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OPTIMAL ENGINE MAPPING PERFORMANCES FOR DUAL SPARK-PLUG IGNITION INTERNAL COMBUSTION ENGINE USING NEURAL NETWORK

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OPTIMAL ENGINE MAPPING PERFORMANCES FOR DUAL SPARK-PLUG IGNITION INTERNAL COMBUSTION ENGINE USING NEURAL NETWORK

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Many variables affect the performance and fuel consumption of internal combustion engines. The most influential main variables include air, fuel, ignition, and compression. Spark plugs that play role in the ignition of fire have limitations in the propagation of fire due to their position because of the dual ignition technology. This study aimed to develop engine maps for dual ignition internal combustion engine using the Artificial Neural Network to predict the fuel consumption, generated torque, and find out the right combination of fire ignition on dual ignition systems to improve performance and reduce fuel consumption. The research was conducted with the initial step of retrieving the data engine map by using an engine scanner to find out the data on the current ECU. Then the data is modified to create a new engine map (modified engine mapping) that combines ignition timing 2 with a range of 0.5o - 2o. The test results show different torque and fuel consumption values in four modified engine maps. The optimum engine mapping is obtained on engine map 3 with an error value (Mean Square Error) of 0.002 and a regression value (R2) of 0.99. Modification map engine 3 with a combination of ignition timing 2 of 1.5o on ignition timing 1 shows the highest torque result with an increase in torque of 14.1% and a decrease in fuel consumption of 17.5%.

Key words: neural network, torque, fuel consumption, engine mapping

INTRODUCTION

The internal combustion engine produces mechanical energy through the combustion process of a mixture of air and fuel with maximum volumetric efficiency. When the combustion process increases, engine performance also increases (torque, power, and fuel consumption). If too much fuel enters the combustion chamber, the performance will decrease and the engine operating costs will increase [1]. In the combustion process, the fuel that cannot be burned often occurs, due to limitations in ignition timing in carrying out its duties, such as the position of the spark plugs and the spark burn time. The position of the spark plug must be adjusted to the construction of the engine cylinder head and camshaft. While the spark burn time is the length of time the spark plug electrodes are ignited, which is very small, which is in milliseconds. Besides, with a little ECU remap, the duration of the spark plug/ignition timing can be adjusted so that the fuel can burn completely [2]. This has also been investigated by Khair, and Ishak [3]. Besides, several researchers also reviewed the moment of ignition [4], the basic adaptation of the ignition angle, and autoignition [5].

Many variables affect the performance and fuel consumption of an internal combustion engine. The main variables to consider are air, fuel, ignition, and compression ratio. One of the requirements of an efficient engine is to have the correct heat stock value and be dispensed at the right time, this can be maximized from the spark plug ignition system. The ignition system generates a high voltage and is distributed to the spark plug at the right time to carry out combustion in the combustion chamber [3]. Therefore, dual ignition technology was created which is applied to internal combustion engines to maximize fuel combustion.

Dual ignition is one of the important design parameters in spark ignition type engines. The main advantage of using dual ignition is getting better and faster fuel combustion so that the engine can operate with a poorer fuel mixture (lean) [6]. The use of dual spark ignition results in better engine performance when compared to conventional engines with single spark ignition which can increase engine efficiency [7]. At the ignition of the spark plug, there is a dwell time before the spark plug generates an electric voltage. This can be minimized by starting the spark plugs sequentially.

A method that is very appropriate for these conditions is the black box modeling technique or artificial neural network modeling which is widely used in engineering [8]. Artificial Neural Networks can be used in machine performance optimization by providing input and output value parameters for learning. This can be obtained by changing the ignition time, based on the ANN prediction. So, with good control of the ignition time, good combustion effectiveness will be obtained so that it indirectly reduces fuel consumption and emission levels [9]. Neural network has been used for modeling, performance prediction, and control of internal combustion engines. Neural network had been studied as a control method to achieve low emissions and fuel consumption in an internal combustion engine [10], control the spark timing to obtain better performance [11]. The neural network was used for model identification of the behavior of the internal combustion engine [12,13]. Researchers have stud-

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ied for implementing a neural network for predicting the performance [14-17], and emission prediction for internal combustion engines [18]. The results showed a high accuracy of performance and emission prediction.

In this study, a machine learning technique is employed as optimum engine mapping for ignition timing, injection timing, generated torque, and low fuel consumption. Two electronic control units (ECUs) i.e standard ECU and programmable ECU are utilized as a control map for a dual spark internal combustion engine. The standard ECU is mapped using neural network sourcing from the database obtained from the engine test. After obtaining the neural network, the model is used for programmable ECU to modify the resulted engine map. Various engine tests are conducted to verify the engine maps generated form neural network regression.

MATERIALS AND METHODS

Hardware and software system

This research implemented the standard engine control unit (ECU) manufactured by Yamaha. It has a 24-pin connector that connects the ECU to the sensors on the engine and the ECU and the actuator to operate the engine under the existing program embedded in the ECU. Meanwhile, the employed programmable ECU is obtained from microquirsts as shown in Figure 1. This ECU is used to improve engine performance and adjust the ignition timing of the two spark plugs. In this stage, manufacturing is carried out to modify the engine mapping by referring to the design that has been performed in the previous research. Programmable ECU for modified engine mapping which has new spark plug holes at an angle of 18° to the horizontal axis. The detail of the new spark plug angle and placement for the modified engine mapping is shown in Figure 2.

(a) (b)

Figure 1: Utilized ECU (a) Standard ECU (b) Modification of engine mapping

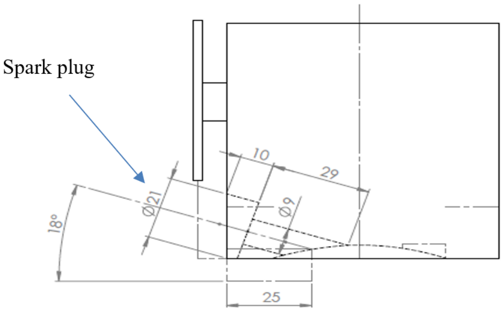


Figure 2: The placement of a modified spark plug angle

Research method

The flowchart of this research method is described in Figure 3. The method used is divided into 2 parts, namely hardware and software development. In the hardware development section, a second spark plug hole was made and a new wiring assembly was carried out on the programmable ECU, while the software was carried out with initial data acquisition for the artificial neural network (ANN) input database in learning to predict the resulting torque, fuel consumption, and air-fuel ratio (AFR) in the range of changing ignition time 2 from 0° to 2° to ignition time 1.

