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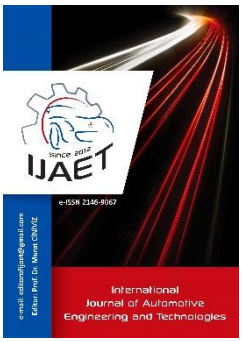

Original Research Article

Determining optimal artificial neural network training method in predicting the performance and emission parameters of a biodiesel-fueled diesel generator

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ABSTRACT

Artificial neural network (ANN) methods were employed and suggested in modeling the emissions and performance of a diesel generator fueled with waste cooking oil derived biodiesel during steady-state operation. These papers are generally built on determining optimal network structure, but the modelling accuracy of an ANN is also highly dependent on employed training method. In modeling, operating conditions and fuel blend ratio were used as the inputs while the performance and emission parameters were the outputs. The modeling results obtained by conventional ANNs that were trained by back propagation (BP) learning algorithm, radial basis function (RBF), and extreme learning machine (ELM) were compared with experimental results and each other. The accuracy of the estimations by ELM was above 95% for all the output parameters except for specific fuel consumption and thermal efficiency. Moreover, ELM performed better than BP and RBF with lower mean relative error (MRE) in case where the emissions were estimated. The ELM provided correlation coefficients of 0.987, 0.950 and 0.996 for unburned hydrocarbons (HCs), nitrogen oxides (NO_x) and smoke opacity (SO), respectively, while for BP, they were 0.973, 0.818, 0.993, and for RBF, 0.975, 0.640 and 0.981. The most suitable training function for each emission and performance parameters of diesel generator was determined based on obtained accuracies.

Keywords: Extreme learning machine; Artificial Neural Network; Radial Basis Function; Back propagation; Biodiesel; Diesel generator; Emissions

1. Introduction

The increasing concerns on global warming and environmental pollution caused by excessive use of fossil fuels, which have limited reserves, have driven the researches to investigate alternative fuels and their efficient use. Biodiesel, which is obtained from oil and fats via transesterification, is considered as diesel fuel surrogate thanks to its emission-reducing potential, its renewability, etc. [1-3]. However, its high nitrogen oxides (NO_x) emissions and production costs are still barriers to its wide use [4]. On the other hand, the use of biofuels is endorsed by the European Commission in the 2009/28/CE directive, and the anticipated target is now to reach 10% of biofuel use by the end of 2020 [5]. Therefore, special devotion has been given to biodiesel use and obliged to use in specified ratios and biodiesel fuels have been reported to reduce diesel emissions except for

NO_x emissions [6-9]. However, for diesel-powered generators run by biodiesel, no consensus has been reported on the changes in emissions likely thanks to the lack of works [10-11]. Numerous experiments should be completed to elucidate the change in emissions of this type of engines, but testing the engine with various fuel-blends under a wide range of working conditions are time-consuming and costly, and this is not an eco-friendly approach. Alternatively, the estimations can be made by machine learning methods, which can estimate the outputs of unknown situations by modeling the physical phenomena in complex systems using experimental results with significantly less engineering effort and high performance [12].

Artificial neural network (ANN), which is one of the most popular machine learning method, known as "parallel distributed processing" or "connectionist model" is based on the findings of biological neurons [12]. Its theory depends on the studies of McCulloch and Pitts in 1943 [13], and it can be expressed as a simple and small sized neuron network that has learning, remembering and deciding with generalization of previous knowledge. ANN requires training for determining optimal weights and biases therefore before modeling a system there must a dataset to describe the system due to its measured inputs and outputs. Recently, ANN techniques have often been used for modeling of biofuel-fueled engines. For instance, Yap and Karri [14] demonstrated the series ANN model as generic virtual power and emission sensors. Kökkülünk et al. [15] estimated the emissions with a very high accuracy by means of the designed ANN structures. Kumar et al. [16] and Patel and Patel [17] developed an ANN model based on a standard back propagation (BP) algorithm to predict the engine responses while Kumar et al. [18] investigated the applicability of radial basis function neural network (RBF), which is a relatively new class of ANNs, and Shi et al. [19] employed RBF for building model of marine diesel-generator. Additionally, Wong et al. employed extreme learning machine (ELM), which was recently introduced [20, 21], in the modeling of biodiesel-engine performance [22, 23].

