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Modelling A Single-Rotor Wankel Engine Performance With Artificial Neural Network At Middle Speed Range

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Abstract

The researches on Wankel engines are very rare and considered new in modelling and prediction. Therefore this study deals with the artificial neural network (ANN) modelling of a Wankel engine to predict the power, volumetric efficiency and emissions, including nitrogen oxide, carbon dioxide, carbon monoxide and oxygen by using the change of mean effective pressure, intake manifold pressure, start of ignition angle and injection duration as inputs. The experiment results are taken from a research which is performed on a single-rotor, four stroke and port fuel injection 13B Wankel engine. The number of data which are taken from experimental results are scarce and varied in six different data set (for example; mean effective pressure, from 1 to 6 bar) at 3000 rpm engine speed. The standard back-propagation (BPNN) Levenberg-Marquardt neural network algorithm is applied to evaluate the performance of middle speed range Wankel engine. The model performance is validated by comparing the prediction data sets with the measured experimental data. Results approved that the artificial neural network (ANN) model provided good agreement with the experimental data with good accuracy while the correlation coefficient R varies between 0.79 and 0.97.

Keywords: Artificial neural network; Engine performance; Exhaust emissions, Scarce data; Wankel engine.

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1. Introduction

The Wankel engine is a rotary type of four-stroke cycle internal combustion engine. Different from the conventional linear piston or reciprocating engine that processes two crankshaft revolutions for one four-stroke cycle, Wankel engine completes one four-stroke cycle with one eccentric shaft revolution [1, 2]. Research and development studies for the Wankel engine have started in 1950s with the NSU Company and continued by various companies, researches [3] and institutes. Since 1961 Mazda is the official company continues the current developments of Wankel engine [4]. Wankel engines attract attention because of their simple rotational motion without reciprocating parts. Beside the weakness in terms of wear, leakage and fuel consumption lead Wankel engines fail in long term usage [2, 6]. Considering heavy and complicated moving parts such as pistons and rods of reciprocating engines, Wankel (Rotary) engines come to the forefront with higher power output, simpler structure, lower NO_x emissions and lower vibration advantages. On one side, these advantages cause the usage of Wankel engine in small devices, unmanned air vehicles and lightweight industrial equipment. On the other side, high fuel consumption that leads lower fuel economy and shorter lifetime in comparison to traditional reciprocating engines can be counted as main disadvantages. To overcome the disadvantages of Wankel engine, there are many academic and industrial researches concentrated on combustion chamber geometry, direct injection and stratified charge port geometry and sealing etc.

The other type of analyzing Wankel engine performance is modelling. Modelling of an internal combustion engine is economical, effortless and reliable tool to predict the effect of design innovations rather than testing it on experimental environment. Considering modelling process, two approaches; thermodynamic models and fluid dynamic models come forward. [2,5]. As can be seen from the modelling approaches, almost all the modelling approaches and related developments are to investigate Wankel engines mechanically except some of the useful studies which are mainly focus on the control for the test and analyze purposes [1, 7].