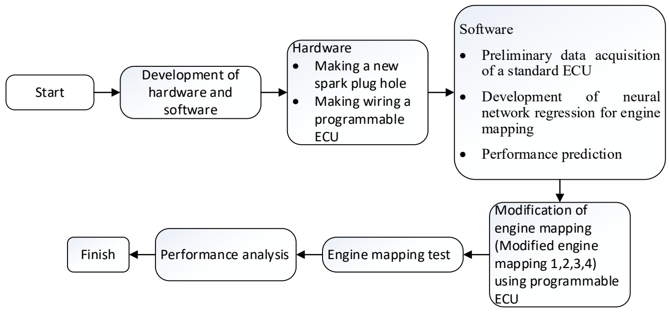


Figure 3: Proposed research flowchart for engine mapping

In the process of developing an engine map using ANN, some procedures must be done so that the engine map produced matches the predicted experimental results. In determining the input variable that provides a correlation to the output variable, the selection of several input quantities must represent the number and target value to be achieved. In the engine with the fuel injection system used, 5 inputs are selected, namely engine speed (rpm), throttle position, air to fuel ratio, ignition time 1, ignition timing 2, and injection time. Input variables that will correlate 3 outputs are fuel consumption, air to fuel ratio, and torque as shown in Figure 4.

Neural network regression is employed as an engine mapping. Levenberg-Marquardt was chosen as a training function in engine mapping development. The training process in ANN will be perfect if the network and target output will be the same. The dashed line on each plot is the perfect result, where the output is the same as the target. The line representing the best linear regression line between output and target is R. If R indicates a value of 1 or close to 1 (R=1) then there is an exact linear relationship between output and target. If R approaches 0, then there is no linear relationship between the output and the target.

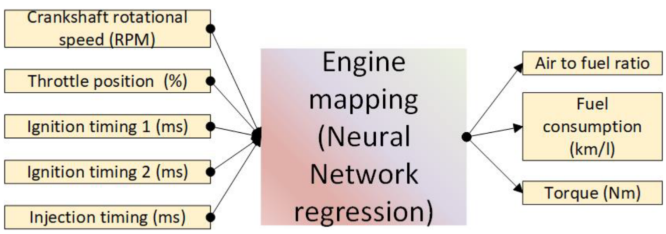


Figure 4: Proposed engine map

RESULTS

Standard ECU

To get the best predictions from ANN, several networks were evaluated and trained using experimental data. The performance of the mean squared error (MSE) is chosen to be the criterion for the error value, if the value is close to 1, the correlation between input and output with the algorithm model and the selected activation function is appropriate and appropriate. A fairly complex network model will quickly recognize the right new pattern while a simple network model will have low performance and many wrong patterns. However, complex models require complex non-linear algorithms. Nonlinear equations and experimental data are needed to obtain error and regression results from ANN learning for topological determination. Table 1 shows the number of hidden layers from Figure 5 which shows the ANN topology. The networks were varied using a constant number of neurons of 5 neurons. Furthermore, this ANN model is simulated in MATLAB which is modeled in Figure 6. Hyperbolic tangent sigmoid is utilized as the activation function in the hidden layer and the linear transfer function is employed in the output layer.

Table 1: Variation in the number of hidden layers

Num. of hidden layers	Training Error (MSE)	R			
		Train	Val.	Test	R^2
1	115.542	0.189	0.169	0.184	0.189
2	0.955	0.996	0.992	0.992	0.993
3	2.596	0.993	0.977	0.982	0.989
4	138.683	0.004	0.089	0.196	0.015
5	128.370	0.369	0.593	0.153	0.365

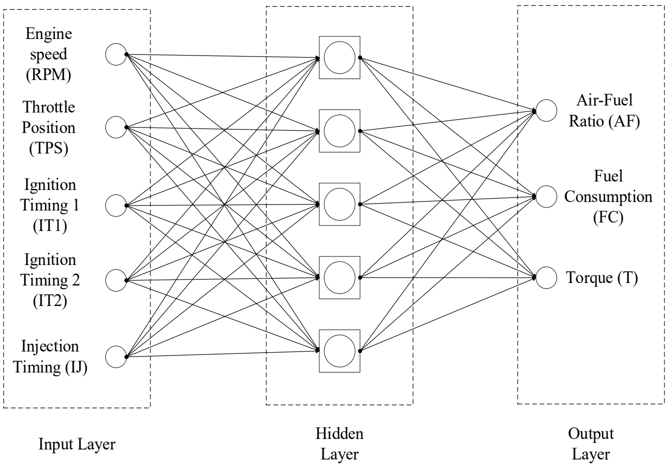


Figure 5: Employed neural network architecture for engine mapping

The number of hidden layers with the best training error and regression (R) results is shown in Table 1. The number of hidden layers also significantly affects the regression results, so the network with a hidden layer of 2 was chosen because it shows a regression value close to 1 and a small Mean Squared Error value. said the pattern is trained exactly according to the target). While the variation of neurons in the hidden layer can be seen in Table 2.

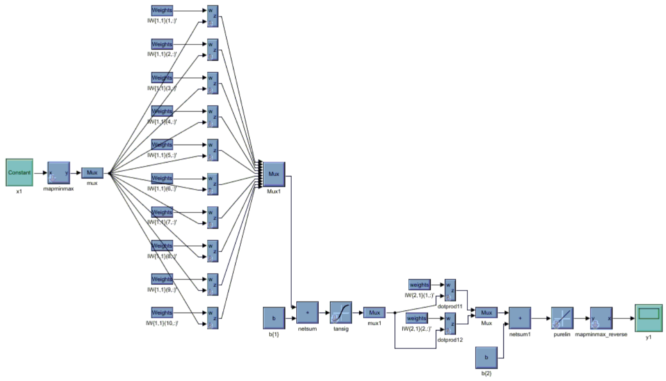


Figure 6: Developed neural network regression blocks

Table 2: Variation results in the number of neurons

Num. of Hidden Layer	Num. of neuron	Train Error (MSE)	R			
			Train	Val.	Test	R^2
2	5	202.505	0.205	0.101	0.558	0.216
2	10	0.898	0.998	0.989	0.992	0.995
2	50	4.936	0.999	0.935	0.723	0.956
2	100	131.592	0.078	0.027	0.217	0.082
2	200	91.682	0.150	0.435	0.321	0.211

Based on testing on experimental data, the best ANN topology is obtained with 2 hidden layers and 10 neurons. In this ANN topology, training is carried out on the standard map engine and the regression value is obtained in Figure 7 with a regression value close to 1 (0.99997).