Hence, it is preferred to build a model to estimate the diesel-powered generator run by biodiesel and diesel-biodiesel blends responses. According to the authors' best knowledge, an extensive study has not been determining the optimal training method to this type of system, yet. Therefore, waste cooking (sunflower) oil derived biodiesel, ultra-low sulphur diesel and their blends (20% and 50% in vol.) were tested in a 3-cylinder diesel engine-powered generator under constant speed and variable load conditions to obtain training data, which were then used to build a model. Afterwards, ANNs, were optimized by determining transfer functions and number of neurons in the hidden layer, and finally, the performance of ELM, BP and RBF based on estimated engine responses, were compared with each other in terms of their accuracy and mean relative error.

In the rest of paper, material and experimental procedure followed for obtaining the training data were explained in Section 2, while the structures of ANN and its learning methods were briefly presented in Section 3. The optimization of the parameters was also studied in Section 4. The modelling results and the comparison of the performance of applied methods were discussed in Section 5. Finally, the concluding notes were presented in Section 6.

2. Material and experimental procedure

The employed dataset was generated from the biodiesel, which was manufactured from transesterification of waste cooking (sunflower) oil that was collected from University cafeteria, with methanol in the presence of an alkali catalyst to use in engine tests. Detailed information about this production processes can be found in Ref. [24]. The reference fuel was an ultra-low Sulphur diesel fuel (ULSD), supplied by local fueling station. Density and kinematic viscosity of biodiesel was found as 884.7 kg/m^3 and 4.7 mm^2/s, respectively, which are higher than those of ULSD, 835 kg/m^3 and 2.8 mm^2/s. The energy content of biodiesel was lower than that of ULSD by about 11%. Tests were carried out in a 3-cylinder and direct-injection diesel engine-powered generator set. It is a type of GEN-SET that represents a large population for energy generation in institutional facilities. Fuel consumption was measured by using an electronic scale and digital chronometer. Emissions were recorded by Capelec Cap 3200

analyzer. Fuels were tested at a constant engine speed of 1500 rpm and at different loads. Each test was repeated three times and the average values were used. Specific-fuel consumption (SFC) and efficiency were calculated by the following equations.

$$SFC = \frac{m_{fuel}\text{x}3600}{Pe}\ (g/kWh) \quad (1)$$

$$Efficiency = \frac{3.6\text{x}10^6}{SFC\text{x}Hu}\ (\%) \quad (2)$$

where $\dot{m}_{fuel}$ is the mass flow rate of the fuel as g/s, *Pe* is the power output in kW, *Hu* is the lower heating value of the fuels in kJ/kg. Only 28 samples for each parameter corresponding to a constant speed, different loads and fuel blends were collected from the experiments [24]. From the viewpoint of machine learning (ML) approaches, 28 points are reflected as a small dataset that leads to the problem of data scarcity. This reduces the accuracy of ML since training is stopped when the error does not decrease anymore or when the error reached to the desired error value. On the other hand, it is reported that the increase in the amount of training data causes a decrease in the generalization error [12]. The model performance depends on the representational power of the dataset and also the number of hidden units (neuron and layer) with the activation function [25]. The change in all the parameters is proportional to the load of the engine and biodiesel content in the fuel, except for smoke opacity (SO) whose values at low-loads were recorded as 0% for blends, leading to decrease the accuracy as "0" values do not give enough knowledge about the characteristics of the system.

3. Modeling of the biodiesel-fueled generator

Artificial neural network (ANN), which is based on the human neural system, have been successfully employed in many purposes [25, 26]. In ANN, many neurons are connected with each other and an ANN is formed based on these connections. ANNs are trained by experiences (training set) and in the training stage, weights and biases are optimized by minimizing training errors. The output of ANN can be calculated by Eq. (3) [27].

$$y = \sum_{j=1}^{m} \beta_{j,k}\, g\left(\sum_{i=1}^{n} w_{i,j} x_i + b_j\right) \quad (3)$$

Here, x_i, y, $w_{i,j}$, $\beta_{j,k}$, b_j, and $g(.)$ represent input, output, weights in the input neurons, weights of output neurons, biases of the neurons in hidden layer, and the activation function, respectively. Furthermore, n, m, and k show number of neurons in the input, hidden, and output layers, respectively [12].

