as the fuel supply is supposed to be based on the engine requirements and not on a constant rate. Hence the research developed in the next section a control system that was able to consider the multi-input variable of the engine and then use the data to control the actuator system.

2.3 Model of the Electronic Engine Control System

MPC is a control system that can produce approximated output from multiple nonlinear constraints. A diesel engine for instance is characterized by many nonlinear constraints which vary with time as the engine is online. MPC is a controller type which used operates by using the model of the plant to make predictions about the feature of plant output, it is employed in the tackling of optimization problems at intervals of the time stamp to find the optimal control actions which define the predicted plant outcome to the reference point as close as possible.

In this case, the data on the dynamics of this engine has to be used as a reference point to control the injector pump which supplies fuel back to the engine. However, the varying behaviour of these engine constraints online makes the MPC struggle to keep up with a precise prediction horizon.Many works have employed various techniques to improve MPC performance like dynamic programming, genetic algorithms, and linear programming among others as identified in the summary of literature (see table1), however despite the success, they still control the injection actuator at a rate at which fuel economy is not properly conserved. To achieve better fuel economy machine learning algorithm was used to train this data and then use the reference model as a set point for the MPC to update. First, the plant model was identified by the MPC as a linear time-invariant (LTI) system as shown in the equations (Liangcheng et al., 2020);

$$x(k+1) = Ax(k) + B_u u(k) + B_v v(k) + B_d d(k) \quad 7$$

$$y(k) = C_x(k) + D_d v(k) + D_d d(k) \quad 8$$

Where the matrices A, B_u, B_v, B_d, C, D, and D_d are the engine parameter (mass flow rate, pressure, fuel consumption rate, torque, temperature, and vehicle speed as presented in figure 2 model) which can be varied with time. The other variables are; k = time (i.e the control interval); u = manipulated input adjustable by the MPC; x= plant model states; v = measured disturbance inputs; d = unmeasured disturbance inputs; y = output.

The models in Equations 7 and 8 presented the LTI and the nonlinear output parameters collected from the actuator sensors. Consequently, the MPC includes nominal operating points to apply the LTI model in equation 7. This is because as the time plant model changes the control parameters use the nominal points to update themselves with the plant. The plant model in terms of the nominal condition is presented as equations9 and 10;

$$x(k+1) = \breve{x} + A(x(k) - \breve{x}) + B(u_i(k) - \breve{u_\iota}) + \widetilde{\Delta x} \quad 9$$

$$y(k) = \breve{y} + C(x(k) - \breve{x}) + D(u_i(k) - \breve{u_\iota}) \quad 10$$

Where the parameters to be updated are A, B, C and D. u_i is the combined plant input made up of u, v and d which are the engine parameters attributes identified from equation 8. The nominal conditions updated are; $\breve{x}$= nominal state; $\widetilde{\Delta x}$ = nominal state increment; $\breve{u_\iota}$= nominal input; $\breve{y}$=nominal output.So far the model in Equations 7 and 8 presents the LTI and the parameters of the nonlinear output. Equations 9 and 10 presented the parameters for the update and the time of update interval using nominal points.

2.4 Model of the MPC reference set point with ANN

The ANN (Mba and Asogwa, 2022) was developed and trained with the engine data to learn the nominal behaviour of the engine online and store it as a reference point for the MPC update of the control performance. The model of the neural network developed was inspired by a single neuron which has weight, bias and activation function. Figure 3presented an activated neuron which was achieved with tanh activation function used for the optimization of the MPC. The reason this activation function was used is to ensure convergence in the output and also to ensure they all fall within the range of -1 and 1. The neuron was interconnected using the attributes of the data collected to form the neural network architecture as shown in figure 3