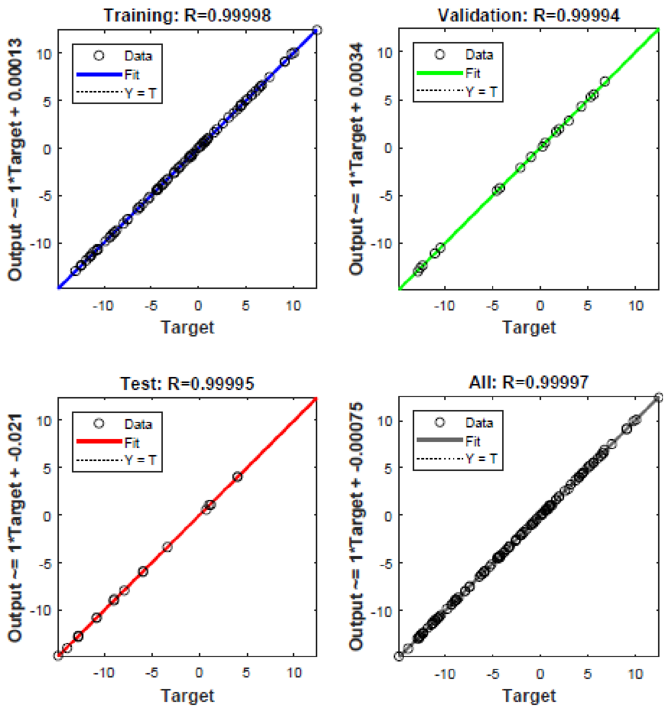


Figure 7: Selected neural network regression result of engine map for standard ECU

The success of the training process can be seen from the validation performance plot in the form of an error value. The error value chosen is the mean square error (MSE) where the best performance is 0.21795 at epoch 13. If the error value is smaller the output results obtained from the training results will be more accurate. The regression value of the error is the correlation between the target and output values after passing the training process. The best regression is if the output and target correlation results are 1 or close to 1 where the training results show that the training value is R=0.99942, R=0.9991 for validation, and R=0.99872 for the test as shown in Figure 8.

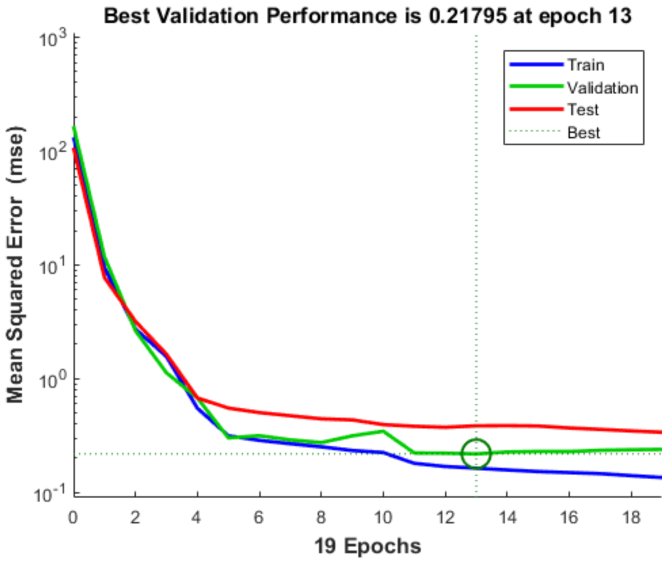


Figure 8: Resulted in MSE during training for standard ECU

Modified engine map using programmable ECU

In engine map using is developed by determining the input and output variables in the programmable ECU. The input variables include engine speed (RPM), throttle position (TPS), air-fuel ratio (AF), fuel consumption (FC), and torque (T). Meanwhile, the output variables used are ignition timing 1 (IT1), ignition timing 2 (IT2), and injection timing (IJ). The neural network developed for the modified engine mapping uses the same architecture as the mapping engine in the ECU standard as presented in section 3.1. In Figure 9, the selected error value is the mean square error (MSE) where the best performance is 0.21795 at epoch 13. If the error value is smaller, the training results will be more accurate. The regression result shown in Figure 10 is the correlation between target and output values. The best regression is if the output and target correlation results are 1 or close to 1 where the training results show that the training value is R=0.99942, validation R=0.9991 and the test R=0.99872.

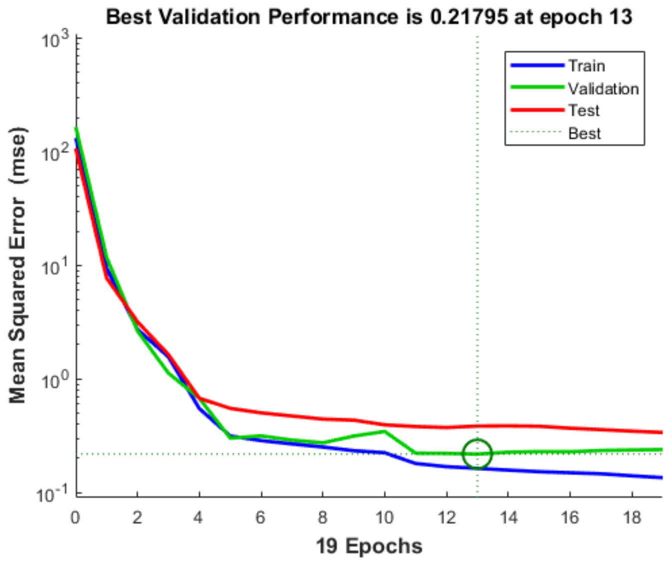


Figure 9: Resulted MSE during training for the programmable ECU

DISCUSSION

Resulted engine map for ignition and injection timing

An engine with fuel injection technology can be controlled by an electronic device called an Electronic Control Unit (ECU). ECU is data in the form of a map or map that presents engine performance based on engine conditions, needs, and load. An engine map on the ECU generally contains the ignition timing and injection timing. In testing using an ECU containing a standard map, it is carried out on a dynamometer chassis with an inertia roller type. The roller ratio on this dyno engine can be changed to simulate loading on the engine.