There are multifarious modelling approaches as physical and mathematical models and related modelling tools. The artificial neural network approach is chosen as the modelling approach for this research with the rare usage in this area despite with the popularity of recent years and high accuracy with respect to the similar approaches [8]. Apart from the conventional physical and mathematical modelling methods, ANN modelling approach increases considerably in the literature in recent years. This method is implemented to different type of internal combustion engines for analyzing various features in terms of performance, emissions etc. Therefore, ANN is used in a wide variety of studies such as modelling, prediction, optimization and calibration [9-14]. Mohd Noor *et al.* modelled a marine diesel engine with using ANN predicting torque, power, fuel consumption and exhaust gas temperature. As a result of this study, they obtained %99 (very high) prediction performance compares to actual experimental data with a determination coefficient (R^2) of 0.99 [10]. Sinaga and Syahrullah investigated the ability of ANN feed-forward back propagation model to optimize and predict the performance of motorcycle fuel injection systems of gasoline. They used variation of engine speed, throttle position, ignition and injection timings as inputs, fuel consumption and engine torque as outputs. In the end, they reached the point that the ANN predicted model has (R^2) of 0.98-0.99 converge to the actual data [11]. Turkson *et al.* elaborated an overview of the various applications of neural networks in the calibration of spark-ignition engines including system identification for rapid prototyping, virtual sensing, use of neural networks as look-up table surrogates, emerging control strategies and On-Board Diagnostic (OBD) applications. Finally, they observed that trained neural networks are able to satisfy a majority of modeling requirements for engine calibration with the advantage of flexibility, avoiding overfitting and eliminating the need of user intervention [12]. Oguz *et al.* developed ANN application on diesel engine using biofuels with different percentages to estimate power, torque and specific fuel consumption. As a result, ANN estimation data set successfully performed with the correlation coefficient R is 0.994 [13]. Correlatively, Yusaf *et al.* investigated ANN modeling to predict power, fuel consumption (BSFC) and emissions of a diesel engine modified to operate with a mixture of compressed natural gas CNG and diesel fuels. Standard back-propagation algorithm of neural network is used, CNG-diesel percentage and engine speed are chosen as inputs to observe the engine performance and emissions. In the end of this study, they found that the ANN model predicted the engine performance and emissions with a correlation coefficient of 0.9884, 0.9838, 0.95570 and 0.9934 for the engine torque, BSFC, NO_x emission and exhaust temperature respectively [14].

Artificial neural networks method is a simple, rapid and evaluative methodology used to solve multi-dimensional and complex systems. Nowadays, artificial neural networks are mostly used in many areas such as estimation, classification, data processing and interpretation. An acceptable estimation of system outputs can be made with the method of artificial neural networks. Thanks to this approach, the ANN approach has provided alternative solutions to systems that contain complex mathematical solutions, especially the automotive industry. [15,16]. The estimative ability of ANN comes from training with experimental data and verification with an external data set. Therefore, if new data comes to the system, the ANN can be adapted and enhance its effectiveness. [13]. The ANN method can provide a model for emission and performance estimation, which is of great importance in the automotive industry, such as internal combustion engines if experimental data are enough [17, 18].

This study presents modelling a single-rotor Wankel engine performance with artificial neural network at middle-speed range. Our study focuses on the control-based modelling for the Wankel engine which is not placed in the literature until now. This work can be considered as the combination of the Wankel engine research and the neural network modeling approach. The main purpose is modelling a Wankel engine in terms of power and emissions. By doing this, the control algorithms can be created to improve the power which is the main advantage of this engine and to reduce the emissions especially hydrocarbons which are the main disadvantages.

Wankel engine test results are modeled for the first time with ANN. As known the Wankel engine is still in use many different areas and will be possibly used for the new purposes [19]. The idea is to collect simple range of data (especially middle range which are more in use) to check if the results are accurate enough for further studies. In the end the results are accurate, and the prediction is acceptable to inspire new studies on this topic.

2. Methodology

In this section, the experimental setup which the data are collected is explained. In addition to this, performing neural network modelling technique on to data set is detailed.

2.1. Working Principle of Wankel Engine

The Wankel engine runs with the four-stroke cycle principle. As can be seen from the comparison on Figure 1, the reciprocating engine performs the four-stroke cycle in two crankshaft revolutions (720 °CA-Crank Angle) while the eccentric shaft of Wankel engine fulfills three revolutions at each rotor revolution (1080°EA-Eccentric Angle) as the rotor completes its own 4-stroke cycle at each revolution.

