ANN Technique to Predict Performances of Diesel Engine Runs by Butanol-Diesel Blends

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Abstract

Performance of a diesel engine running under butanol-diesel blends one of important cases to evaluate the variance in the engine performance due to the fuel type change. Many efforts exerted in this field. Artificial neural network (ANN) model one of modern technique is used to predict the engine performance. ANN using a multi layer feed forward back propagation learning algorithm is developed to evaluate diesel engine performance. The brake efficiency, fuel consumption and exhaust temperature are predicted. The data required for training of ANN model are collected from experimental tests carried out on multi cylinder diesel engine. More than forty different architectures are tested for obtaining best fitting model. Maximum, minimum as well as average percentage errors are calculated for each architecture and R & σ test is carried out to decide upon the best architecture for this model. The training process is set to stop when all errors are below 0.01 for training and below 3% for the validation. The results obtained from trained model are compared with experimental data of engine performance. The numerical investigation demonstrated that the ANN model is the best approach and assessment program for diesel engine performance with only 0.7% absolute average errors. The precise results of the model indicated an excellent and prompting training of ANN model.

Keywords: ANN, Modeling, Diesel engine , Butanol blends, Performance.

الخلاصة

تعتبر دراسه الاداء لمحركات الديزل التي تعمل بخليط من البيوتانول– ديزل واحدة من حالات البحث المهمة. و قد بذلت جهود كبيره في ابحاث و دراسات عمليه و نظريه في هذا المجال. ان تقنيه استخدام الشبكات العصبيه الصناعيه واحدة من الطرق المستخدمه لدراسه وتخمين اداء محركات الديزل التي تعمل بخلائط البيتانول – الديزل. ان الشبكه العصبيه الصناعيه تستخدم مايسمى بخوارزميه التغذيه الاماميه و التقدم الرجعيه. تمثلت خواص الاداء ب الكفاءه المكبحيه و كميه صرف الوقود و درجه حرارة غازات العادم.

تم دراسه اكثر من اربعين تشكيل للموديل موضع البحث. ولكل تشكيل تم حساب معدل الخطا و اعلى خطا و اقل خطا و قد استخدمت الانحرافات المعياريه من الاحصاء لدراسه افضل تشكيل و الذي يعطي اقل خطا و اسرع وصول الى الحل. تم ضبط الخطا في برنامج الموديل ليكون فقط 1% و نسبه الخطا في التعديل و التصويب و3%. لقد اكدت النتائج المستقاه من هذا الموديل كفاءه الشبكات العصبيه الصناعيه في تخمين سلوك الاداء لمحرك يعمل بوقود الديزل و استخدم خليط البيوتانول كوقود نظيف له .

الكلمات المفتاحية :– ANN الذكاء الصناعي ، النمذجة ، المحرك الديزل ، بيوتانول خليط ، الاداء .

Nomenclature

Avg	Average	R	Evaluation factor for average accuracy
I	Counter	Speed	Engine rated speed (rpm)
Load	Engine load by dynamometer (kg)	Σ	Evaluation factor for scatter accuracy
Max.	Maximum	Subscripts	
Min.	Minimum	E	Experimental
N	Number of results in the set of results	P	Predication

1. Introduction

Diesel engines are the main operator for different industrial, commercial, and economical activities. These types of engines are threatened by the depletion of conventional fuel sources and new environmental rules to control their emissions. Specifically bio butanol is one of the promising sustainable fuels from other alcohols. Butanol is produced naturally during the fermentation of carbohydrates. Bio butanol might be produce from the analysis process of organic materials. Experimental and theoretical researches are conducted to investigate the performance diesel engine fuelled by butanol-diesel mixtures as in work of **Gábor *et.al.*, 2007; Hajaba *et.al.*, 2001; Evangelos *et.at.* ,2013 .**

Potential efforts in field of numerical and modeling researches used different techniques and applications to simulate diesel engine performance and/or diesel engine outlet gases constituents analyzing. Modeling using artificial neural network (ANN) is one of these active and promising approaches. One of those efforts represented by **(Anderson and McNeil ,2012).**

