Artificial neural network and fuzzy expert system comparison for prediction of performance and emission parameters on a gasoline engine

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1. Introduction

Engine tests are being done by automotive manufacturers and researchers for the aims of determining engine performance values, putting forward effects of engine modifications versus engine performance and determining variations that are brought about when alternative fuels are used. As the results of the experiments (EXP) and researches that go on hundreds of years on the engine, big advances have been recorded. Not only these experiments are expensive, time consuming and costly but also cause negative conditions for human health, environment pollution and labour force (Tasdemir, 2004).

Computers are used in a wide variety of fields in automotive sector such as diagnosing failure and designing of vehicles, obtaining high performance, reliable and safe running from vehicles. Artificial intelligence (AI) systems are widely accepted as a technology offering an alternative way to tackle complex and ill-defined problems. The usage of artificial neural networks (ANN), genetic algorithm (GA) and fuzzy logic (FL) are increasing a rapid way with the usage of computers. It is possible to remove disadvantages in the field of determination of the characteristics of engine performance and emission where these characters are complex and uncertain with an intelligence system designed by assist of an expert (Altrock & Krause, 1994; Guillemin, 1994; Gusikhin, Rychtyckyj, & Filev, 2007; Sayin, Ertunc, Hosoz, Kilicaslan, & Canakci, 2007; Sozen, Arcaklioglu, Erisen, & Akçayol, 2004; Yücesu, Sozen, Topgül, & Arcaklioglu, 2007).

In the experimental studies, some of the operating points of the system have been investigated. For this type of work, experts and special equipment are needed. It also requires too much time and high cost. ANNs and FESs have been used to solve nonlinear and complex problems that are not exactly modeled mathematically. ANNs and FESs eliminate the limitations of the classical approaches by extracting the desired information using the input data. Applying ANN to a system needs sufficient input and output data instead of a mathematical equation. Furthermore, it can continuously re-train for new data during the operation, thus it can adapt to changes in the system. Also, ANNs can be used to deal with the problems with incomplete and imprecise input data. A well trained ANN can be used as a predictive model for a specific application. Nowadays, ANNs and FESs can be applied to problems that do not have algorithmic solutions or algorithmic solutions that are too complex to be found. To overcome this problem, these systems use the samples to obtain the models of such systems. Their ability to learn by example makes ANNs very flexible and powerful. Therefore, these systems have been intensively used for solving regression and classification problems in many fields. ANNs and FES are used to solve a wide variety of problems in science and engineering, particularly for some areas where the conventional modelling methods fail. Recently, these systems have been widely

Keywords:
Fuzzy expert system
Artificial neural network
Engine performance
Engine emission

Abstract

This study is deals with artificial neural network (ANN) and fuzzy expert system (FES) modelling of a gasoline engine to predict engine power, torque, specific fuel consumption and hydrocarbon emission. In this study, experimental data, which were obtained from experimental studies in a laboratory environment, have been used. Using some of the experimental data for training and testing an ANN for the engine was developed. Also the FES has been developed and realized. In this systems output parameters power, torque, specific fuel consumption and hydrocarbon emission have been determined using input parameters intake valve opening advance and engine speed. When experimental data and results obtained from ANN and FES were compared by t-test in SPSS and regression analysis in Matlab, it was determined that both groups of data are consistent with each other for p > 0.05 confidence interval and differences were statistically not significant. As a result, it has been shown that developed ANN and FES can be used reliably in automotive industry and engineering instead of experimental work.

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used in the areas that require computational techniques, such as pattern recognition, robotics, prediction, medicine, power systems, optimization, manufacturing, optical character recognition, predicting outcomes, problem classification, engineering fields, and social/psychological sciences (Akçayol, Çınar, Bülbül, & Kılıçarslan, 2004; Dincer, Tasdemir, Baskaya, & Uysal, 2008; Dincer, Tasdemir, Baskaya, Üçgül, & Uysal (2008); Kafkas, Karatas, Sozen, Arcaklioglu, & Saritas, 2007; Kalogirou, 2003).