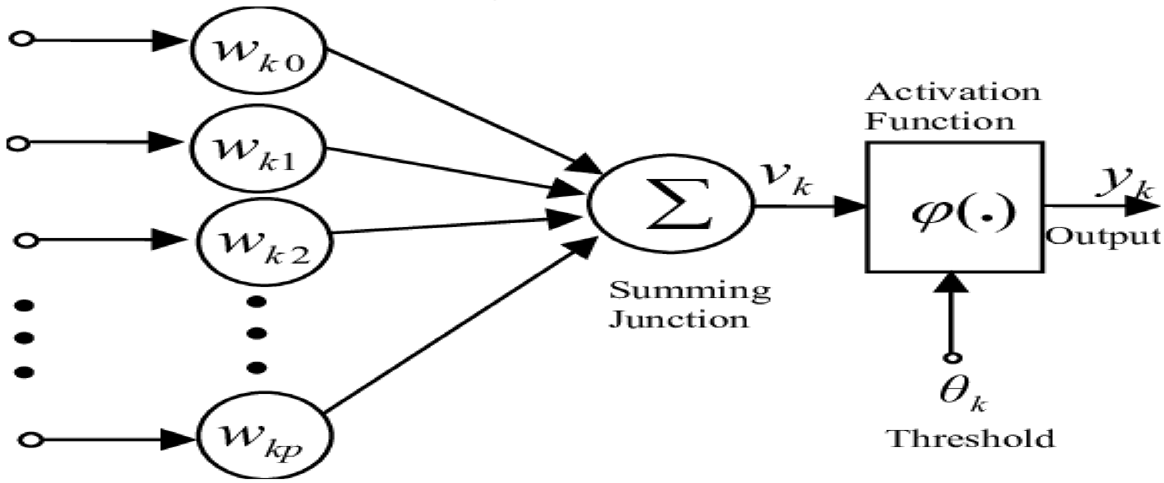

Figure 3: Architectural model of the ANN

Figure 3 presented the architectural model of the ANN was developed as a feed-forward neural network, interconnected with the neurons and activated to produce the output. In the diagram Wk is the weights, Vk is the bias function, φ is the activation function and Yk is the output. The neural network was trained with engine data collected from Zenix Engineering whose attributes are made up of fuel rate and speed as shown in figure 4 using back-propagation training algorithmMba and Asogwa (2022) to generate the reference set point for the MPC.

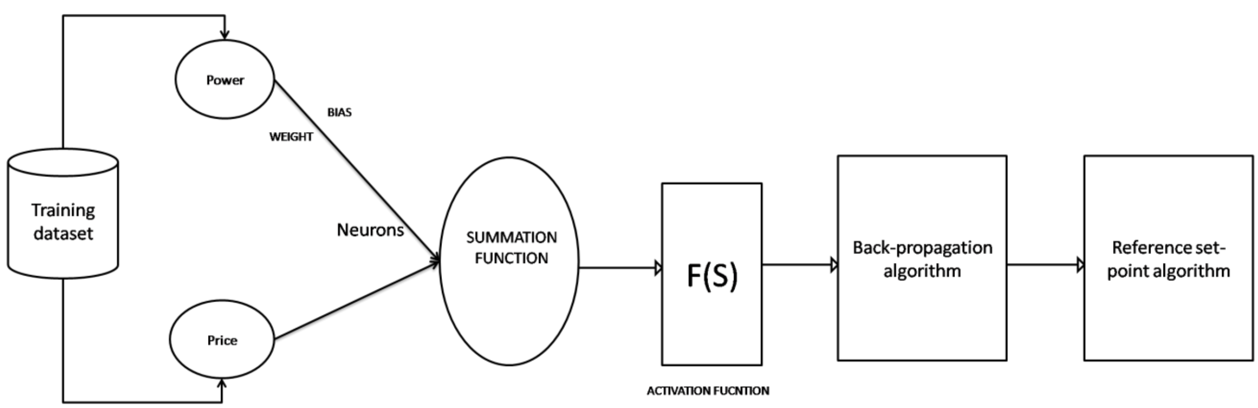

Figure 4: Model of the neural network architecture

Figure 4 presented the modelling diagram of the neural network. showing how the engine training data was fed to the neurons which have weight and bias for activation and training to generate the reference set-point. The number of neurons was decided based on the attributes of the engine training set among other parameters used for the configuration of the neural network reported in table 1;

Table 1: Simulation Parameters

Parameters	**Values**
Training epochs	20
Size of hidden layers	35
Training segments	30
No. delayed reference input	2
Maximum feature output	2
Maximum feature input	2
Number of non-hidden layers	10
Maximum interval per sec	2
No. delayed output	1
No. delayed feature output	2
Minimum reference value	-0.7
Maximum reference value	0.7
Time	0.05sec