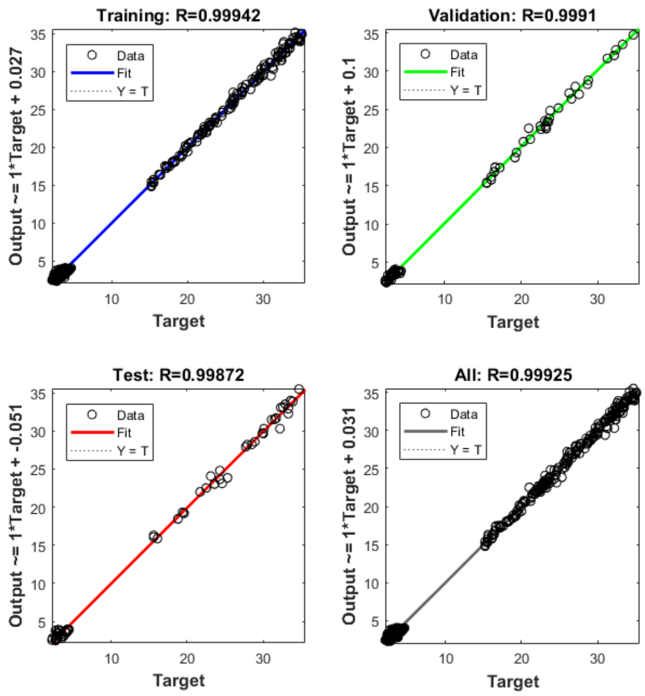
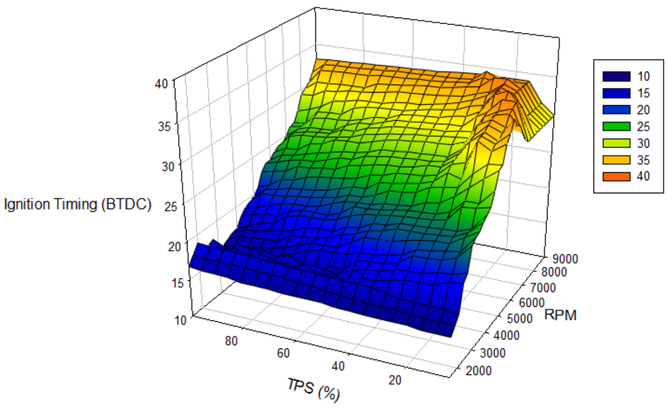
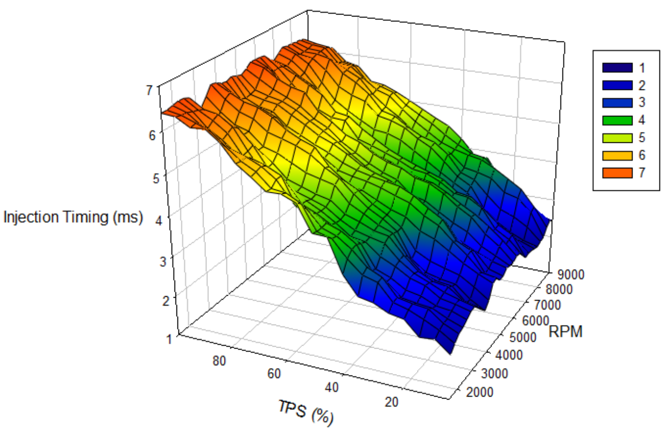


Figure 10: Mapping result on programmable ECU

Figure 11 (a) shows that the higher the engine speed, the greater the ignition timing value. In other words, the ignition of the spark plugs will be done earlier, this is conducted to anticipate the occurrence of premature combustion and compensate for the long ignition time from the high engine speed. Meanwhile, the greater the throttle position, the smaller the ignition timing value. In standard map ignition timing, the ignition timing value 2 (IT2) is the same as the ignition timing value 1 (IT1), so it can be said that the spark plug ignition occurs simultaneously. In the standard ECU injection timing map shown in Figure 11 (b) it can be stated that the length of time/ pulse-width of the injector to spray fuel will increase as the throttle position value increases. This happens when the throttle position angle is opened, the volume of the incoming airflow increases so that it requires more fuel to burn in the combustion chamber which is close to the AFR stochiometric value.



(a)



(b)

Figure 11: Ignition and injection timing; (a) Ignition timing map; (b) Injection timing map

The training results from the engine map can be seen in Table 3 which shows an increase in the maximum torque of each engine training map on the programmable ECU. Map modification is done by advancing the ignition timing 2 of the dual ignition system by 0o-0.5o before the ignition timing 1/main spark plug turns on in the acceleration area, both during low to high engine loading and when receiving high loads at low engine speed. This is done so that the search for the ignition timing is not too broad. The 3-dimensional illustration of ignition timing 2 from engine map modification 1 is shown in Figure 12.

Based on data from ignition timing 2 on engine map modification 1, it is obtained ignition timing 2 engine map modification 2 which is illustrated in Figure 12 (a). In modified engine map 2, ignition timing 2 advances with a range of 0o-1o from the ignition degree of the main spark plug, ANN training produces a smoother 3D contour of ignition timing 2, besides that there is a correction of the value at low throttle at high engine speed, this is This can result in lower injection timing as shown in Figure 12 (b).

The ignition timing 2 engine map modification 3 is obtained from the modified engine map training process data 2. The reduction of the ignition timing 2 value with a value of 0o - 1.5o is expanded to the low engine speed area because the expected increase in torque is not in accordance with the desired target. So that we obtain the ignition timing 2 engine map modification 3 which is illustrated in Figure 12 (c). The results of the contours of the ignition timing 2 engine map modification 3 have similarities to the modified engine map 2. However, there is a shift in the value of ignition timing 2 at the 0% - 30% throttle opening with engine speed between 4,000 RPM–6,000 RPM which has a lower value than modified engine map 2. The results show the gradient of the ignition timing value 2 on the modified engine map 3 is not too steep and tends to be stable at every displacement of the throttle opening position. In engine map modification 4, modification of ignition timing 2 is done with a range of 0°-2°. The 3D plot of the modified engine map table 4 is shown in Figure 12 (d). The resulting contours on the modified engine map 4 have unevenness at 50%-100% throttle opening at 2,000 RPM to 8,000 RPM.

Another parameter that can affect the performance and fuel consumption of an engine is the injection timing. On the modified engine map 1, the injection map value is obtained as the output of the ANN training results. The 3-dimensional injection map illustration is shown in Figure 13 (a), the surface contour of modified injection timing map 1 looks different from the standard injection timing map because it has gone through ANN training. When the injection timing has a greater value, what happens is that the injector experiences a longer opening of the solenoid valve, this is what determines the high or low fuel consumption.

The training for injection timing modification 2 is shown in Figure 13 (b). The contours of the injection timing map on the modified engine map 2 are smoother than the modified engine map 1. This can happen because of the repeated training process carried out on the modified engine map 2. The effect of the smoother contour map is that the engine does not experience changes in conditions automatically. suddenly, so that both power and torque can be maintained properly and fuel consumption can be decreased.