There have been many investigations with ANN and FES. Some are briefly mentioned below. Diesel engine control design (Hafner, Schüler, Nelles, & Isermann, 2000), an analysis for effect of cetane number on exhaust emissions from engine (Yuanwang, Melin, Dong, & Xiaobei, 2002), performance maps of a diesel engine (Çelik & Arcaklioglu, 2005), engine optimization of efficiency and NOx emission (Keskin, 2004), specification of automotive equipments using LEDs (Ortega & Silva, 2005), fuzzy diagnosis and advice system for optimization of emissions and fuel consumption (Kilagiz, Barana, Yildiz, & Cetin, 2005), analysis of an automobile air conditioning system (Hosoz & Ertunc, 2006), fault diagnosis in a scooter (Wu, Wang, & Bai, 2007). ANN approach on automobile-pricing (Karlik and Işeri, 2007), a crude oil distillation column with the neural networks model (Motlaghi, Jalali, & Ahmadabadi, 2007), engine fault diagnosis (Wu & Liu, 2007), mathematical and experimental analysis of spark ignition engine performance used ethanol-gasoline blend fuel (Yücesu et al., 2007), performance and exhaust emissions of a gasoline engine (Sayin et al., 2007), a fuzzy logic approach to forecast energy consumption change in a manufacturing system (Lau, Cheng, Lee, & Ho, 2008), are some examples there ANN is used.

The purpose of this article deals separately with ANN and FES modelling of a gasoline engine to predict engine power, engine torque, specific fuel consumption, and hydrocarbon emission of the engine. To acquire data for training and testing the proposed ANN and FES a single-cylinder, four-stroke test engine was performed with gasoline having various valve timing of engine (0°, 10°, 20° and 30°), and operated at different engine speeds (1200, 1400, 1600, 1800, 2000, 2200, 2400, 2600, 2800, 3000, 3200, 3400 rpm) and full load. In the modelling, experimental data, which were obtained from experimental studies in a laboratory environment, have been used.

2. Experimental study and apparatus

The experimental study was conducted on a single cylinder, four-stroke spark ignition engine called as Briggs and Stratton Vanguard trade mark. The general specifications of the engine are shown in Table 1.

![Fig. 1. Schematic view of the test equipments.](image)

A Cussons P8160 brand electrical dynamometer and Sun MGA-1200 exhaust gas analyzer were used for the tests. The schematic view of the test equipments is shown in Fig. 1.

According to the original valve timing of the engine, intake valve timing has been changed from 10° crankshaft angle (CA) advance to 30° CA advance for 3 timings value at 10° CA intervals. A special camshaft has been produced for the experiments and cam profiles have not been changed. Experiments have been performed at eight different engine speeds, from 1200 rpm to 3400 rpm at 200 rpm intervals at wide open throttle (WOT).

In this study, the data (Çınar & Salman, 1998) obtained from experiments on Briggs and Stratton Vanguard trade mark single cylinder, 182 cc swept volume, four-stroke, spark ignition engine is used (Tasdemir, 2004). The reason for choosing this engine is to have the ability of comparing data obtained from ANN-FES and experiment that were previously done on this engine and recorded to the literature.

3. The basis of artificial neural network and designed system

ANN is a massive parallel-distributed information processing system that has certain performance characteristics resembling biological neural networks of the human brain. ANN has been developed as a generalization of mathematical models of human cognition and neural biology. An ANN model can accommodate multiple input variables to predict multiple output variables. The

![Fig. 2. Proposed ANN for prediction of gasoline engine performance and emission parameters.](image)
available data set is partitioned into two parts, one corresponding to training and the other corresponding to validation of the model. The purpose of training is to determine the set of connection weights and nodal thresholds that cause the ANN to estimate outputs that are sufficiently close to target values. This fraction of the complete data to be employed for training should contain sufficient patterns so that the network can mimic the underlying relationship between input and output variables adequately (Abbassi & Bahar, 2005; Dincer et al., 2008; Satish & Setty, 2005).

They can learn from examples, are fault tolerant in the sense that they are able to handle noisy and incomplete data, are able to deal with non-linear problems, and once trained can perform prediction and generalization at high speed. The prediction by a well-trained ANN is normally much faster than the conventional simulation programs or mathematical models as no lengthy iterative calculations are needed to solve differential equations using numerical methods (Kafkas et al., 2007).

There are many types of ANN architectures in the literature; however, a back-propagation multi-layer feed-forward network (MLN) is the most widely used for prediction and in engineering applications. A MLN typically has an input layer, an output layer, and one or more hidden layers (Akçayol et al., 2004; Şencan, 2006).