The strong points in the ANN represent by modeling complex relations, high ability to solve nonlinear equations, and formulation of equations for variables has no direct relation between each other. i.e dependent parameters gathering in one equation depends on experimental results of actual case as in research of (**Anderson and McNeil , 2012).** ANN is using the learning scenario so for that generate a strong mathematical equation covers and relates all independent variables, each one has weight depends on base of its importance on empirical results. Hence, Artificial neural network (ANN) can be described as the interconnected group of artificial neurons that uses a mathematical model or computational model for information processing based on a connectionist method for computation. This idea given by **(Arvind ,2008).** The study of similarity between the conventional simulation methods and ANN is clarified that ANN attempts many paths to figure out data and to give the correct patterns within that data from being generic non-linear approximator, (**Arvind, 2008).** Many techniques are there predicting the trends of data and artificial intelligence looks as the best solution for predicting engine outlet gas emissions since it does not demand any additional sensor installation (**Kemal and Novruz ,2002; Hafner *et.al.*, 2000)** is demonstrated the using of high speed models such as ANN using for control design of diesel engine. This team has developed (RBFN) a special local linear radial basis function network to help them in building of adequate engine model. On board diagnoses system is adopted to control engine emission as a part of full control optimize control unit, (**Thompson *et.al.*,2011**). The substitute of high coast prototype building by fast and active model to draw the performance atlas of internal combustion engines over a wide range of running conditions. The study contains two approaches show the advantage of model. Mapping the performance of an IC engine over a wide range of operating conditions is a common procedure during development, **(Stevens *et.al.*,1995).** ANN model is built to simulate the controller of engine injection pressure and the opening throttle valve timing for diesel engine, the effects of different injection pressures value and timing of valve throttle openings on the engine performance and emissions by(**Yuanwang *et.al.*,2002).** ANNs can be used in the case of a diesel engine for predicting the exhaust emissions and performance. Another study using neural-networks shows how different composition parameters affect the rate of fuel consumption as in **(Sykes ,1988 ; Haykin ,1994).**

Last but not least, the performance and outlet gas emission of a diesel engine is modeled as a respect to pressure, engine speed and throttle position by **(Sykes ,1988; Haykin ,1994).**

In this numerical investigation work, multi-layer ANN model is built using the feed forward back propagation algorithm and its performance is investigated to predict the performance of multi cylinder diesel engine which is represented by brake efficiency, fuel consumption, and exhaust temperature at various loads and butanol-diesel blends.

2. Experimental Set-Up and Procedures

In the present study, the experimental setup used to gather experimental data consists of two parts: the first part is represented by diesel engine (all technical details are given in table 1). Second part is the measuring system to collect the experimental data in performance form. To measure the engine output torque, electric dynamometer is applied. Load is varied by current regulator. Intake air flow and fuel flow are counted by suitable flow meter. K type thermometer is put to be read the temperature.

Table (1) diesel engine specifications at this research

Make and model	Stride Engine 1.5 E2 DSL
General details	Compression ignition, 4 cylinder and stroke, vertical cylinder, direct injection chamber design.
Bore	73 mm
Stroke	88.9 mm
Clearance volume	17 cm^3
Compression ratio	23:1
Max. power	37hp at 4000 rpm
Max. torque	83.4 Nm at 2250 rpm
Capacity	1489 cm^3
Lubricating oil	SAE 30/SAE 40
Cooling system media	Water

The experimental data is recoded at constant engine speed 4000 rpm with variable load at no load (0 Ampere), half load (1 Ampere), and full load (2 Ampere). The engine fueled by blend of 0%, 5%, 10%, 20%, 30% butanol by volume and 100%, 95%, 90%, 80%, 70% of diesel. The calculated experimental data are tabulated in Table (2).

Table (2) experimental data

Load	**Blend**	**Exhaust Temperature (^oC)**	**Fuel Consumption (g/sec)**	**Brake Thermal Efficiency (%)**
0	0	160	0.21	9.5
1	0	299.22	0.22	12.4
2	0	308.7	0.69	23.0
0	5	162	0.23	9.7
1	5	191.6	0.34	12.6
2	5	309.5	0.69	23.1
0	10	165	0.23	10.2
1	10	185.3	0.36	12.7
2	10	310.4	0.71	23.2
0	20	170	0.23	10.6
1	20	139.4	0.49	12.8
2	20	278.3	0.80	23.4
0	30	172	0.25	11.2
1	30	127.5	0.55	13.0
2	30	281.5	0.81	235.00

3. ANNs Modeling Algorithm Approach

Nowadays, many algorithms are used to initiate the artificial neural network. Among of them, the back propagation learning algorithm is used widely. This algorithm widely used in the applications field. In this work, the algorithm of back propagation learning is modeled to study theoretically engine performance. In such algorithm, Networks have input, output, and hidden layers. The input and output have fixed numbers of cells. Cells in hidden layers are varied. To get the optimum cells number that gives high accuracy and fast network with minimum error. The number of cells in hidden layer is changeable. Normally the increment in hidden layers cells makes the network more artificial, but more slow and vice versa.