Injection timing on engine map modification 3 is shown in Figure 13 (c). The injection timing contour on the mod-

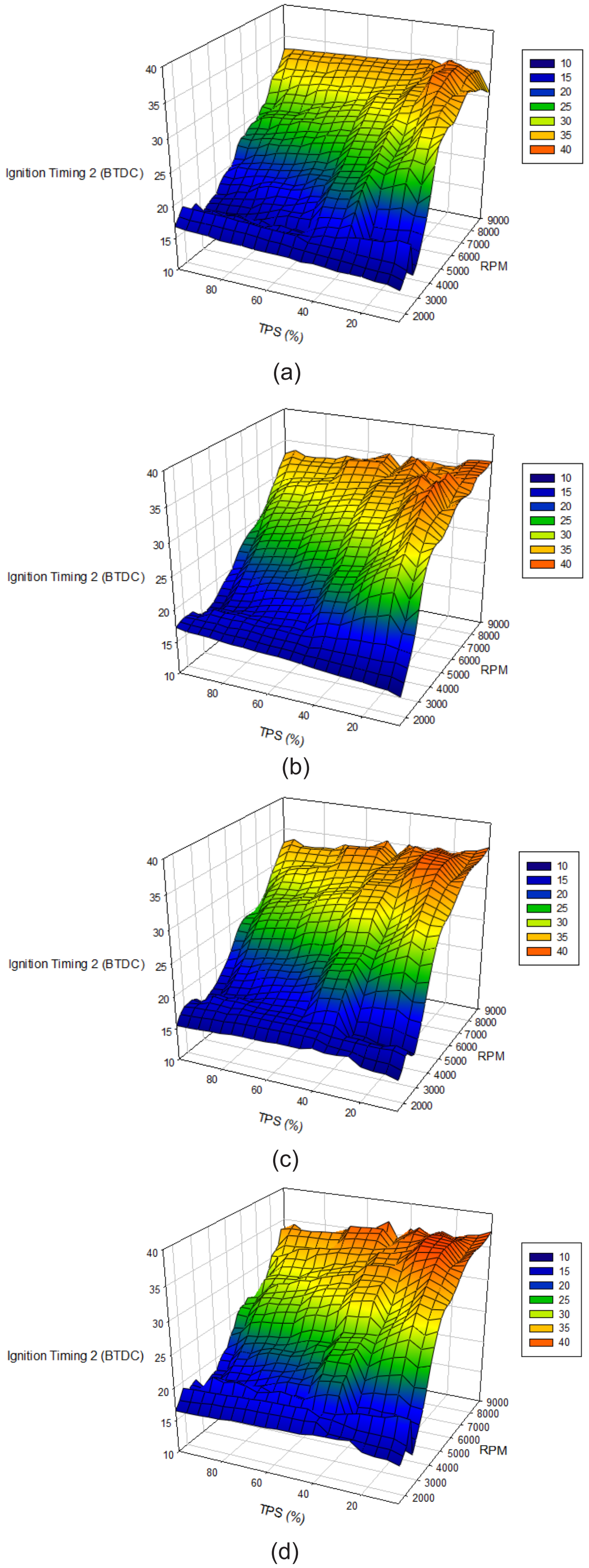


Figure 12: Ignition timing 2 map (a) Modification 1; (b) Modification 2; (c) Modification 3; (d) Modification 4

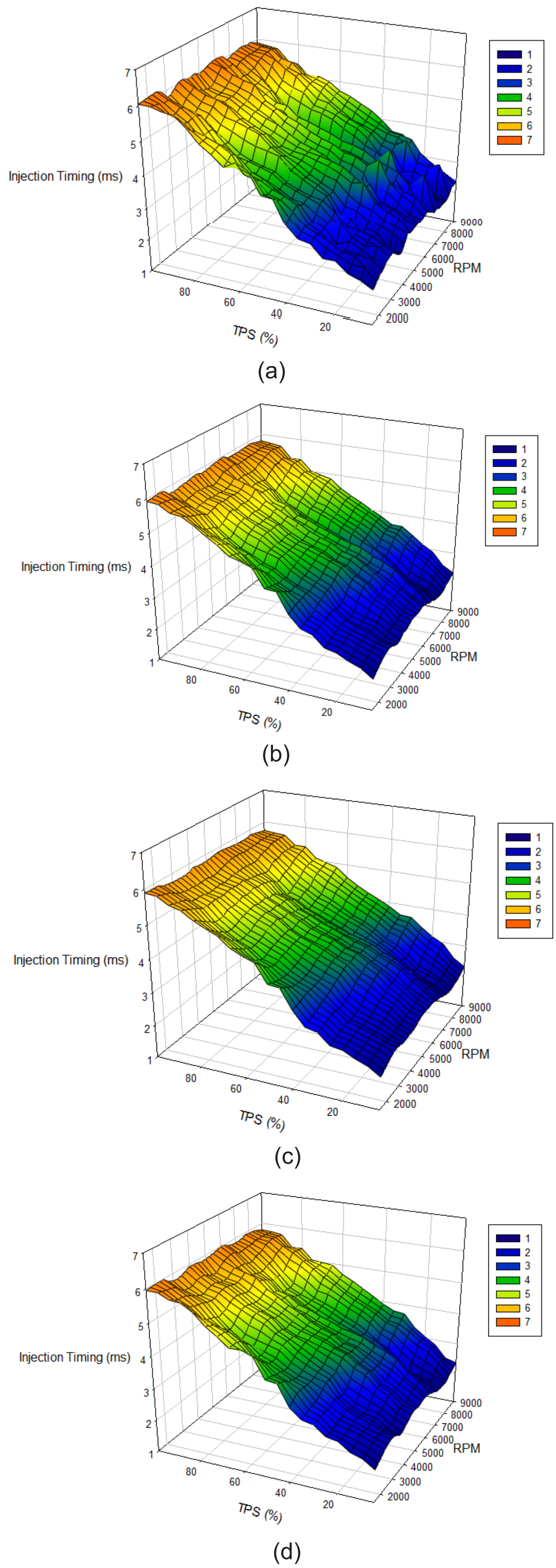


Figure 13: Injection timing map; (a) Modification 1; (b) Modification 2; (c) Modification 3; (d) Modification 4

ified engine map 3 is not smooth when compared to the modified engine map 2, this can be seen in the position of the throttle opening 0°-60° at an engine speed of 1,500 RPM–3,000 RPM which value is unstable. Injection modified engine timing map 4 is shown in Figure 13 (d). The resulting contour is not smooth, this is due to the greater value range of ignition timing 2 and the result of modified ignition timing map 4 which is also coarse, therefore it affects the injection timing value on modified engine map 4.

Based on the value generated from the ignition timing 2 and injection timing generated from the training on the engine map, the maximum torque value from each engine map modification can be obtained. The highest increase in torque from the standard engine map owned by engine map modification 3 can be seen in Table 3.