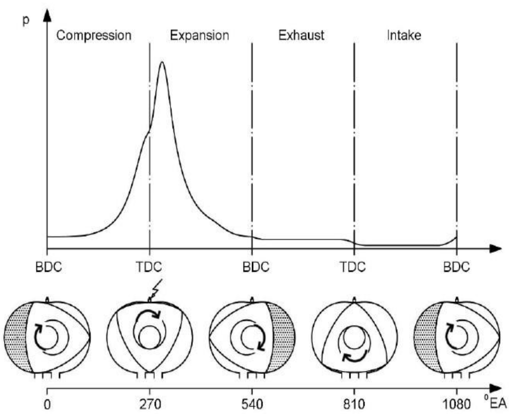


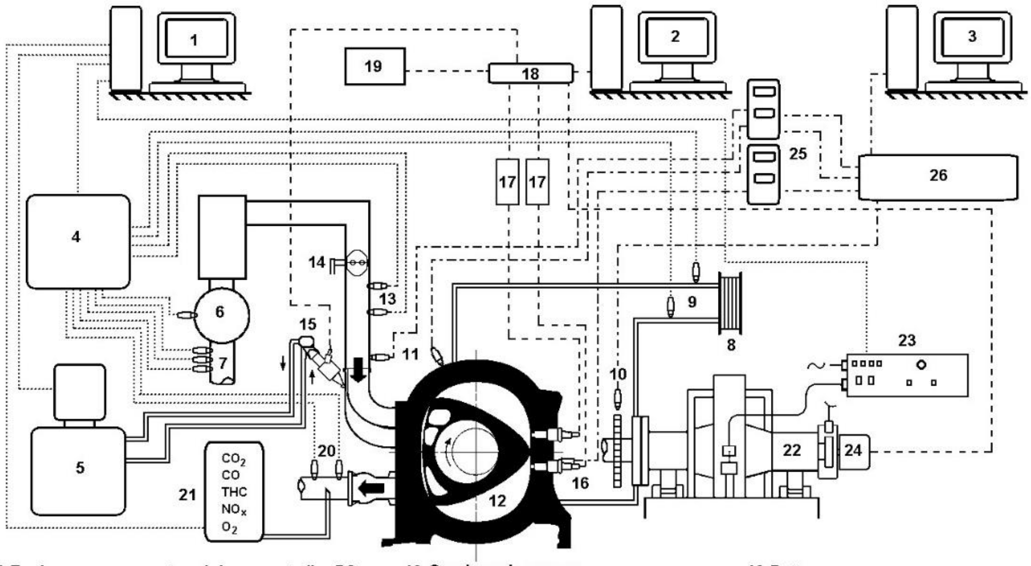
Fig. 1. Four-stroke cycle for Wankel engines [2].

This means that each eccentric revolution in the shaft corresponds to one four-stroke and let engine generate power accordingly [2]. So that according to the working principle, Wankel engine has advantages in terms of efficiency, smoothness, compactness, high revolutions per minute and a high power-to-weight ratio compared to reciprocating engines.

2.2. Experimental Setup

Wankel engine experiments were performed at 3000 rpm engine speed, 1 bar to 6 bar bmep (brake mean effective pressure) and λ=1 conditions [1]. The experimental setup is represented schematically in Figure 2.
The test environment mainly contains Schenck / W70 electromagnetic brake, water cooler unit, AVL fuel conditioning and measuring device, Kistler Kibox combustion chamber pressure measuring device, Bosch exhaust gas analyzer, Horiba Mexa 7500 exhaust gas analyzer.

The Wankel engine test dynamometer uses a Shenck W70 model electromagnetic engine brake shown in Figure 3. Dynamometer force was measured with load cell. The sensitivity of the load sensor is ± 0.02%. Exhaust gas temperature, lubricating oil temperature, throttle position, intake and exhaust manifold pressures, and many other sensor information are transferred to the sensor board. Wankel engine has redesigned as single rotor engine for the test purposes. The specifications of the Wankel engine are given in Table 1. Regarding the detailed experiments for modelling purposes, the data can be extended and better modelling approaches can be applied to this Wankel engine as mentioned section 3, results and discussions.