ELM- ELM is a kind of learning methods in ANN that has a number of attractive features such as an extremely fast train stage and a high generalization performance [28] and train speed on account of the fact that the output weights can be analytically determined by Moore–Penrose generalized inverse method when the input weights, hidden layer and its biases are randomly assigned. But it has two limitations, which are the employed transfer function is infinitely differentiable and also, the number of neurons in the hidden layer is less than the number of samples in the training dataset. ELM network architecture is shown in Figure 1.

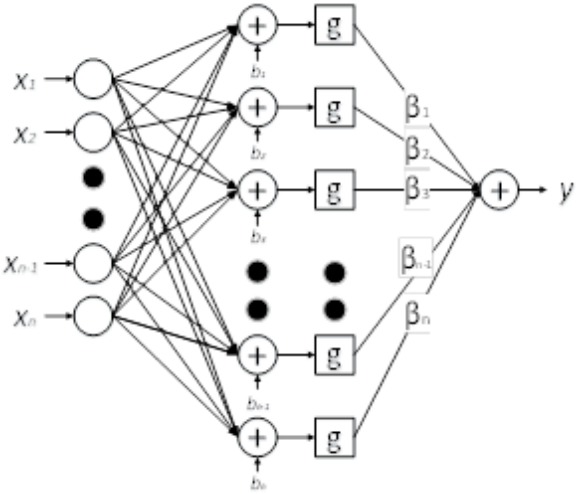

Figure 1. A single hidden layer neural network

The outputs can be calculated by using Eq. (4) [20, 21] and can be rewritten as:

$$H\beta = y \quad (4)$$

where *H* is hidden layer output matrix stands for Eq. (5) [20, 21]:

$$H(w_{i,j}, b_j, x_i) = \begin{bmatrix} g(w_{1,1}x_1 + b_1) & \cdots & g(w_{1,m}x_m + b_m) \\ \vdots & \ddots & \vdots \\ g(w_{n,1}x_n + b_1) & \cdots & g(w_{n,m}x_m + b_m) \end{bmatrix} \quad (5)$$

Finally, the weights of neurons in the output layers ($\beta_{1\cdots m,1\cdots k}$) is analytically computed by

Moore–Penrose generalized inverse method (Eq. (4)).

$$\hat{\beta} = H^{+}y \quad (6)$$

where H^{+}denotes the Moore–Penrose generalized inverse matrix of H.

BP- BP, a gradient descent learning algorithm, is a conventional ANN method that has emerged as the standard algorithm for the training of multilayer perceptron's against which other learning algorithms are often benchmarked [24]. In BP, optimum weights are determined by back propagating the errors from output layer [25, 29]. As a simple way, the errors are taken into account in backward direction. Although backpropagation has been successfully employed in many research areas, it has some major problems such that its long training stage and the probability of falling into local minima [29]. In delta rule the weights are changed by;

$$\Delta w_{jk} = -\gamma \frac{\partial E}{\partial w_{jk}} \quad (7)$$

where γ is constant of proportionality and E is the error term (mean square error) which is found by Eq. (8).

$$E = \frac{1}{2}\sum_{i=1}^{N}(d_i - y_i)^2 \quad (8)$$

where N is the number of data at train dataset, d is the desired output, y is actual output and i is the data order. The error of train dataset was back propagated to optimize network parameters.

By chain rule $\frac{\partial E}{\partial w_{jk}} = \frac{\partial E}{\partial G}\frac{\partial G}{\partial w_{jk}}$ while $y = \frac{\partial G}{\partial w_{jk}}$ and $\delta_k = -\frac{\partial E}{\partial G_k}$ can be defined where G is defined as the sum of all inputs entering the neuron. Then the weight update rule for each neuron can be calculated by Eq. (9).

$$\Delta w_{j,k} = \gamma \delta_k y_j \quad (9)$$

Here in δ_k must be computed for each unit k in the network. δ_k for output layer $\delta_o = (d - y)\frac{\partial y_o}{\partial G_o}$ and for the hidden layer $\delta_h = \frac{\partial y_o}{\partial G_o}\sum_{o=1}^{N_o}\delta_o w_{ho}$ where N_o is the number of neurons in hidden layer, while G_o shows the value that come to the output neuron [25].