Table 3: Resulted in engine map training results for standard ECU and programmable ECU

Engine map	Maximum torque (Nm)	Increased torque (Nm)
Standard ECU	8.92	-
Modification 1	9.55	0.58
Modification 2	10.11	1.14
Modification 3	10.18	1.21
Modification 4	9.06	0.09

Generated torque

The torque test is carried out using a dyno test with the wide-open throttle method on the internal combustion engine. The highest maximum torque value is obtained at modified engine map 3, with a value of 10.18 Nm at an engine speed of 5,561 RPM as shown in Figure 14.

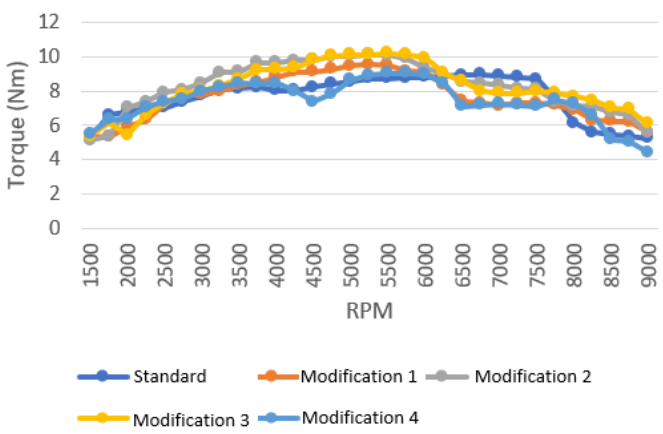


Figure 14: Generated torque obtained from the engine test

The torque on the standard engine map is obtained by simulating the results of the neural network training by applying a load to the engine. So that the torque value at each throttle opening point is obtained in the entire engine speed range. The values of torque points on the standard engine map are shown in Figure 15. Based on the results in the Figure, it can be seen that based on training from ANN, the peak torque of the standard map engine is at 50% throttle opening at an engine speed of 6,500 RPM with a value of 8.97 Nm. Meanwhile, based on standard specifications, the torque it has is 8.92 Nm at an engine speed of 6,850 RPM. When viewed from the contour you have, at a certain point the torque will decrease, especially after reaching its maximum point. This can happen because the energy produced is wasted after reaching the highest engine speed through friction and other mechanical factors.

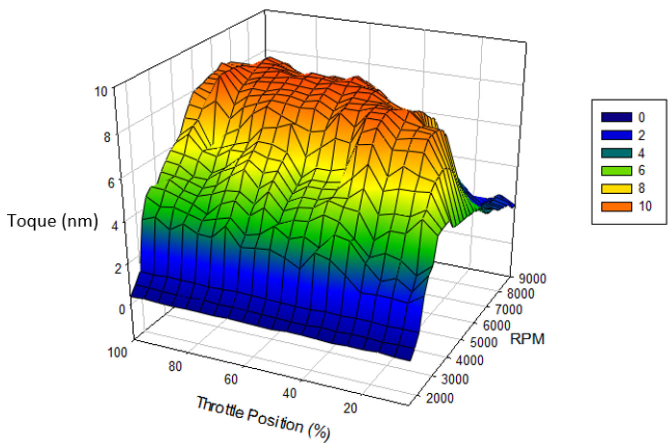
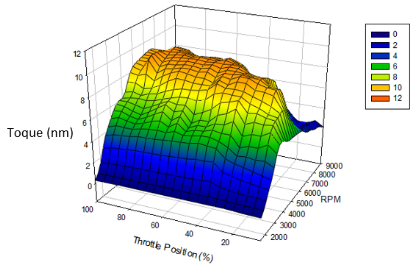


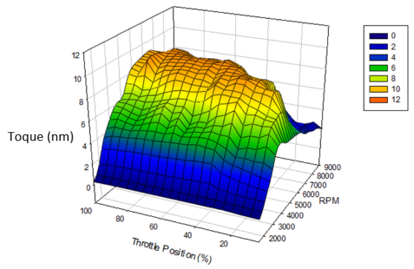
Figure 15: Generated torque by standard ECU

The maximum torque value on the modified engine map 1 is 9.54 Nm at an engine speed of 5,250 RPM as shown in Figure 16 (a). Whereas in the torque test on the dyno test engine, the maximum torque is obtained with a value of 9.55 Nm at an engine speed of 5,240 RPM. Based on the results of ANN training, the maximum torque value on the modified engine map 2 is 10.06 Nm at an engine speed of 6,250 RPM as shown in Figure 16 (b). Whereas in the torque test on the dyno test engine, the maximum torque is obtained with a value of 10.11 Nm at an engine speed of 5,250 RPM. There is a difference in the value between the ANN training and the dyno test, this can be caused when the input and target data are collected at the beginning of starting ANN training. Inaccuracy in the initial data collection used as a parameter can affect the results of ANN training, although the error value generated from the training is relatively small.

The maximum torque value from ANN training results on the modified engine map 3 is 10.18 Nm at 5,750 RPM engine rotation speed, while the dyno test results obtained the maximum torque is 10.18 Nm at 5,561 RPM engine rotation speed as shown in Figure 16 (c). In the graph of the torque map generated by engine map modification 3, the high torque value is obtained evenly in the cruising map area based on the map table defined by Turnbull [19]. In addition, the contours generated by the torque map on the engine map are smoother when compared to the modified engine torque map 1, 2, and 4, so it can be concluded that the combustion process that occurs for this map is good when viewed from the torque value at various rotations. machine. A significant and uniform increase in torque occurs at 30% - 90% in the engine speed range of 4,500 RPM – 7,000 RPM. Based on the dyno test on engine map modification 4, the maximum torque is 9.06 Nm at 5,556 RPM engine rotation speed, while on the torque map produced by ANN, the maximum torque is obtained at a value of 9.06 Nm at the engine rotation speed of 5,500 RPM to 6,000 RPM as shown in figure 16 (d). The contours of the torque map that is owned by the modified engine map 4 are not smooth on the engine speed of 2,000 RPM to 4,500 RPM which is evenly distributed at the throttle opening of 30% to 90%, from the contours of the torque map it can be concluded that the engine acceleration is not as fast as the modified engine map 3.



(a)



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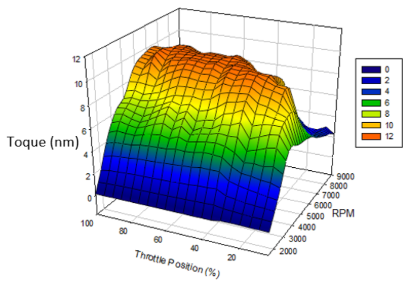

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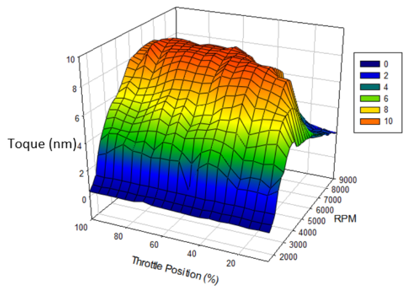


(d)

Figure 16: Resulted engine map for generated torque; (a) Modification 1; (b) Modification 2; (c) Modification 3; (d) Modification 4

Fuel consumption

The fuel consumption rate test is carried out based on the wide-open throttle method by providing load on the wheels and the engine speed range from 1,500 RPM to 9,000 RPM. The fuel consumption comparison value is shown in Figure 17. Based on the results of the fuel consumption test, the lowest fuel consumption rate is obtained by the modified engine map 2.