The training algorithm shows how the neural network weights and biases are activated to learn the engine behaviour. The algorithm uses a computation of gradient loss function for the weights and bias to fine-tune the neurons, based on the updated values until an acceptable error margin is recorded. The input of the neural network is presented with x(t) at unit delay interval time lag. The activation function used is a tansig hyperbolic mathematical function (Okafor et al., 2017) which was used at the middle layer of the neural network to calculate the middle layer's output from the net input of the input layers. It was used because it can handle values between -1 and +1. This is good in case there is a negative input value. At the output layer, the purelin function (Okafor et al., 2017) was used because it has the capability of handling variable inputs and producing a single output as the training result which is the attack reference model as shown in equation 13;

The Set-Point Pseudo-Code (Algorithm 2)

1. **Start**
2. *Load engine dataset*
3. *Identify engine behaviours as a nonlinear autoregressive model*
4. *Configure neural network and training parameters*
5. *Train the neural network with a back-propagation algorithm*
6. *Check training performance until desired epoch is achieved*
7. *If*
8. *Desired epoch is achieved = true*
9. *Then*
10. *stop training*
11. *Else*
12. *Retrain until desired epoch is achieved*
13. *Stop*
14. *Generate a reference engine mode set point*
15. **End**

The Neuro-MPC (ALGORITHM 3)

1. **Start**
2. *Identify engine behaviour as a linear time-invariant model (x+1) in equation 7*
3. *Determine the LTI constraints as (A, B_u, B_v, B_d, C, D_v, and D_d)*
4. *Compute the constrained matrices*
5. *Get the nonlinear output y(k) as equation 8*
6. *Apply nominal operating conditions on y(k) using equation 9*
7. *Update the parameters constraints*
8. *Add all disturbance inputs and manipulated variables*
9. *Initialize the neural network reference set point*
10. *Initialize nominal update*
11. *Classify the updated constraints with the reference neuro set point*
12. *Update the control response time*
13. **Return**
14. **End**

3. SYSTEM IMPLEMENTATION

The DCS was implemented using a neural network toolbox, a model predictive toolbox, the algorithms developed, mathematical models, the modelling diagrams and Simulink. The Simulink used the model predictive toolbox developed with the MPC algorithm (Algorithm 1) to monitor the behaviour of the engines such as torque, speed, air-to-fuel ratio and mass flow rate. Then a neural network trained with an engine dataset collected from Zenix Engineering LTD, generated a reference engine model as shown in algorithm 2 which the MPC use to update the multi-engine constraints at nominal points to control the injection point model in figure 4. Before the training begins, the neural network tool automatically divided the data into test, training and validation sets in the ratio of 70:15:15. The aim is to simultaneously learn and self-evaluate its performance, before deploying the setpoint algorithm for the MPC update. The model of the Neuro-MPC was presented as shown in algorithm 3 as the improved electronic control unit for the injection actuator pump. The improved MPC which is the Neuro-MPC algorithm was used as the Electronic Control Unit for the DSC system. The Simulink was presented in figure 5;