By following Haykin research steps (Thompson,2001), the experimental data that took from experimental research is used for training and learning the ANN. The experimental data show how the network parameters are changed, which parameter is more important than other, and how these important parameters effect on each other and on other weak parameters. In this model the thirty five different structure model of ANN are tested to find the best model which contains the minimum hidden layers and then less cells in each single hidden layer. Statistical equations are used to find the average error and calculate the percentage of deviation between the experimental data and model data. Maximum number of cyclic trail is important also. The number of cyclic should be the minimum in comparing with all other trail of network testing and learning. In this investigation the acceptable average error should not increase than 1%. And acceptable error in validation should not exceed more than 3%. The training cycles are limited by 10^6 cycles to avoid the divergent in results. The training of model will stop after reach any one of these essential conditions to its limit. In mean while the learning rate and momentum rate is fixed. These two rates are fixed at that limits to to expedite stable and quicker learning by larger variation in weights so that a larger set of weight values are discovered within bulk of allowing learning cycles. Figure 1 showed the ANN model flow chart. And table 1 gives the main details of ANN model separately for this work.

The first architecture built is 2,3,4 architecture for model. Training conditions are kept as mentioned above, the first architecture with single hidden layer is evaluated. It does pass the error criteria. Subsequently, this scenario is repeated, the numbers of cells in the hidden layers are increased one at a time up to 10. Same scenario is repeated to initiate two hidden layers are estimated and so on.

4. Results and Discussion

By principle of a trial and error, ANN modeling is processed in terms of determining the most suitable architecture for a given system. The R & σ test is one way of ascertaining the best network model. Another faster method is to compare the average or RMS error values. These values can be determined using following equations (1-4) by (Thompson *et.al.*,2011).

$$\mathrm{Error}\% = \frac{|A_e - A_P|}{A_e} \tag{1}$$

$$\mathrm{Error}_{rms} = \sqrt{\sum_{i=1}^{N} \frac{1}{N} \left(\frac{A_e - A_P}{A_e}\right)^2} \tag{2}$$

$$R = \frac{1}{N} \sum_{i=1}^{N} R_i = \frac{1}{N} \sum_{i=1}^{N} \frac{A_e}{A_P} \tag{3}$$

$$\sigma = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (R - R_i)^2} \tag{4}$$