RBF- RBF has been offered by Broomhead and Lowe [30] and it has the following differences from BP: there is not any assigned weight in the input layer and the transfer function of hidden layer is radial basis function as shown in Eq. (10).

$$f(x) = \exp[-(x - M)^2/2\sigma^2] \quad (10)$$

where M and σ are mean and standard deviation respectively. In RBF, the linear mapping from hidden layer to output layer is the single parameter that is adjusted in the learning process therefore it does not suffer from local minima.

These three models were employed for modeling the performance and emission parameters of a biodiesel-fueled generator. The data obtained at constant engine speed and different loads were used as inputs while SFC, thermal efficiency (TE), exhaust gas temperature (EGT), hydrocarbons (HCs), NO_x and smoke opacity (SO) were outputs. In this study, ELM was used as the base model while BP and RBF were for testing the performance of ELM and to determine the most suitable learning model for each parameter of biodiesel-fueled generator.

4. Optimizing the parameters

Determining the structure and learning coefficients is the most important stage in developing model, and this may increase the success. These coefficients are related to the characteristics of the dataset. Therefore, to increase the success that obtained from each model, for each dataset, the parameters of learning algorithms were determined by trials. Besides, to make a more equitable comparison among the models, the parameters of all methods used should be optimized for each parameter. To obtain optimum network parameters, many iterative learning steps may be required in order to obtain a good learning performance [21]. In ELM, the number of hidden layer and neurons is limited to single hidden layer and the number of observations, respectively [31]. Therefore, the networks were tested with 5-25 neurons in one hidden layer. Also in BP, hard-limit (hardlim), log-sigmoid (logsig), hyperbolic tangent sigmoid (tansig), triangular basis (tribas) and radial basis (radbas) transfer functions were used in trials since in theory, any activation function that has a first derivative can be used in BP. Unlike BP, ELM can use any nonlinear activation function. In this study sigmoid (sig), sinus (sin), hardlim, tribas

and radbas transfer functions were tested for ELM. In RBF, the optimization was done in terms of the spread of radial basis function. For having a fair comparison, the general structure of ANN was picked out to be a single hidden layer feed forward neural network (SLFN). Here, the input layer consists of three neurons which represent the speed and load and fuel blending ratio. The number of neurons in hidden layer and transfer functions was determined after an optimizing stage which will be described in this section. Finally, one output neuron is used as unique network structures were determined for each parameter. In Figure 2, a flow chart that shows the optimization stage of data.

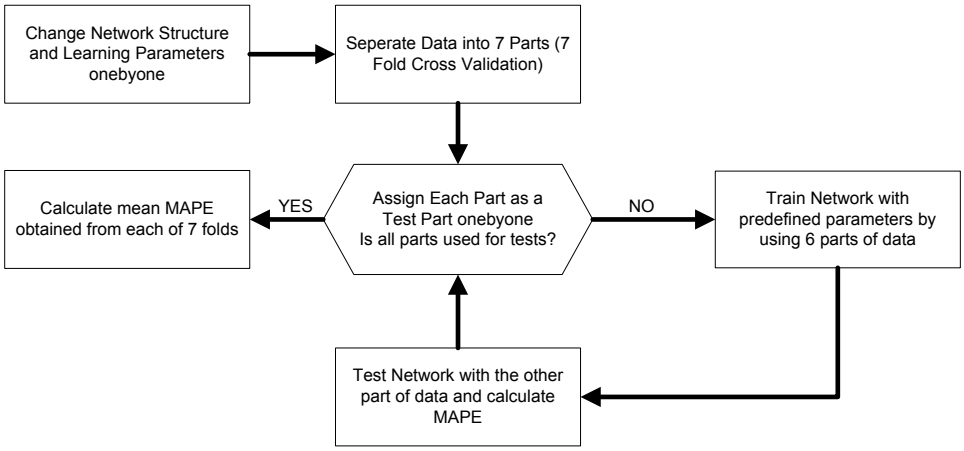

Figure 2. Flow chart of optimization stage

The optimal values and transfer functions were obtained by picking the network parameters, and it was shown by the least average mean absolute percentage error (MAPE), which was calculated following equation $\left(MAPE = \frac{100\%}{n}\sum_{i=1}^{n}\left|\frac{f_i - y_i}{y_i}\right|\right)$, where f is estimated and y is true value. In 7-fold cross validation, the data is partitioned into 7 equal sized (each subset contains 4 observations) subsets and one is used as a validation (test) data and the rest is used as training data [32]. The optimized parameters, which are transfer function (TF), number of neurons in the hidden layer (NN) and spread, are sorted in Table 1.