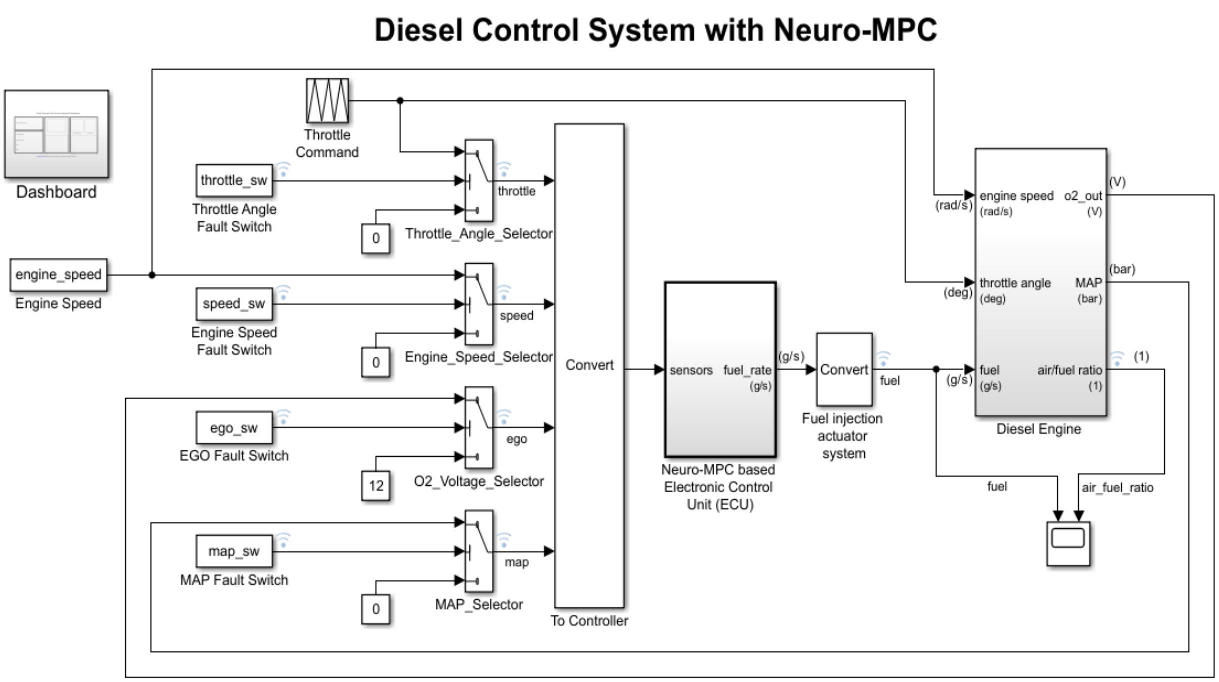

Figure 5: Simulink model of the DCS

The Simulink in figure 5 presented the DCS implemented with the Neuro-MPC control system developed and then simulated with the parameters in Table 3

Table 3: Simulation parameters

Parameter	Value
Engine type	4stroke
Mean effective pressure	980kpa
Maximum Engine of Speed	700 rpm
Distance	5.6km

Minimum Engine of Speed	300 rpm
Engine inertia value	0.12 kg·m2
Pump inertia value	0.02 kg·m2
Caloric value	48 MJ/kg
The maximum displacement of the injection pump	55 cm3·rev−1
Brake power	11.67KW
The maximum displacement of the injection pump	75 cm3·rev−1
Brake torque	110Nm
Swept volume per cylinder (SVC)	0.4L

4. RESULT OF THE NEURO-MPC TRAINING

This section presented the performance of the Neuro-MPC training process. Recall that the neural network was used to develop a reference set point for the MPC update as developed in algorithm 2. This was achieved by training the neural network with the engine data as already performed in chapter three. This section evaluated the training performance to be sure that the neural network perfectly learns the engine data for better MPC update results. This was done using the regression analyzer in figure 6;