Fig (1) Artificial Neural Network Modeling Approach

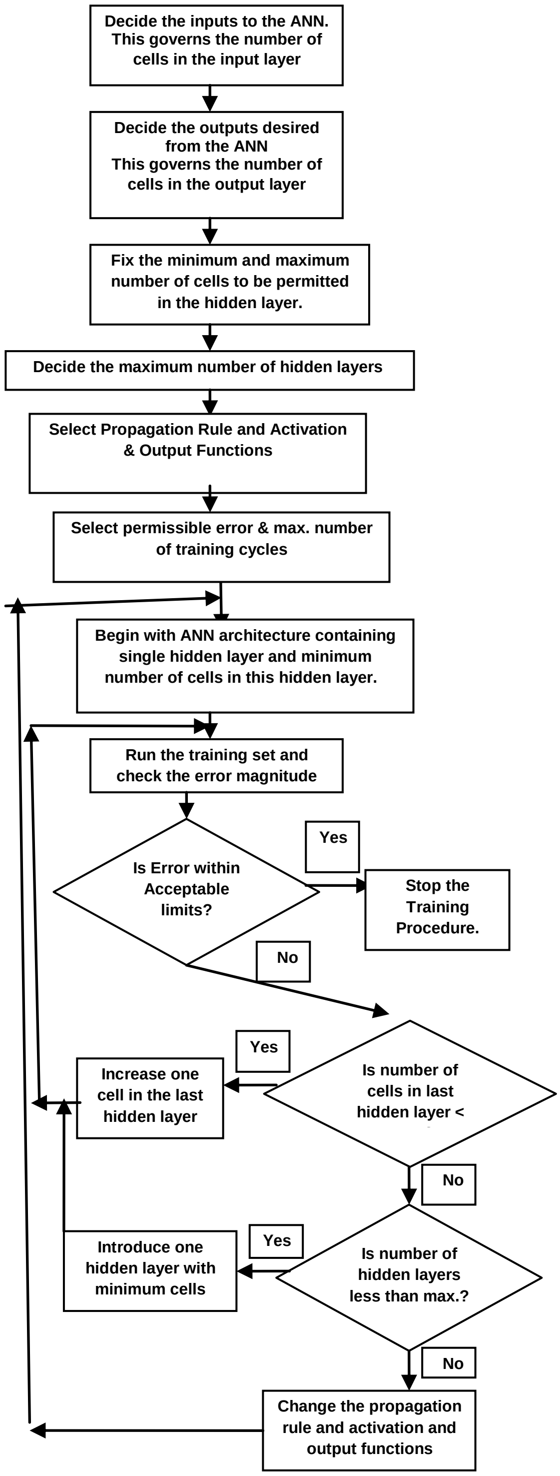

Table (3) ANN Modeling for Diesel Engine Performance

Network type	Feed forward, back propagation
Input of the ANN model	Load, Blend
Number of cells in input layer = number of inputs to the ANN	Two
Output of neural network model	Exhaust Temperature, Fuel Consumption, Brake Thermal Efficiency
Output ANN model parameters	Three
Initial number of hidden layers	One
Max. number of hidden layers	Two
Max. number hidden layers cells	Ten
Activation formula	Logistic formula
Output function	Identity function
Learning rule	Back propagation

Forty network architectures are attempted for training and it is observed that the network architectures having two or three hidden layers with high number of cells could not be trained to meet the error limitations. Nineteen different architectures are tested successfully and the results of training these networks are listed in Table (4). It is observed that the average error, RMS error and σ values are found to be the best for 2,,5,8,3 architecture. The 2,4,7,3 architecture has slightly better values of minimum error, maximum error and R compared to the 2,,5,8,3 architecture. But comparing one to one both these architectures, the slight benefit in minimum error and maximum error is on account of individual data rows and there is a very minor difference in R values between the two architectures. On the other hand, there is a significant difference in the average error and σ values favoring 2,5,8,3 architecture. The number of training cycles required for 2,5,8,3 architecture is also less. Hence, 2,5,8,3 architecture appears better. Hence, the architecture 2,5,8,3 is chosen as the optimum model for this case. The results of the R and σ test for these models are listed in Table (4). Fig. (2) and (3) indicate the 2,5,8,3 architecture and its error propagation during training.

Table (4) ANN Model Training Result and Test Errors

Model	Avg. Error %	Min. Error %	Training error		Training Cycles	Test error	
			Max. Error %	RMS Error		R	σ
2.4.3	1.188222	0.064173	4.66795	0.017234	24836	0.813845	0.0165
2.7.8	0.603584	0.036581	3.675819	0.011668	36881	0.818378	0.0119
2.10.3	2.129971	0.004453	7.263065	0.031088	9518	0.816868	0.0314
2.4.4.3	1.096364	0.145455	4.384411	0.01513	115113	0.814578	0.0154
2.4.7.3	1.103119	0.098592	2.716765	0.013257	5087	0.819109	0.0132
2.4.10.3	1.258401	0.098304	3.634778	0.016587	3265	0.81888	0.0166
2.5.5.3	1.489955	0.185185	5.845881	0.022066	6689	0.814998	0.0228
2.5.8.3	0.711852	0.138538	2.983638	0.010125	4500	0.816187	0.0099
2.5.10.3	1.144117	0.076061	4.571704	0.016548	4610	0.816283	0.0162
2.6.4.3	1.283433	0.098592	4.908566	0.017602	4356	0.81582	0.0172
2.6.6.3	1.284467	0.091881	4.52358	0.017123	4292	0.816708	0.0164
2.6.9.3	0.806931	0.040043	2.646776	0.011505	5817	0.816449	0.0113
2.7.4.3	1.151893	0.01896	5.437921	0.017766	10467	0.81492	0.0172
2.7.8.3	1.31823	0.036061	4.234841	0.01728	4561	0.815799	0.0171
2.7.9.3	1.287957	0.006641	4.66795	0.018411	3624	0.819004	0.0182
2.7.10.3	0.939174	0.024026	5.149182	0.016922	7008	0.815366	0.0166
2.8.4.3	0.771883	0.012522	3.542958	0.012919	151141	0.814675	0.0129
2.8.6.3	1.117729	0.090909	3.224254	0.014545	3920	0.814784	0.0142
2.8.10.3	1.16185	0.11569	4.379211	0.01687	4323	0.816274	0.0167