The training process in the MLN involves presenting a set of examples (input patterns) with known outputs (target output). The system adjusts the weights of the internal connections to minimize errors between the network output and target output. Each variable is normalized within the range of 0–1 for ANN modelling. Since the transfer functions generally modulate (Eq. (1)) the output to values between 0 and 1 (Ayata, Čavuşoğlu, & Arcaklıoglu, 2006; Islamoğlu & Kurt, 2004)

\[ S_N = \frac{S - S_{\min}}{S_{\max} - S_{\min}}, \]  

where \( S_N \) is the normalized value of a variable \( S \) (real value in a parameter), \( S_{\max} \) and \( S_{\min} \) are the maximum and minimum values of \( S \), respectively.

The training process continues until the network output matches the target, i.e. the desired output. The calculated difference between these outputs and target outputs is called “error”. The error between the network output and the desired output is minimized by modifying the weights. When the error falls below a determined value, or the maximum number of epochs is exceeded, the training process is terminated. Then, this trained network can be used for simulating the system outputs for the inputs that have not been introduced before (Hosoz & Ertunc, 2006; Rakesh, Kaushikb, & Gargb, 2006; Şencan, 2006).

A personal computer and Matlab 7 (licensed to Saritas) were used as ANN software development material for this study to predict of performance and emission parameters on a gasoline engine.

The ANN structure is three layers namely, inputs, outputs, and hidden layer. The input layer consists of two neurons; the output layer consists of four neurons, and the one hidden layer. Engine speed (n) and intake valve opening advance were taken as the input parameters and the output parameters were taken as engine power (Pe), torque (Me), specific fuel consumption (be) and hydrocarbon (HC) for which experiments were conducted in this study (see Fig. 2).

The ANN developed according to these parameters are shown in Fig. 3. The back-propagation learning algorithm has been used in feed forward single hidden layers. The back-propagation algorithm has been implemented to calculate errors and adjust weights of the hidden layer neurons. Hyperbolic Tangent–Sigmoid (tansig)

![Fig. 3. The present developed model of ANN.](image)

![Fig. 4. Variation of the mean square error with training and test epoch.](image)

![Fig. 5. Structure of developed FES with fuzzification and defuzzification.](image)
was developed by using the approach (Eq. (3)).

\[ \text{MSE}_{\%} = \frac{1}{n} \sum_{i=1}^{n} (d_i - O_i)^2. \] (4)

Here, \( d_i \) is targeted or real value, \( O_i \) is network output or predicted value, and \( n \) is the output data number.

4. Fuzzy expert system and developed system

Fuzzy logic (FL) is a mathematical discipline that we use every day and helps us to reach the structure in which we interpret

<table>
<thead>
<tr>
<th>Number of rule</th>
<th>( n(x) )</th>
<th>Advance (( y ))</th>
<th>Pe (( k ))</th>
<th>Me (( l ))</th>
<th>Be (( m ))</th>
<th>HC (( r ))</th>
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<tbody>
<tr>
<td>1</td>
<td>If ( L_2 ) and ( L_3 ) then ( L_2 ) ( L_1 ) ( H_4 ) ( H_5 )</td>
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<td>If ( L_2 ) and ( L_4 ) then ( L_3 ) ( L_5 ) ( H_2 ) ( H_5 )</td>
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<td>3</td>
<td>If ( L_2 ) and ( M_2 ) then ( L_3 ) ( M_2 ) ( M_3 ) ( H_3 )</td>
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<td>4</td>
<td>If ( L_2 ) and ( H_2 ) then ( L_3 ) ( M_3 ) ( H_1 ) ( H_3 )</td>
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<td>25</td>
<td>If ( M_3 ) and ( L_3 ) then ( M_3 ) ( H_3 ) ( L_2 ) ( L_4 )</td>
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<td>26</td>
<td>If ( M_3 ) and ( L_4 ) then ( H_2 ) ( H_5 ) ( L_2 ) ( L_4 )</td>
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<td>27</td>
<td>If ( M_3 ) and ( M_2 ) then ( H_2 ) ( H_5 ) ( L_2 ) ( H_3 )</td>
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<td>28</td>
<td>If ( M_3 ) and ( H_2 ) then ( M_3 ) ( H_2 ) ( L_3 ) ( L_3 )</td>
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<td>45</td>
<td>If ( H_4 ) and ( L_3 ) then ( H_4 ) ( H_1 ) ( L_3 ) ( M_1 )</td>
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<td>46</td>
<td>If ( H_4 ) and ( L_4 ) then ( H_2 ) ( L_5 ) ( L_5 ) ( H_1 )</td>
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<td>47</td>
<td>If ( H_4 ) and ( M_2 ) then ( H_2 ) ( L_5 ) ( M_1 ) ( H_1 )</td>
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<td>48</td>
<td>If ( H_4 ) and ( H_2 ) then ( H_2 ) ( L_2 ) ( M_2 ) ( H_1 )</td>
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| Fuzzy membership functions for two input variables \( n(a) \), advance (b) and four output variables Pe (c), Me (d), Be (e) and HC (f).}
our own behaviours. FES is an expert system that uses a collection of fuzzy rules, instead of Boolean logic, to reason about data (Liao, 2005). Unlike the classical Boolean set allowing only 0 or 1 value, the fuzzy set is a set with a smooth boundary allowing partial membership. FESs are developed using the method of FL, which deals with uncertainty (Kilagiz et al., 2005; Liao, 2005; Lee, Howlett, & Walters, 2004).