1-Engine measurement and dyno controller PC
2-Engine operation PC
3-Indicating PC
4-Engine data acquisition system
5-Fuel conditioner and balance
6-Air flowmeter (Roots type)
7-Air pressure, temperature and humidity
8-Engine cooling unit
9-Cooling water in and out flow temperatures
10-Crank angle sensor
11-Pressure transducers
12-Wankel research engine
13-Intake temperature and pressure
14-Throttle valve
15-Fuel injector
16-Spark plug and pressure transducer
17-Ignition coils
18-Engine controller unit
19-Battery
20-Exhaust temperature and pressure
21-Exhaust gas anlayser
22-Eddy current dynamometer
23-Dynamometer controller
24-Incemental encoder
25-Indicating charge amplifiers
26-Indicating data acqusition

Fig. 2. Schematic view of experimental setup.

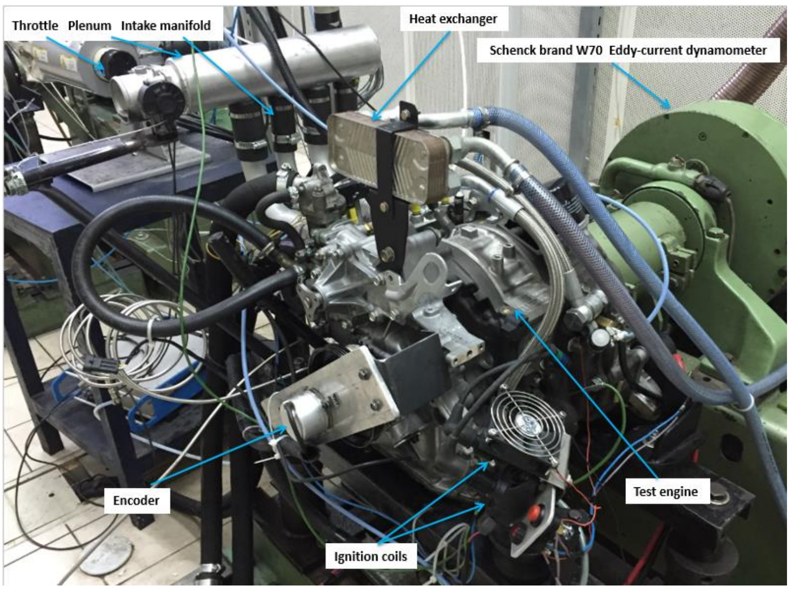


Fig. 2. Wankel engine test environment.

Table 1. Basic and geometric data related to 13B MSP Wankel engine [1].

Term			Value	Unit
Ignition (Twin spark plug)			Spark ignition	-
Mixture preparation			Port fuel injection	-
Fuel			Gasoline	-
R (Rotor corner-center length)			105	mm
e (Eccentricity)			15	mm
b (Rotor width)			80	mm
ε (Compression ratio)			10	-
Vh (Stroke volume)			654	cm^3
Port Timing	Intake port	Open (ATDC)	12^0	EA
	Intake port	Close (ABDC)	36^0	EA
	Exhaust port	Open (BBDC)	50^0	EA
	Exhaust port	Close (BTDC)	3^0	EA
Intake Charge Type			Natural Aspiration	

2.3. Artificial Neural Network Design

ANN is a numerological model that simulates the learning mechanism in biological organisms with being one of the most well-known techniques of machine learning [17, 20]. Polynomial classifiers can model decision surfaces of any shape; but their practical usefulness is restricted by the ease with which they over fit noisy training data, and by the often impractically large number of trainable parameters.

ANN methods take the popularity with the simpler neuron units which are connected into larger structures of extremely high performance [21].