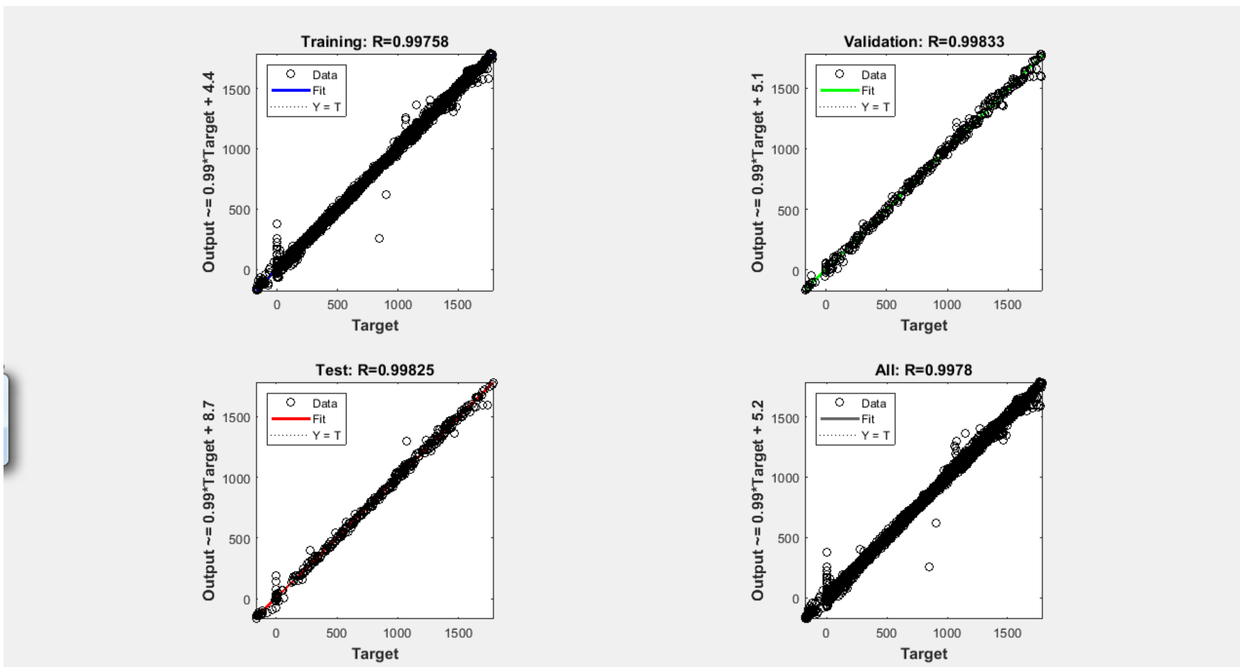

Figure 6: Regression performance of the Neuro-MPC

Figure 6 presented the regression performance of the new controller developed. This regression process aims to achieve a regression value of equal or approximately 1 which indicated that the neural network correctly learns the engine behaviour and also that the reference set point is reliable. The regression result here was summarized using the mean score for the training, test and validation regression values respectively and then the overall result achieved is R= 0.9978, indicating a very good training process.To further justify the result a Mean Square Error (MSE) analyzer was used to measure the neural network performance and the result is presented in figure 7;