Table 1. Optimized network parameters for models employed

Parameters	ELM		BP		RBF
	TF	NN	TF	NN	Spread
BSFC	Sin	25	tansig	10	1.9
BTE	Sin	20	logsig	5	1.0
EGT	Sin	25	tansig	5	1.1
HC	Sin	20	logsig	5	1.1
NO_x	Sin	20	logsig	5	3.2
SO	Tribas	15	tansig	5	7.8

5. Results and discussion

For minimizing the classification errors that arise from data distribution, the estimations were done by leave-one-out cross-validation [32] where a single data in the dataset are used as a validation data, and the rest is used as the training data. The average of all estimation accuracies of optimized ELM, BP and RBN learning algorithms for each engine parameter are assumed as the accuracy of ML systems. The relative errors (RE) calculated for the estimations of the engine fueled with pure biodiesel (B100) as example, which are found by using following equation ($RE = \left|\frac{f-y}{y}\right|$), are tabulated in Tables 2 and 3, and mean relative errors (MRE) are given in Table 4. As can be seen in Tables, amongst models employed, ELM is a useful tool for estimating NO_x, smoke and EGT while BP is more successful in estimating of SFC and HC in relation to RE and

MRE. For TE, it is seen that ELM and BP have very similar performance. In case of RBF, the values of mean relative error are above in all cases.

Table 2. The Relative Errors of the performance parameters for biodiesel

Estimated Parameters	Power Output	Measured Value	Estimated by ELM	Relative Error	Estimated by BP	Relative Error	Estimated by RBF	Relative Error
SFC (g/kWh)	1.4	947.14	996.93	0.0526	964.6	0.0184	984.33	0.0393
	2.9	591.72	592.04	0.0005	565.69	0.0440	675.49	0.1416
	4	489	446.32	0.0873	439.86	0.1005	456.63	0.0662
	5.3	417.74	422.82	0.0122	435.59	0.0427	423.28	0.0133
	5.8	411.72	417.39	0.0138	421.9	0.0247	406.17	0.0135
	6.5	423.69	415.57	0.0192	411.45	0.0289	431.57	0.0186
	7	420	498.94	0.1880	403.72	0.0388	396.52	0.0559
TE (%)	1.4	10.14	10.41	0.0266	9.94	0.0197	13.39	0.3205
	2.9	16.22	16.42	0.0123	17.42	0.0740	18.39	0.1338
	4	19.63	19.06	0.0290	20.54	0.0464	23.04	0.1737
	5.3	22.98	23.23	0.0109	21.9	0.0470	22.76	0.0096
	5.8	23.32	23.14	0.0077	22.04	0.0549	22.71	0.0262
	6.5	22.66	23.38	0.0318	23.65	0.0437	23.02	0.0159
	7	22.86	23.63	0.0337	23.12	0.0114	22.67	0.0083
EGT (˚C)	1.4	136	120.43	0.1145	142.14	0.0452	154.62	0.1369
	2.9	150	162.28	0.0819	165.77	0.1051	164.35	0.0957
	4	166	171.48	0.0330	171.61	0.0338	174.59	0.0518
	5.3	176	172.39	0.0205	181.34	0.0303	178.63	0.0149
	5.8	205	203.43	0.0077	201.02	0.0194	202.92	0.0101
	6.5	229	228.25	0.0033	227.74	0.0055	234.34	0.0233
	7	274	280.1	0.0223	280.58	0.0240	278.94	0.0180