The results of fuel consumption on a standard engine map using a neural network at various conditions of throttle opening and engine speed are shown in Figure 18. An increase in the rate of fuel consumption occurs throughout the engine speed and throttle position, the greater the value of the throttle position and engine speed, the higher the rate of fuel consumption. The highest rate of fuel consumption occurs at 90% throttle position and at 9,000 RPM engine speed, which is 40.40 ml/minute. While the lowest fuel consumption rate occurs at 5% throttle opening conditions and 1,500 RPM engine rotation speed with fuel consumption of 2.83 ml/minute. The engine experiences high engine speed, the combustion chamber will require the need for a mixture of fuel and air more.

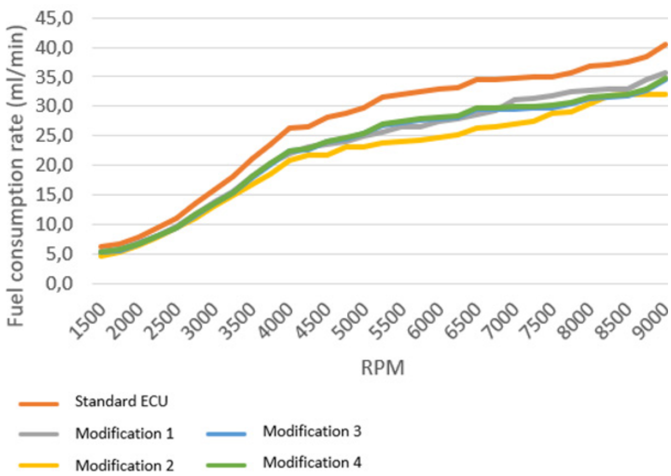


Figure 17: Actual fuel consumption rate test

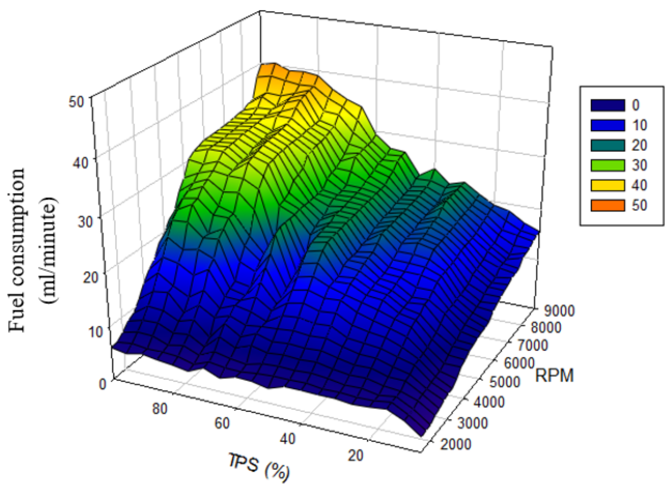


Figure 18: Fuel consumption rate on the standard map engine

Figure 19 (c) shows the value of the highest fuel consumption rate that occurs at 95% throttle opening conditions at 9,000 RPM engine speed with a value of 33.91 ml/minute. The lowest fuel consumption rate occurred at the 5% throttle opening point and the engine speed of 1,500 RPM with a value of 2.4 ml/minute. The contour of the fuel consumption rate map resulting from ANN training has a smooth surface, indicating that the point shift is in conditions of throttle opening and engine speed without the occurrence of large gradients. When compared with the results of the fuel consumption rate with modified engine map 2, modified engine map 3 has a higher fuel consumption rate than modified engine map 2, but the torque value of modified engine map 3 has a higher peak torque. higher. From the ANN training results, it was found that the highest fuel consumption rate in modification 4 occurred at 95% conditions and the engine speed was 9,000 RPM with a value of 34.7 ml/minute. Meanwhile, the lowest fuel consumption rate point based on the ANN training results lies in the 5% throttle opening condition and the engine rotation speed of 1,500 RPM, which is 2.6 ml/minute. The 3-dimensional contour of the resulting fuel consumption rate in Figure 19 (d) is not smooth due to modified ignition timing 2 and injection timing on modified engine map 4 but is still smoother when compared to the fuel consumption rate map on the standard engine map.

Figure 19 (c) shows the value of the highest fuel consumption rate that occurs at 95% throttle opening conditions at 9,000 RPM engine speed with a value of 33.91 ml/minute. The lowest fuel consumption rate occurred at the 5% throttle opening point and the engine speed of 1,500 RPM with a value of 2.4 ml/minute. The contour of the fuel consumption rate map resulting from ANN training has a smooth surface, indicating that the point shift is in conditions of throttle opening and engine speed without the occurrence of large gradients. When compared with the results of the fuel consumption rate with modified engine map 2, modified engine map 3 has a higher fuel consumption rate than modified engine map 2, but the torque value of modified engine map 3 has a higher peak torque. higher. From the ANN training results, it was found that the highest fuel consumption rate in modification 4 occurred at 95% conditions and the engine speed was 9,000 RPM with a value of 34.7 ml/minute. Meanwhile, the lowest fuel consumption rate point based on the ANN training results lies in the 5% throttle opening condition and the engine rotation speed of 1,500 RPM, which is 2.6 ml/minute. The 3-dimensional contour of the resulting fuel consumption rate in Figure 19 (d) is not smooth due to modified ignition timing 2 and injection timing on modified engine map 4 but is still smoother when compared to the fuel consumption rate map on the standard engine map.