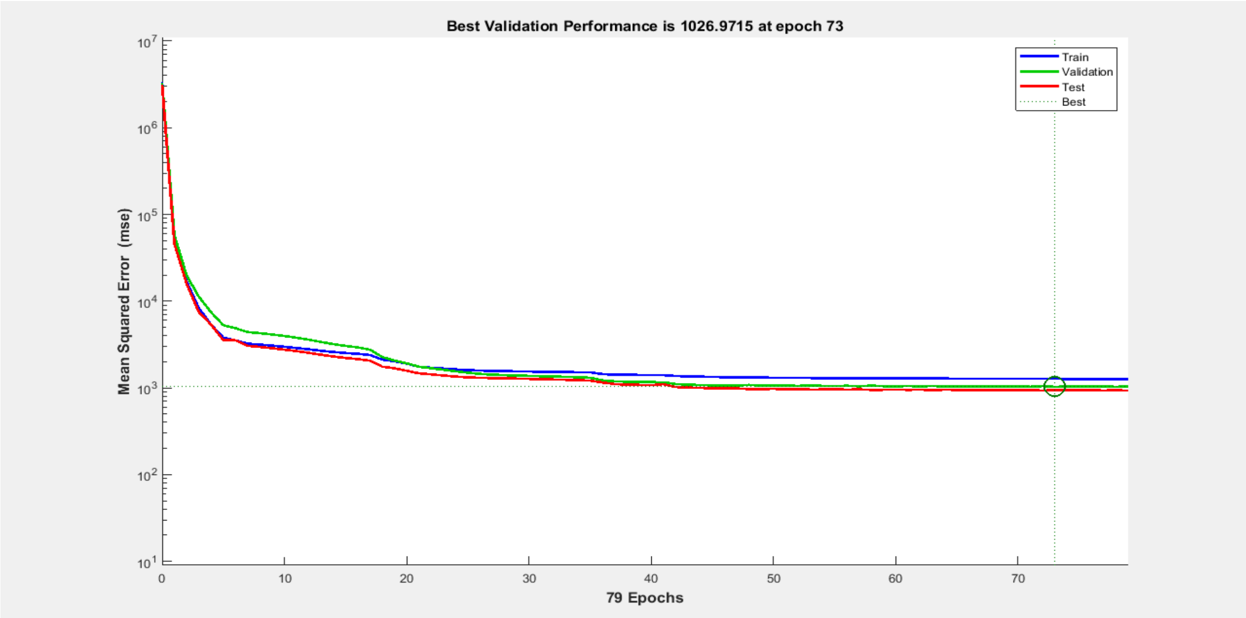

Figure 7: MSE performance

The reason for MSE is to measure the amount of error in the decision-making of the controller, although the aim is to achieve an MSE of zero or approximately zero. From the result of the MSE analyzer in figure 8, it was observed first that the multisets (training, test and validation) patterns correlated in the same direction, indicating that the training process experienced no overshoot which is a good sign. Secondly, it was observed that the neural network achieved that bet learning result at epoch 73, with a mean MSE for the multiset at 1023.9715e which is very good, indicating a negligible training error. The control step response is presented in figure 8;

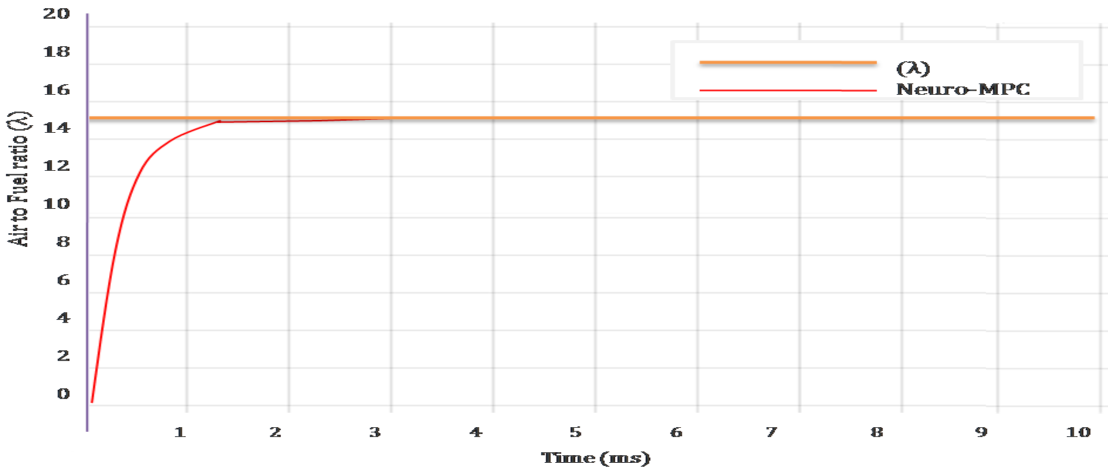

Figure 8: Step response performance

Figure 8 presented the step response of the control air-to-fuel ratio which produced the desired pressure to pump the injector and supply regulated fuel to the engine. From the result, it was observed that the training process experienced no overshoot and also that the Neuro-MPC controller was able to achieve this control objective within 1.37ms and supply desired fuel to the engine. This controller was integrated on a DCS and simulated as discussed in the next section.

4.1RESULT OF THE NEURO-MPC ON SIMULATED DSC

This section presented the performance of the DCS simulation. The result presents the fuel consumption rate of the engine, the performance of the throttle position sensor which monitors the cylinder behaviour and then the air-to-mass flow rate performance. During the driving process, the engine speed increases decreases or remains constant depending on the driver's behaviour. These behaviours are dependent on the throttle performance monitored by the throttle position sensor as shown in figure 9;