Table 3. The Relative Errors of the emission parameters for biodiesel

Estimated Parameters	Power Output	Measured Value	Estimated by ELM	Relative Error	Estimated by BP	Relative Error	Estimated by RBF	Relative Error
HC (ppm)	1.4	27	29.73	0.1011	27.23	0.0085	24.92	0.0770
	2.9	51	52.03	0.0202	48.23	0.0543	61.66	0.2090
	4	77	71.64	0.0700	75.03	0.0256	76.15	0.0110
	5.3	99	106.81	0.0789	115.03	0.1619	95.27	0.0377
	5.8	116	111.15	0.0418	104.71	0.0973	103.64	0.1066
	6.5	129	124.38	0.0358	121.46	0.0585	122.47	0.0506
	7	132	138.61	0.0501	135.67	0.0278	131.25	0.0057
NO_x (ppm)	1.4	371	339.03	0.0862	416.39	0.1224	492.89	0.3285
	2.9	565	614.04	0.0868	649.01	0.1487	697.15	0.2339
	4	707	632.15	0.1059	684.16	0.0323	691.76	0.0216
	5.3	853	910.25	0.0671	813.82	0.0460	975.1	0.1431
	5.8	960	1000.79	0.0425	881.29	0.0820	927.16	0.0342
	6.5	973	996.92	0.0246	923.53	0.0508	1005.83	0.0337
	7	986	956.83	0.0296	901.14	0.0861	862.04	0.1257
SO (%)	1.4	0	0	0	0	0	0	0
	2.9	0	0	0	0	0	0	0
	4	0	0.01	0	0	0	0	0
	5.3	7.4	7.2	0.0270	8.43	0.1392	8.05	0.0878
	5.8	17.2	17.72	0.0302	20.49	0.1913	19.43	0.1300
	6.5	28.7	28.69	0.0003	29.86	0.0404	28.76	0.0021
	7	32.3	32.06	0.0074	32.33	0.0009	32.4	0.0031

Table 4. Mean Relative Errors

Method	SFC	TE	EGT	HC	NO_x	SO
ELM	0.0559	0.0470	0.0357	0.0457	0.0608	0.0520
BP	0.0324	0.0430	0.0729	0.0525	0.1170	0.0724
RBF	0.0367	0.1325	0.0709	0.0605	0.1912	0.0935

The comparisons of estimated and measured results, which can be used to illustrate the deviations from the actual value for estimations, for all parameters of using biodiesel are shown in Figure 3. As shown in the figure, the actual and estimated values are very close to each other, however, HC and NO_x values do not match enough especially at high loads. This is mainly due to the nature of emissions that it is hard to estimate due to the difficulty of the burning process. Furthermore, there was an interesting trend for estimating SO values; they were almost exactly fit with the experimental values.