Figure 20 shows the relationship between the fuel consumption rate predicted by ANN and the experimental results. In the engine speed range of 7,000 RPM to 9,000 RPM, the experimental test result value is higher than

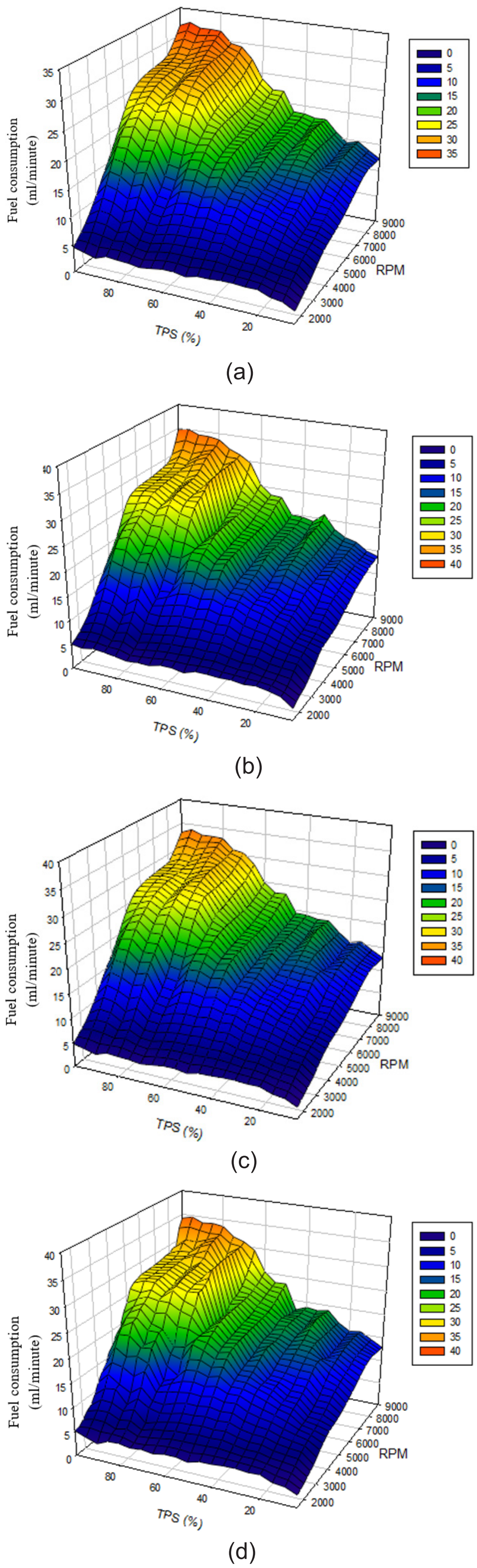
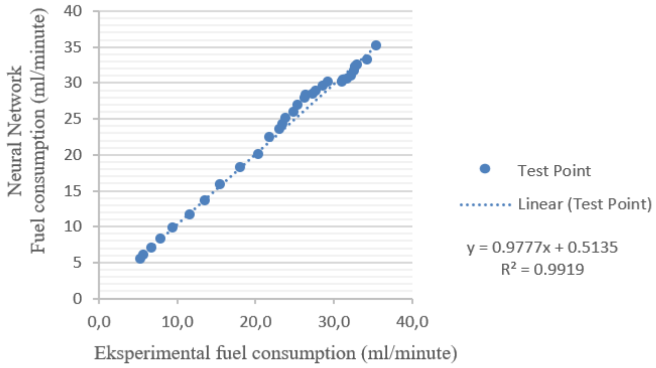
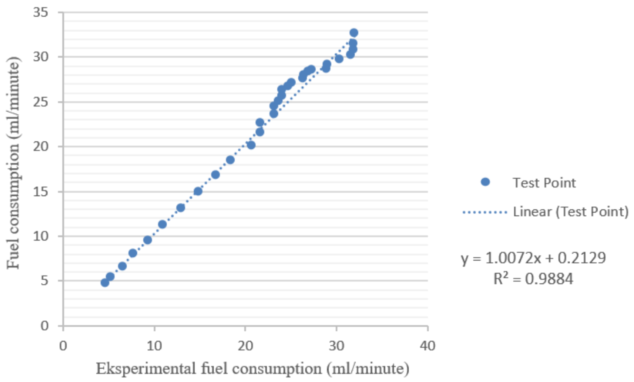


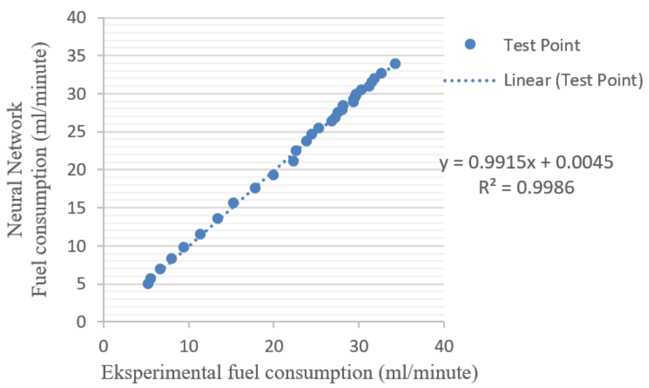
Figure 19: Fuel consumption rate: (a) Modification 1; (b) Modification 2; (c) Modification 3; (d) Modification 4



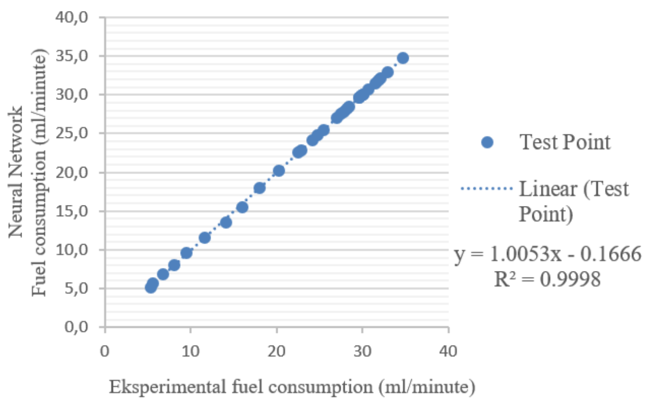
(a)



(b)



(c)



(d)

Figure 20: The relationship between the fuel consumption at ANN and the experimental results (a) Modification 1; (b) Modification 2; (c) Modification 3; (d) Modification 4

the predicted ANN value. The maximum regression value (R2) is 9.9998 which is obtained by the engine map of modification 4. The lowest engine map regression value is obtained by modification 2. Overall, the engine map modification regression value gets closer to 1, the engine map prediction results using ANN have an accuracy that is close to the experimental test value.

CONCLUSIONS

Engine map modification 3 was selected as the best engine map for an increase in torque of 14.1% and a decrease in fuel consumption of 17.42% with a fuel consumption value of 64.1 km/liter with the JISHA 899.183 driving cycle test method. The best fuel consumption is obtained in modified engine map 2 with a reduction of 19.74% in fuel consumption of 65.4 km/ liter based on testing with the JISHA 899.183 driving cycle method. While the AFR value for the best fuel consumption on a dual ignition engine is on the modified engine map 2, which is 18.5: 1 in the cruising engine state. Based on the test results, the optimal value of the ignition angle for the secondary spark plug is -1.5o to the ignition angle of the primary spark plug.

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