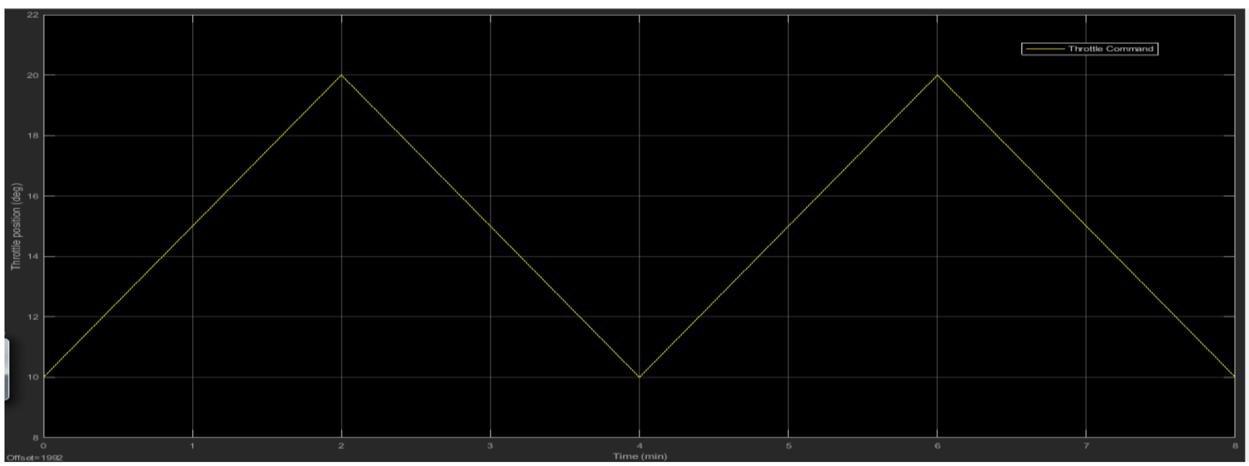

Figure 9: Throttle position of the engine

Figure 9 presented the position displacement performance of the engine due to the throttle position as modelled in equation 6. From the result, it was observed that as the behaviour of the throttle changes, the position of the cylinders due to air compression also changes to produce the internal combustion process. The next result presents the amount of fuel supplied by the injection pump which is controlled by the Neuro- MPC into the engine during this process.

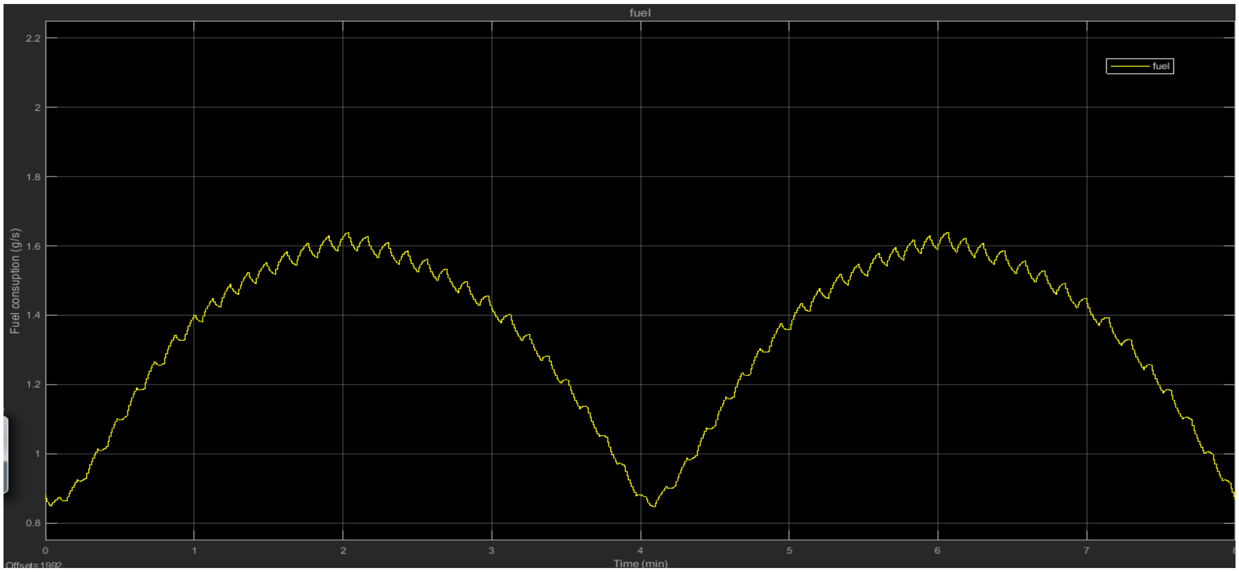

Figure 10: Mass of fuel consumed

Figure 10 shows the rate at which fuel is consumed by the engine using the mass flow rate in equation 4 which used the engine torque in equation 1 and speed in equation 3 to measure the fuel consumption. From the result, it was observed that the rate at which the injector supplies the fuel on the engine is dependent on the amount of torque and also the mass of air compression which determined the rate of cylinder displacement. When this process increases as shown in equation 6, the fuel supplies by the controlled injection pump increase and vice versa. To see the average fuel consumed by the engine see table 4.3 presented after the result of the Air to Fuel Ratio (AFR).