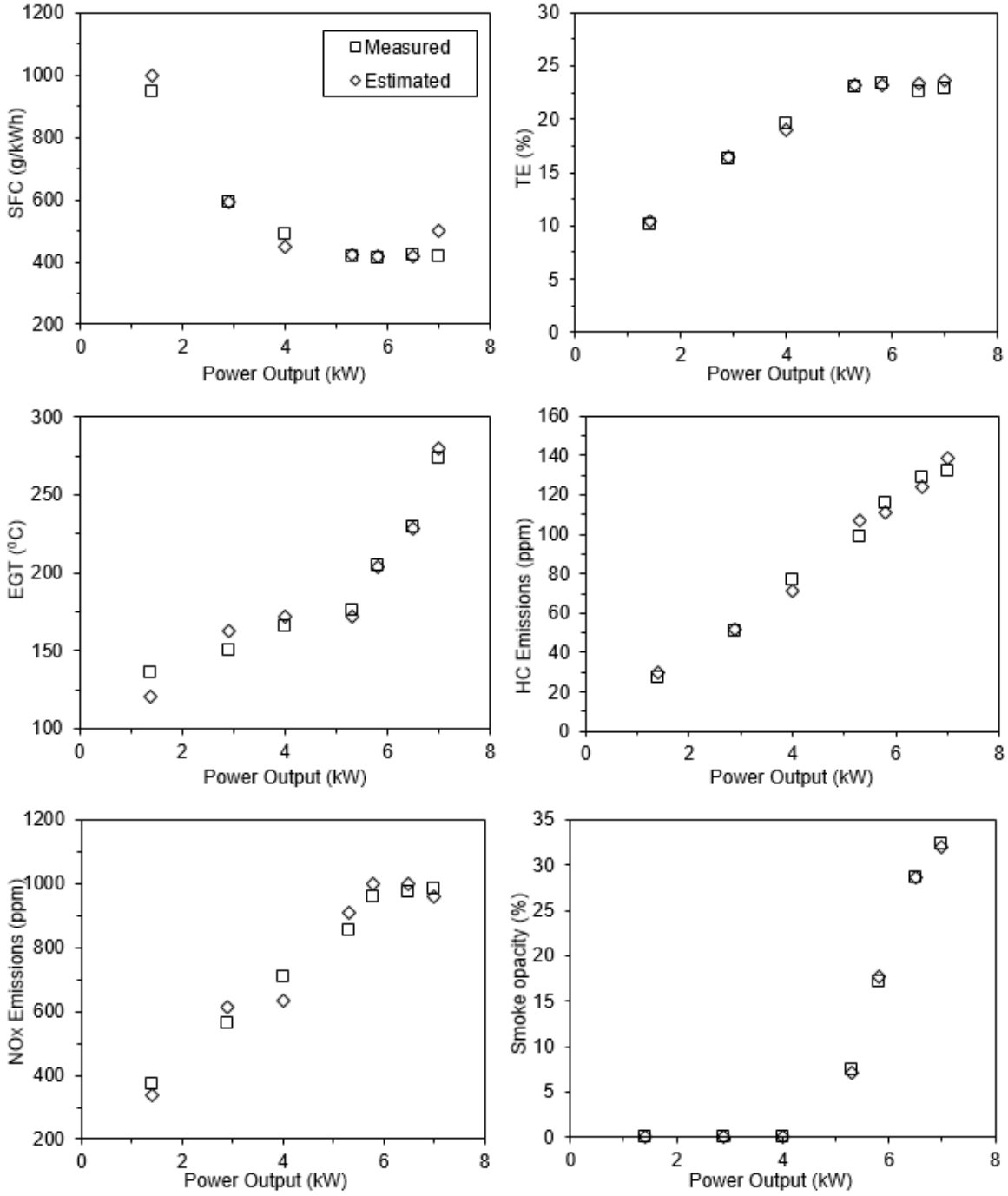

Figure 3. Comparison the measured and estimated parameters obtained for B100

To compare the performance of models, the estimation error was presented by MAE, RMSE, MAPE, R^2 in Table 5. They are evaluated against the experimental data using following equations; mean absolute error $\left(MAE = \frac{1}{N}\sum_{i=1}^{n}|f_i - y_i|\right)$, root mean square error $\left(RMSE = \sqrt{E[(f-y)^2]}\right)$, mean absolute percentage error $\left(MAPE = \frac{100\%}{n}\sum_{i=1}^{n}\left|\frac{f_i - y_i}{y_i}\right|\right)$ and coefficient of determination $\left(R^2 = 1 - \frac{\sum_{i=1}^{n}(f_i - y_i)^2}{\sum_{i=1}^{n} y_i^2}\right)$, where E is expected, f is estimated and y is true value.

Table 5. Comparing the performance of the models

Parameter	Method	MAE	RMSE	MAPE	R^2
SFC	ELM	28.65036	42.47032	5.585456	0.938683
	BP	16.7275	21.53959	3.239972	0.984228
	RBF	20.70679	32.52362	3.670709	0.964041
TE	ELM	0.826071	1.160392	4.718433	0.928886
	BP	0.818571	1.18921	4.339911	0.92531
	RBF	2.055	2.73098	13.24645	0.606102
EGT	ELM	6.659286	8.168776	3.572118	0.969049
	BP	13.72929	17.26228	7.287562	0.861783
	RBF	12.99821	15.46812	7.093514	0.889021
HC	ELM	2.710714	3.530919	4.570164	0.987182
	BP	3.589643	5.062206	5.252892	0.973654
	RBF	3.973929	4.922028	6.045235	0.975093
NO_x	ELM	40.91071	51.90364	6.082621	0.950288
	BP	68.29607	99.22855	11.69917	0.818308
	RBF	109.2182	139.4934	19.12019	0.640937
SO	ELM	0.596679	0.933658	3.958771	0.996605
	BP	0.863214	1.324569	7.240231	0.993167
	RBF	1.363857	2.155505	10.73633	0.981905