As it is seen in Fig. 5, in FES model the input and output values of the system are crisp values. By fuzzification these crisp input values, its fuzzy membership values and degrees are obtained. In the inference mechanism fuzzy results are inferred from the memberships of fuzzy sets with the aid of knowledge base. In the inference subprocess, the truth value for the premise of each rule is computed, and applied to the conclusion part of each rule. The knowledge base is built on a collection of fuzzy IF-THEN rules. The human expert should introduce these rules and they have to be analyzed again whenever there are new objects to distinguish. Many shapes of the membership function are possible (e.g., triangular, gaussian, trapezoidal shapes), each will provide a different meaning for the linguistic variable. Membership function is determined by experts (Dincer et al., 2008; Kilagiz et al., 2005; Lee et al., 2004; Liao, 2005; Nguyen, Prasad, Walker, & Walker, 2003). Here, the fuzzy output values which are also obtained by using rule-base are sending to the defuzzification unit, and from this unit the final

Fig. 7. Comparison of change graphics of Pe, Me, be and HC values with respect to engine speed values for different advantages.
crisp values are obtained as output (Saritas, Ozkan, Allahverdi, & Argindogan, 2009).

Since the most important effects during the determination of engine performance and emission parameters are engine speed \((n)\) \((x - \text{rpm})\) and intake valve opening advance change \((y^-)\) and they also affect directly the output variables, they are accepted as input parameters of the developed system in this study. Output parameters of the developed FES system have been determined as engine power \((P_e)\) \((k - \text{kw})\), torque \((M_e)\) \((l - \text{Nm})\), specific fuel consumption \((b_e)\) \((m - \text{g/kWh})\) and hydrocarbon \((H)\) \((t - \text{ppm})\) emission parameter. Thus, a FES with two inputs, four outputs has been designed. While choosing of these parameters, an expert view has been taken into consideration.

Input and output crisp numerical data have been fuzzified with human expert and converted into linguistic variables such as extreme low \((L1)\), lowest \((L2)\), lower \((L3)\), low \((L4)\), almost low \((L5)\), under medium \((M1)\), medium \((M2)\), over medium \((M3)\), upper medium \((M4)\), almost high \((H1)\), high \((H2)\), higher \((H3)\), highest \((H4)\), extreme high \((H5)\) as shown in Table 2. Range of values of these linguistic expressions can be determined and expressed as formulas via meeting with expert.

As can be seen from Table 2, system knowledge base has been constituted from 48 fuzzy rules. For example, rules 26 from Table 2 can be explained as follow. If engine speed is over medium and intake valve opening advance is low, then engine power is high, engine torque is extreme high, specific fuel consumption is lowest
and hydrocarbon is low. The structure of the developing a FES consisting of a fuzzification, a knowledge base (rule base), fuzzy inference engine and defuzzification is shown in Fig. 5.

Linguistic expression of Advance input variable advance (let $y$) have been determined as $L_3$, $L_4$, $M_2$, $H_2$ with the help of an expert and triangular membership functions are determined as follow. Here, $\mu_{\text{advance}}(y)$ is the membership degree of the advance and $y$ is a member of the advance fuzzy set. Sets have been formed for other parameters in similar way and here only the results are presented.