ANN approach mainly contains three fundamental layers, as follows the input, hidden and output layers. The input vectors with the input information are replaced in input layer then carried over to the hidden layer to be processed and the output vector is computed in the output layer. Every node is based on an activation function and can transmit signals from previous layer nodes [22]. This approach is additionally robust, efficient and appropriate for nonlinear and complex processes. Back propagation neural network (BPNN) is a well-known algorithm of ANN used to supervise training as the network weights and biases are initialized randomly at the initial phase. Levenberg–Marquardt neural network algorithm is used for the evaluation of the model performance. The Levenberg–Marquardt algorithm briefly, was developed to solve nonlinear least square problems especially curve fitting, by reducing the sum of the squares of the errors between the function and the measured data points. This algorithm operates as the combination of Gauss-Newton method and gradient descent method. Levenberg–Marquardt algorithm takes the shape of gradient descent in case the parameters are far from their optimal value and behaves like Gauss-Newton in case the parameters are close to their optimal value. Detailed theoretical information about ANN and Levenberg–Marquardt algorithm can be found in [23-25]. The network model was developed and trained using MATLAB Neural Network Toolbox in this study. ANN model structure can be divided into two stage, namely training the model network and validating with new data which are not evaluated in training. An ANN model for the Wankel engine is constructed by using the data collecting from the experimental setup. The ANN model contains 70 percent of data as training data which are selected random, 15 percent of data for testing the performance and the rest 15 percent for validating the model. The back-propagation algorithm was selected for the weight calculation of the neural network. The back-propagation algorithm ANN structure for the Wankel engine is shown in Figure 4 [12].

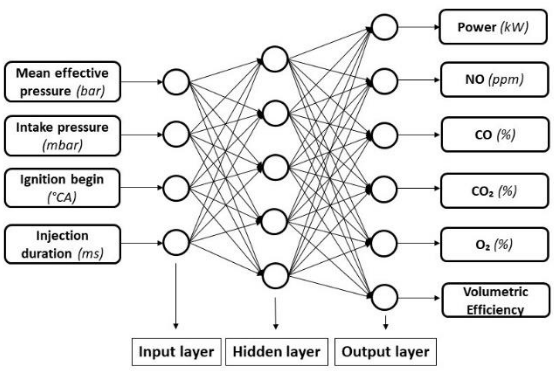


Fig. 4. Neural network architecture.

The network is divided into three layers: input layer, hidden layer and output layer. Input layer occurs with 4 inputs as mean effective pressure, intake pressure, ignition begin angle and injection duration. Number of hidden layers are chosen as 5 and the output layer occurs with 6 performance and emission related outputs as power, NO emission, CO emission, CO_2 emission, O_2 emission and volumetric efficiency. The neural network structure in terms of training was developed in accordance with the specification indicated in Table 2. Network accuracy was measured using the determination coefficient (R^2). R^2 is a calculation of how successful the regression line reflects the sets of actual data which differs between 0 and 1. An R^2 value close to 0 corresponds to unsuccessful prediction, while 1 indicates that the ANN model perfectly predicts the output [10]. The R^2 is represented as the eq 1 below:

$$R^2 = 1 - \frac{\frac{1}{N}\sum_{i=1}^{N}(y_i - y_k)^2}{\frac{1}{N}\sum_{i=1}^{N}(y_i - \bar{y})^2} \quad (1)$$

Where yi is target and yk is predicted value of the ith output neuron, $\bar{y}$ represents the target mean value while N is the overall data [10].

Table 2. Neural network configuration

Number of neurons in input layer	4
Number of neurons in hidden layer	5
Number of neurons in output layer	4
Training function	Levenberg–Marquardt
Performance function	Mean square error
Activation function	Tangent-sigmoid

3. Results and Discussions

The prediction of Wankel engine performance in the middle speed range was practiced by using the artificial neural network (ANN) back-propagation model with the Levenberg–Marquardt training algorithm in the Matlab Neural Network tool. The architecture of the ANN model was formed as 4 inputs, 5 hidden layers and 6 outputs. The network evaluation is performed with the criteria of R^2. Detailed evaluation for the network reaction was done by way of a regression analysis that was performed between the output of network and related targets. The results proved that the model developed from the neural network was useful for predicting the performance of the Wankel engine at middle speed range with the variation of mean effective pressure (1 bar to 6 bar), intake manifold pressure, ignition begin and injection duration. The comparison between experimental data and neural network predicted values of power, NO, CO, CO_2, O_2 emissions and the volumetric efficiency was represented in Figure 5, 6 and 7 respectively.