The AFR is a very vital measure for the tuning and controlling of the engine performance and anti-vehicle emission pollution reasons. This is a stoichiometric mixture that ensures the amount of air necessary for the complete combustion of the diesel within the engine. When the AFR is high excessively, the cylinder pressure is very high which results in wasted energy and poor efficiency result, when this AFR is low excessively, the engine gives out thick smoke and high exhaust gas temperature. The performance of the simulated engine AFR is presented in figure 11;

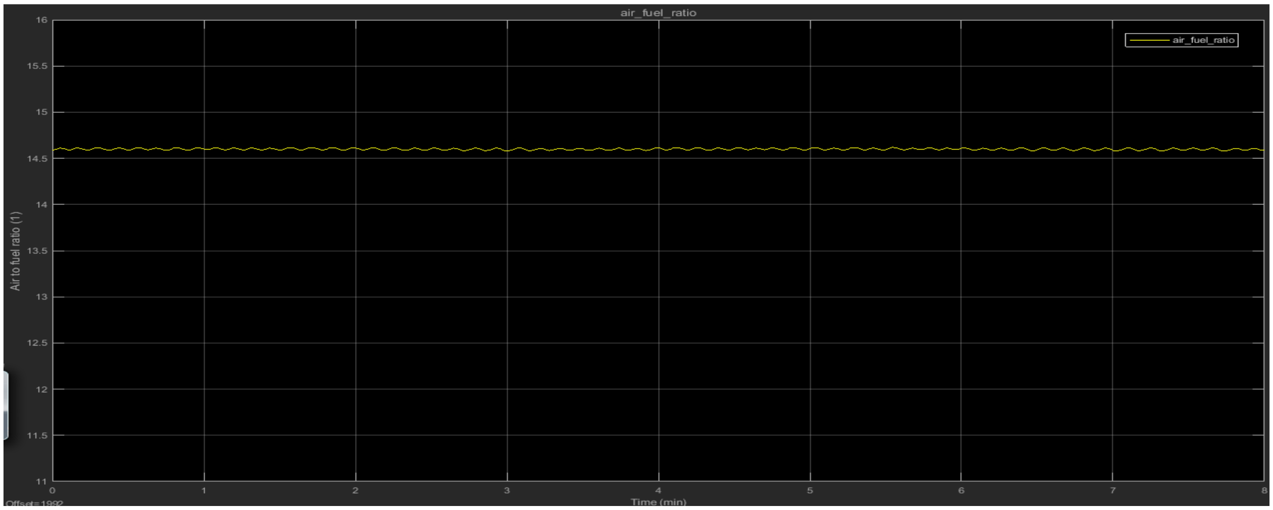

Figure 11: Air-to-fuel ratio performance

The AFR result in the figure was measured using the AFR model in equation 4 using the mass of fuel consumption model supplied by the injector in equation 3 and the amount of oxygen in the air. From the result, it was observed that the engine achieved the best AFR at 14.53 and the average AFR recorded in the engine is 14.577. The Ford stoichiometric in Tri et al. (2014), specified diesel engine AFR as 14.5: 1 for ideal efficiency of 94.5%, however from the result achieved it was observed that the engine AFR is approximately 14.53 which gives a *tolerable error of* $\pm$ *(0.03)*indicating a mechanical efficiency of 94.3%.

5. CONCLUSION

A diesel engine is one of the most used engines all over the world; however, the increase in fuel price due to economic reasons and the complex design nature of the diesel engine makes it very cost-effective to manage, especially during long-distance driving. Recently the introduction of the diesel control system was embraced as an alternative to help control the rate of fuel into the engine, however, to achieve precision in this, all the engine parameters must be considered and then collectively processed to conclude on the among of the fuel to be supplied to it.

This research reviewed the literature and identified MPC as the best to approximate multiple constraints and make good decisions, but suffers limitations in the ability to update itself in a highly nonlinear complex system like a heavy-duty engine. To address this problem, an artificial neural network was trained with the engine dataset and then used to develop a reference set point model for the MPC and then deployed as a DSC. The result was measured with necessary instrumentation tools like a dynamometer, and fuel gauge among others and it was observed that efficiency of 94.3%.

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