$$\mu_{L_3}(y) = \begin{cases} 0, & 0 \leq y \leq 10 \\ \frac{10-y}{10}, & y \geq 20 \end{cases}$$

$$\mu_{L_4}(y) = \begin{cases} 0, & y \leq 0 \\ \frac{y}{10}, & 0 < y < 10 \\ \frac{20-y}{10}, & 10 < y < 20 \\ 0, & y \geq 20 \end{cases}$$

$$\mu_{M_2}(y) = \begin{cases} 0, & y \leq 10 \\ \frac{y-10}{10}, & 10 < y < 20 \\ 0, & y \geq 30 \end{cases}$$

$$\mu_{H_2}(y) = \begin{cases} 0, & y \leq 10 \\ \frac{y-10}{10}, & 20 < y < 30 \\ 0, & y \geq 30 \end{cases}$$

The fuzzy sets for advance are formed from the Eqs. (6)–(8):

$\mu_{L_3}(\text{Advance}) = \{1/0 + 0.5/5+ \ldots +0.3/7 + 0/10\}$,

$\mu_{L_4}(\text{Advance}) = \{0/0 + 0.5/5+ 1/10+ \ldots +0.5/15 + 0/20\}$,

$\mu_{M_2}(\text{Advance}) = \{0/0 + 0.3/3+ \ldots +0.5/25 + 1/30 + 0/35\}$,

$\mu_{H_2}(\text{Advance}) = \{0/20 + 0.3/23+ \ldots +0.5/25 + 1/30 + 0/35\}$.

Membership functions of the used parameters have been obtained from Eqs. (6)–(8) and their graphics are shown in Fig. 6.

When the input data is entered to the system, one or more than one rule can be fired. In this case, inference mechanism determines what the output is going to be. Mamdani approach has been used as fuzzy inference mechanism because of being simple and easy to use. It has been used to determine degree of truth for each rule when Mamdani max–min inference is applied. For each rule, degree of truth is calculated and these degree of truth are used to calculate $P_e$, $M_e$, $B_e$ and $HC$.

At the defuzzification process, the exact expression is obtained with “centroid” method according to a validity degree by using formula given in Eq. (9)

$$Y^* = \frac{\int_{y} y \mu_{\dot{y}}(y) \, dy}{\int_{y} \mu_{\dot{y}}(y) \, dy}$$

This kind of defuzzification determines $y^*$ point as the middle of area where membership function of $B$ and cover field intersect. Here $\int_{y} -$ is the traditional integral symbol.

In similar way, results have been obtained for various engine speed and advance from FES.

5. Results and discussion

In this study, performance and emission parameters of a gasoline engine are estimated based on engine speed, independently at 0°, 10°, 20°, 30° advantages by using the experimental data for both ANN and FES methods. The experimentally obtained and
estimated values are compared graphically. In Fig. 7, it can be seen that the data obtained from developed system and experimental data are fitting and close.

Realized system results and experimental data are evaluated by using regression analysis. The regression graphic between the estimated ANN–FES values and experimental measurement values for engine performance and emission are shown in Figs. 8 and 9. As the correlation coefficients get closer to 1, estimation accuracy increases. In the case presented in this study, the correlation coefficients obtained are very close to 1, which indicates a perfect match between ANN–FES estimation values and experimental measurement values (Table 3).

As seen in Figs. 8 and 9, the estimation results and experimental results are in a good agreement. The deviation between experimental and estimated results is very small and negligible for engine performance and emission parameters. In other words, designed ANN-FES and ANN represent the realized experiment values. There were no meaningful difference between the experimental results and ANN and FES results (Table 3).

Engine performance and emission parameters experimental-ANN (Table 4) and experimental-FES (Table 5) results are applied on statistical t-test resulting in the 95% confidence interval. Performed independent t-test for ANN training and test data analyzed one by one with experimental data. The results of these analyses are 0.937 for Pe, 0.966 for Me, 0.994 for be, 0.998 for HC in training data, 0.836 for Pe, 0.993 for Me, 0.935 for be, 0.901 for HC values are obtained in the testing data (p > 0.05).

According to results of performed t-tests, there is no difference between data obtained form ANN-FES and experiments significantly but a great relationship as statistically and differences were statistically not significant. Also designed systems successfully model the system on which experiments are performed. Moreover, the engine speed and advantage values which are not carried out in the experiment are applied to FES and ANN to obtain intermediate values. First, advantages (0°, 10°, 20°, 30°) is fixed and engine speed is changed (1300, 1500, 1700, 1900, 2100, 2300, 2500, 2700, 2900, 3100, 3300 rpm) and Pe, Me, be and HC results are obtained (Fig. 10a). Then, engine speed is fixed and Pe, Me be and HC are calculated for the intermediate advantage values (5°, 15°, 25°) (Fig. 10b).