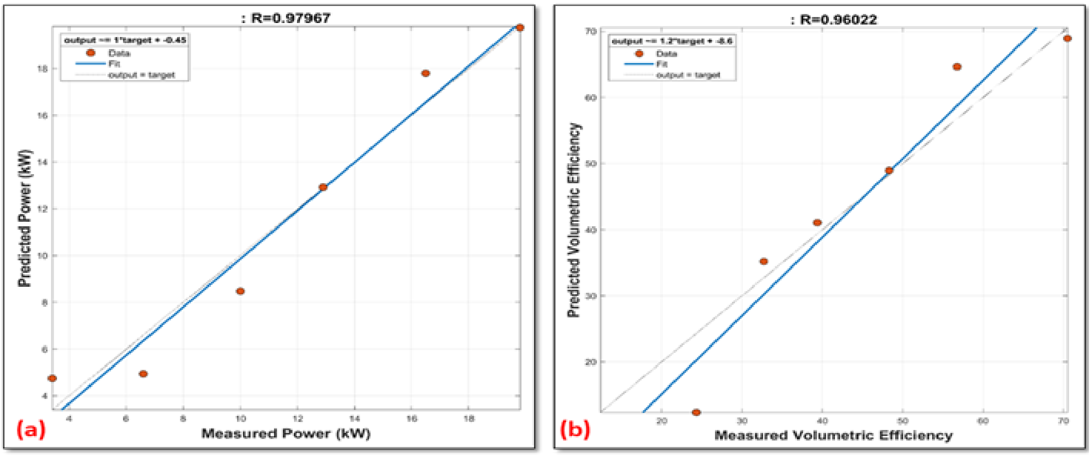


Fig. 5. The comparison between measured and predicted data, (a) power, (b) volumetric efficiency.

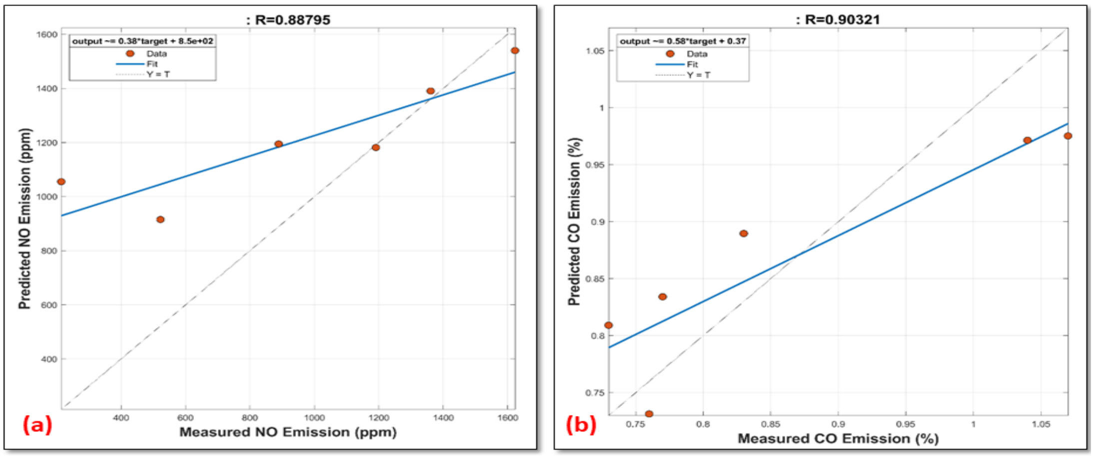


Fig. 3. The comparison between measured and predicted data, (a) NO emission, (b) CO emission.

