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

Mehmet Ilter Ozmen1*, Omer Cihan2, Osman Akın Kutlar3, Osman Azmi Ozsoysal4, Cemal Baykara5

0000-0002-0566-63331, 0000-0001-8103-30632, 0000-0002-4795-35413, 0000-0001-6358-61744, 0000-0002-3797-65635

1Istanbul Technical University, Faculty of Naval Architecture and Marine Engineering, Istanbul, 34469, Turkey
2Hakkari University, Engineering Faculty, Department of Mechanical Engineering, Hakkari, 30000, Turkey
3Istanbul Technical University, Faculty of Mechanical Engineering, Istanbul, 34469, Turkey
4Istanbul Technical University, Faculty of Naval Architecture and Marine Engineering, Istanbul, 34469, Turkey
5Istanbul Technical University, Faculty of Mechanical Engineering, Istanbul, 34469, Turkey

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.

* Corresponding author
Mehmet Ilter Ozmen
m.ilterozmen@gmail.com
Adress: Faculty of Naval Architecture and Ocean Engineering, Istanbul Technical University, Istanbul, Turkey
Tel:+902122856516
Fax: +902122126454

Research Article

Manuscript
Received 18.07.2020
Revised 20.08.2020
Accepted 28.08.2020

Doi: 10.30939/ijastech.771165
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 modellings 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
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.

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.
Fig. 2. Schematic view of experimental setup.

Fig. 2. Wankel engine test environment.
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].

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, CO₂ emission, O₂ emission and volumetric efficiency. The neural network structure in terms of training was developed in accordance with the

| 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 cm³        |      |
| Intake port                   | Open (ATDC)    | 12⁰  |
| Intake port                   | Close (ABDC)   | 36⁰  |
| Exhaust port                  | Open (BBDC)    | 50⁰  |
| Exhaust port                  | Close (BTDC)   | 3⁰   |
| Intake Charge Type            | Natural Aspiration |      |

Fig. 4. Neural network architecture.
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:

\[ R^2 = 1 - \frac{\sum_{i=1}^{N} (y_i - y^k)^2}{\sum_{i=1}^{N} (y_i - \bar{y})^2} \]  

(1)

Where \( y_i \) is target and \( y^k \) 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, CO2, O2 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.](image)
ANN’s estimation values of power, NO, CO, CO₂, O₂ 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 CO₂ emission, 0.88795 for the NO emission, 0.79686 for the O₂ 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.

References

[1] Cihan, O. (2017). Wankel motoru ve çevrime atlatma sisteminin deneySEL ve sayisal olarak incelenmesi. Doktora Tezi, Istanbul Teknik Universitesi, Fen Bilimleri Enstitüsü, Türkiye.

[2] Kutlar, A. and Malkaz, F. (2019). Two-stroke Wankel type rotary engine: a new approach for higher power density energies. Energies, 12, 1-22.

[3] Malkaz, F. (2011). Iki zamanlı Wankel tipi döner pistolu motorun analizi. Yüksek Lisans tezi, İstanbul Teknik Üniversitesi, Fen Bilimleri Enstitüsü, Türkiye.

[4] Yamamoto, K. (1981). Rotary engine. Toyo Kogyo Co., Ltd., Hiroshima.

[5] Cihan, O., Dogan, H.E., Kutlar, O.A., Demirci, A. and Javadzadehkalhkar, M. (2020). Evaluation of heat release and combustion analysis in spark ignition Wankel and reciprocating engine. Fuel, 261, 1-10.

[6] Warner, M. (2009). Street rotary. Penguin Group, New York.

[7] Ozmen, M. L., (2015). Tek rotorlu Wankel motorunun ateşleme ve pişikürtme unütelerinin (kontrol ünitesinin) tasarımı, imalati ve bilgisayar arayüzü ile kontrolu. Yüksek Lisans tezi, İstanbul Teknik Üniversitesi, Fen Bilimleri Enstitüsü, Türkiye.

[8] Ozener, O., Yusksek, L. and Ozkan, M. (2013). Artificial neural network approach to predicting engine-out emissions and performance parameters of a turbo charged diesel engine. Thermal Science, 17, 153-166.

[9] Ko, E. and Park, J. (2019). Diesel mean value engine modeling based on thermodynamic cycle simulation using artificial neural network. Energies, 12, 1-17.

[10] Mohd Noor, C.W., Mamat, R. and Ahmed, A.N. (2017). Comparative study of artificial neural network and mathematical model on marine diesel engine optimization of the NOx emissions and performance parameters of a turbo charged diesel engine. Energies, 10, 1917-1930.

[11] Sinaga, N. and Syahrrullah, L.O.I. (2016). Optimization and prediction of motorcycle injection system performance with feed-forward back-propagation method Artificial Neural Network. American Journal of Engineering and Applied Sciences, 9, 222-235.

[12] Turkson, R.F., Yan, J., Ali, M.K.A. and Hu, J. (2016). Artificial neural network applications in the calibration of spark-ignition engines: An overview. Engineering Science and Technology, an International Journal, 19, 1346-1359.

[13] Oguz, H., Saritas, I. and Baydan, H.E. (2010). Prediction of marine diesel engine performance using artificial neural network model. Journal of Mechanical Engineering and Sciences, 10, 1917-1930.

[14] Yusaf, T.F., Butsworth, D.R., Saleh, K.H., Yousif, B.F. (2010). CNG-diesel engine performance and exhaust emission analysis with the aid of artificial neural network. Applied Energy, 87, 1661-1669.

[15] He, Y. and Rutland, C.J. (2004). Application of artificial neural networks in engine modeling. International Journal of Engine Research, 5, 281-296.

[16] Zhou, H., Cen, K. and Fan, J. (2004). Modeling and optimization of the NOx emission characteristics of a tangentially fired boiler with artificial neural networks. Energy, 29, 167-183.

[17] Mohd Noor, C.W., Mamat, R. and Ahmed, A.N. (2017). Comparative study of artificial neural network and mathematical model on marine diesel engine performance prediction, International Journal of Innovative Computing, Information and Control, 14, 959-969.
[18] Shivakumar., Pai, P.S. and Rao, B.R.S. (2011). Artificial neural network based prediction of performance and emission characteristics of a variable compression ratio CI engine using WCO as a biodiesel at different injection timings. *Applied Energy*, 88, 2344-2354.

[19] URL 1: PRESS EU (2018). Mazda rotary engine to return as EV range-extender. Mazda Press EU. https://www.mazda-press.com/eu/news/2018/mazda-rotary-engine-to-return-as-ev-range-extender/, Leverkusen, last accessed: 03.06.2020

[20] Kubat, M. (2017). *An introduction to machine learning*. Springer, Florida.

[21] Aggarwal, C. (2018). *Neural network and deep learning*, Springer, New York.

[22] Celik, V. and Arcaklioglu, E. (2005). Performance maps of a diesel engine. *Applied Energy*, 81, 247-259.

[23] Haykin, S. (1999). *Neural networks: a comprehensive foundation*. Macmillan, New York.

[24] Abraham, A. (2011). *Artificial Neural Networks*. John Wiley & Sons, Ltd., Oklohoma.

[25] Gavin, H. P. (2019). *The Levenberg-Marquardt algorithm for nonlinear least squares curve-fitting problems*. Department of Civil and Environmental Engineering, Duke University.