Generally, when it is obtained the smaller the MAE, RMSE and MAPE, and the higher R^2, then the model accuracy is the better. In addition, according to the error results obtained, the most suitable models for the investigated parameters are given in Table 6, and computational time for each model is given in Table 7. Tables show that ELM performed better than the traditional ANN (i.e., BP and RBF) in terms of estimation accuracy (for emissions and EGT) and computational time (for all). The overall error results showed that MAPE, RMSE and MAPE errors of ELM, which are 13.39, 18.03 and 4.75, respectively, is smaller than those of both BP and RBF (they are 17.34, 24.27 and 6.51 for BP and 25.05, 32.88 and 9.99 for RBF, respectively). Furthermore, R^2 of ELM is 0.96, and it is higher than R^2 values of both BP and RBF (0.93 and 0.84, respectively). ELMs' training time is 15 and 30 times faster than that of BP and RBF. BP has given some successful results in estimating performance parameter, e.g. BSFC was estimated with highest accuracy by BP. The accuracy of the RBF is also acceptable in estimating HC and SO and it has a high test speed in comparison with BP while its accuracy is less than that of others because the RBF network requires good coverage of the input space by radial basis functions. The accuracy of BP depends on tuning all network parameters (weights and biases) until the error does not decrease anymore [12] therefore BP can easily fall into local minima when there is a much deeper global minimum [21, 25]. Mao et al. [33] demonstrated that ELM tends to get unsatisfactory results when facing non-linear datasets. As seen in Table 7, ELM is much faster

than BP and RBN. The BP, gradient-based learning, has very slow training stage because it needs much iteration for optimizing the network parameters. The long training process may be the result of non-optimum learning rate and momentum [21]. The results obtained in this study is agreed with the literature view, as it was reported by Huang et al. [21] that the learning speed of ELM can be thousands of times faster than BP. The results show that ELM can be easily used with high accuracy because (1) it is not only tends to reach the smallest training error but also the smallest norm of weights that means the network tends to have better generalization performance [21], (2) it is simple and needs less parameter (transfer function and number of neurons in hidden layer) than traditional classic gradient-based learning algorithms (number of hidden layer, number of neurons in hidden layer, transfer function, learning rate, momentum, maximum number of iteration), (3) optimization of ELM weights in hidden layer are calculated analytically and input weights and biases are determined randomly. Therefore, there is no any trouble of ELM such as over or under trained and local minima.

Table 6. The most suitable method for each parameter

Parameter	Method
SFC	BP
Efficiency	ELM, BP
EGT	ELM
HC	ELM, BP, RBF
NO_X	ELM
SO	ELM, BP, RBF

Table 7. Computational time for each model (s)

Method	Stage	SFC	TE	EGT	HC	NO_x	SO
ELM	Train	0.0468	0.0312	0.0312	0.0312	0.0312	0.0468
	Test	0.0312	0	0	0	0	0
BP	Train	0.7800	1.0296	0.9516	0.8268	1.6224	0.9516
	Test	0.0312	0.0312	0.1248	0.1404	0.1248	0.1872
RBF	Train	0.6084	0.5304	0.5304	0.5616	0.4992	0.5460
	Test	0	0.0156	0	0	0	0

6. Conclusion

In this study, ELM, BP and RBF models have been successfully constructed to estimate the emission parameters of a biodiesel-fueled generator-set. The accuracy of estimations could be improved by employing ELM despite the number of dataset for training is small. A comparison of actual and estimated values showed that the correlation of the results agrees well with each other. Also, the comparison between ELM and traditional ANN techniques revealed that ELM performed better than BP and RBF, and the slower train stage is observed with BP in terms of MAE, MAPE, RMSE and R^2 which are resulted from high generalization capacity and simpler optimization. Also, the lower accomplishment of BP may be caused by not having enough number of train data, local minima problem or complexity of determining the BP parameters. As a result, this work contributes to existing knowledge by providing the applicability of ELM which is a newly employed model in this area.

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7. References

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