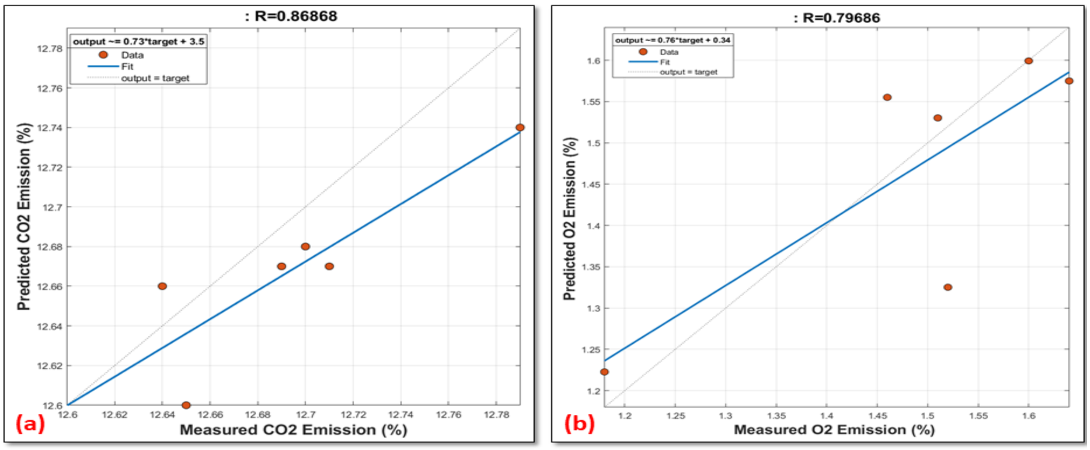


Fig. 4. The comparison between measured and predicted data, (a) CO_2 emission, (b) O_2 emission.

ANN's estimation values of power, NO, CO, CO_2, O_2 emissions and volumetric efficiency were assessed with regression analysis between estimated and experimental data. As mentioned above, accuracy of estimation increases as the correlation coefficients get closer to 1. In the case implemented in this study, correlation coefficients obtained are mostly close to 1, which indicates a good match between ANN estimation values and experimental measurement values. The artificial neural network predictions in terms of correlation coefficient R are 0.90321 for CO emission, 0.86868 for CO_2 emission, 0.88795 for the NO emission, 0.79686 for the O_2 emission, 0.96022 for volumetric efficiency and 0.97967 for the power. These comparisons prove that artificial neural network model which was constructed with the differentiation of mean effective pressure, intake manifold pressure, ignition begin and injection duration at 3000 rpm has properly represents the engine characteristics even if there are scarce data sets.

The results were proved that the ANN backpropagation model (BPNN) with the

Levenberg-Marquardt algorithm was sufficient enough in predicting power, NO, CO, CO2, O2 emissions and volumetric efficiency for different mean effective pressure, intake manifold pressure, ignition begin and injection duration at constant middle speed range.

Considering scarce data conditions, ANN performance can be thought successful especially on the outputs volumetric efficiency and power. However the emission related predictions can be comparatively improved. Especially with the prediction of NO emission which converges %79 to the experimental result, the model could be retrained with the different number of training data to obtain better validation and test results.

4. Conclusion

As a beginning of artificial neural network applications on Wankel engines, an artificial neural network model has been created and trained with six different scarce data points taken from experimental results. Wankel engine test results are modeled for the first time with ANN. No such study has been found in the literature.

This means good accuracy with the correlation coefficient between 0.79 – 0.97. The power and volumetric efficiency outputs, also the CO emission are estimated relatively more sufficient than the other emission outputs with the correlation coefficient R is more than 0.9 which represents %90 of successful estimation.

In general, the estimation performance of ANN model can be improved by doing following steps separately or all together:

• Increasing data points; the experimental results can be increased with newly tests or mathematical extrapolation methods

• Increasing features (inputs); the number of inputs as engine speed variation, can be increased so that the dependency of outputs to the inputs might be determined better. This would also lead the model to be generalized for all the working points

• Improving the model with hidden layer numbers and changing the evaluation algorithms; the number of hidden layers and the different evaluation algorithms might help better mathematical connections so that better prediction as the complexity of model increases

Since the other mathematical or traditional modelling algorithms have difficulties to converge the real data for the engine performance and emissions regarding its nonlinearity, ANN proves the advantage of being simple, fast and accurate. This study has resulted the ANN algorithms are compatible and successful on the evaluation of Wankel engine performance and with the proper improving both on the experimental setup and ANN modelling algorithm, the results would become an inspiration further studies hence the modelling and control based development of Wankel engines.

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