Unperformed experiments are predicted with developed systems for engine performance and emission parameters such as Pe, Me, be, and HC. When the engine is examined for engine performance and emission parameters, it is seen that the Pe, Me, be, and HC predicted with developed systems give similar values to experimental values. When Pe, Me, be, and HC predicted with developed systems are compared with the results from the experimental study, it can be found to be better results and when compared with the results of experimental study pertaining to Pe, Me, be, and HC (Fig. 10). As seen from the graphics, intermediate values which are not performed on the experiment set, but obtained from the developed system are fitting with the experimental results.

Table 3
<table>
<thead>
<tr>
<th></th>
<th>Pe</th>
<th>Me</th>
<th>be</th>
<th>HC</th>
</tr>
</thead>
<tbody>
<tr>
<td>EXP.-FES</td>
<td>0.98248</td>
<td>0.99304</td>
<td>0.99103</td>
<td>0.99561</td>
</tr>
<tr>
<td>EXP.-ANN</td>
<td>0.97286</td>
<td>0.95381</td>
<td>0.98594</td>
<td>0.98647</td>
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</table>

Fig. 9. Comparison of experimentally results and FES-predicted values of engine performance and emission parameters.
When the Pe, Me, be and HC values examined together, FES gives more close results to experimental values than the ANN. This means that FES estimates the engine performance and emission parameters better compared to ANN. By using the all values, the regression analyses are resulted 0.99938 and 0.99965 for experiment-ANN and experiment-FES respectively (Fig. 11).

![Graphs showing predicted results of FES and ANN](image-url)

**Fig. 10.** Predicted results of FES and ANN that unperformed experiments, according to engine speed and advance values.
Fig. 10 (continued)

b. Engine Speed is constant
It is also shown that FES estimates better results than ANN by using mean relative percentage error (MRE-Eq. (10)), (Sayin et al., 2007) evaluation. Mean absolute percentage accuracies are 0.9743 for FES and 0.9622 for ANN.

\[
\text{MRE} = \frac{1}{n} \sum_{i=1}^{n} \left[ \frac{|d_i - O_i|}{d_i} \right] \times 100.
\]

Here, \(d_i\) is targeted or real value, \(O_i\) is network output or predicted value, and \(n\) is the output data number.

Comparisons of the ANN, FES predictions and the experimental results demonstrate that engines using gasoline with various valve timing can accurately be modelled using ANN and FES.

The usage of ANN and FES may be highly recommended to predict the engine’s performance and emissions instead of having to undertake complex and time-consuming experimental studies.

6. Conclusions

In this study, the ANN and FES approach has been applied comparatively to a gasoline engine for predicting engine power, torque, specific fuel consumption, and emission of hydrocarbon. The performance and exhaust emissions values of a gasoline engine fuelled with the different advances are predicted using ANN and FES for different engine speeds at full load conditions.

The biggest advantages of the ANN and FES compared to classical methods are speed of calculations, simplicity, and capacity to learn from examples and also do not require more experimental study. So, engineering effort can be reduced in the areas. Especially this study is considered to be helpful in predicting the residual stress. Results from this model will allow to improve determination of the engine torque and specific fuel consumption and to understand in a short time the behaviour of the experimental results. The model does not need any preliminary assumptions on the underlying mechanisms in the modelled process. As a result, it is seen that generally ANN and FES can be used and applied in complex and uncertain fields such as the determine engine performance and emission parameters.

The study performed for only one engine can be improved by using different engines. With these models, unperformed advantages and engine speed values can be calculated successfully. Moreover, new systems and models which may obtain better results can be developed by using hybrid artificial intelligence techniques. Optimum engine productions can be realized by using the developed models in the production phase.

This study can be a guide for future studies that will use different advance and turn that are determined by an expert. In this way, better results may be obtained for different inputs. This study can also be used as a guide for designing ANN and FES for different engine types.

Moreover, quite close results to engine test results can be obtained by either increasing number of input, output parameters and linguistic variables or including other artificial intelligence techniques such as genetics algorithms, and data mining.

Consequently, with the use of ANN and FES, the performance and exhaust emissions of the internal combustion engines can easily be determined by performing only a limited number of tests instead of a detailed experimental study. The experimental data and the developed system analyses showed that ANN and FES reduce disadvantages such as time, material and economical losses to a minimum, thus saving both engineering effort and funds.

Acknowledgements

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References