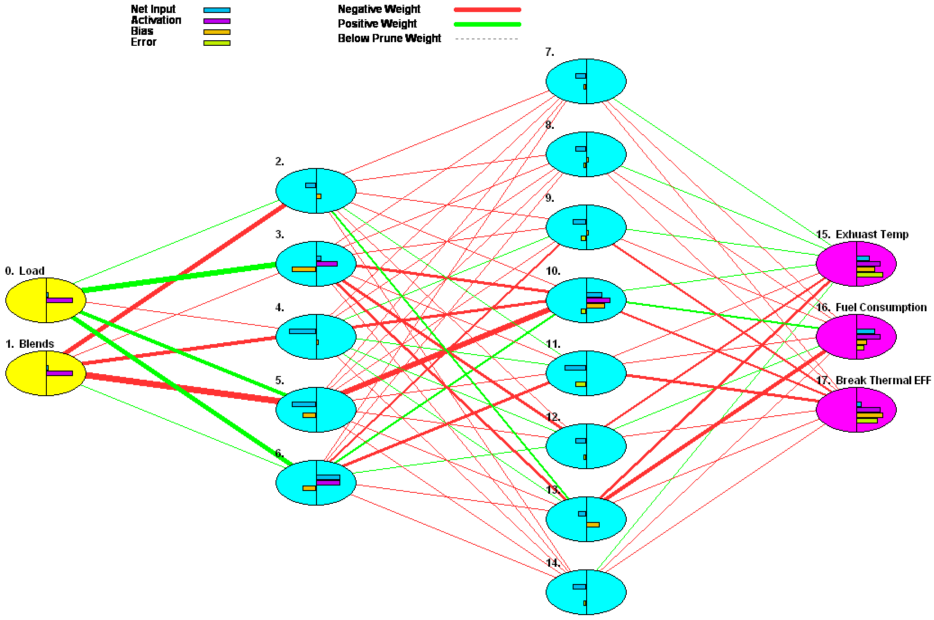

Fig (2) The 2,5,8,3 Architecture Layers for Predicting Engine Performance

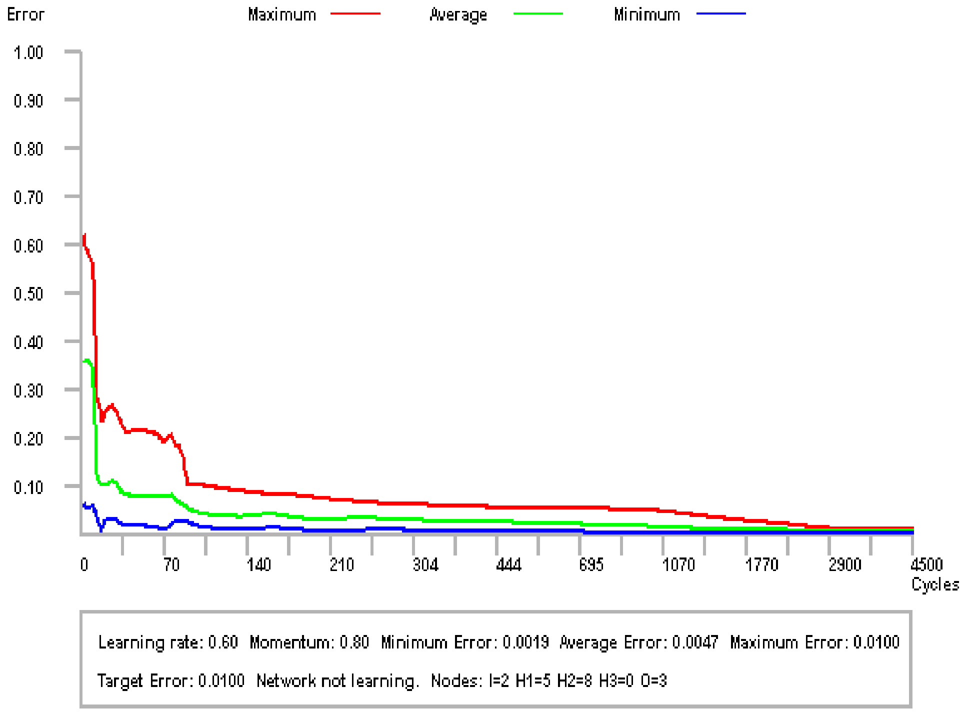

Fig (3) Error Propagation for the 2,5,8,3 Architecture

5. Conclusion

A feed forward back propagation neural network model with a 2,5,8,3 configuration is found most suitable, fast and reliable. The results are in agreement giving less than 0.01% root mean square error compared with those obtained experimentally. This new approach can be considered as an alternative and practical technique to predict the engine performance.

Gábor Nagy *et.al.*, 2007; Hajaba et.al., 2001; Evangelos *et.at.*,2013

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