Application of ANN-ICA Hybrid Algorithm toward Prediction of Engine Power and Exhaust Emissions

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Abstract

Artificial neural network was considered in previous studies for prediction of engine performance and emissions. ICA methodology was inspired in order to optimize the weights of multilayer perceptron (MLP) of artificial neural network so that closer estimation of output results can be achieved. Current paper aimed at prediction of engine power, soot, NOx, CO2, O2, and temperature with the aid of feed forward ANN optimized by imperialist competitive algorithm. Excess air percent, engine revolution, torque, and fuel mass were taken into account as elements of input layer in initial neural network. According to obtained results, the ANN-ICA hybrid approach was well-disposed in prediction of results. NOx revealed the best prediction performance with the least amount of MSE and the highest correlation coefficient(R) of 0.9902. Experiments were carried out at 13 mode for four cases, each comprised of amount of plastic waste (0, 2.5, 5, 7.5g) dissolved in base fuel as 95% diesel and 5% biodiesel. ANN-ICA method has proved to be self-sufficient, reliable and accurate medium of engine characteristics prediction optimization in terms of both engine efficiency and emission.

***Keywords**: ANN, biodiesel, Imperialist competitive algorithm, correlation coefficient, performance, emission.*

1. Introduction

Main challenges for R&D facilities of engine research centers were to find outlets for engine efficiency increase and simultaneously reduce exhaust emissions. Due to escalating concerns about air pollution, several fuels were investigated by addition of a percentage of biodiesel or other materials to have a better prospect for PM dissemination. Fuel combustion can be implemented ideally if stochiometric composition of air-fuel mixture can be utilized. Excess air factor (λ) can bring about misfire in engine and increase the fraction of HC, CO while rich mixture can account for knock phenomenon and NOx emission [1-3]. According to Celic et al.[4] a comprehensive research was carried out on the effect of pure methanol use on engine power and emissions. In other investigation, the impact of methanol-diesel and ethanol-diesel mixture was surveyed on engine performance and exhaust emissions [5]. The results showed nitrogen oxide increased while carbon monoxide and total hydrocarbon decreased. As alcohol concentration increase NO decrease but with cost of HC and CO increase [6,7]. Another feature Which is taken into account in input datasets is engine speed as to explore its impact on emissions and engine performance. According to previous investigations, engine speed increment brings about increase in engine power and temperature while hydrocarbon and CO emissions tend to increase [6]. On the other hand, torque can influence emissions and engine power [6]. Artificial intelligence modeling provides simple simulation over input and output data and process information to yield prediction for output results. A new algorithm recently has been developed by Atashpaz-Gargary and Lucas [8] that is inspired socio-politically dubbed as imperialist competitive algorithm. This method has two paramount features; (1) high capacity of the algorithm to search overall optimization despite facing nonlinear problems and (2) fast convergence rate [9]. ICA is used to determine initial weights of the neural network. New INN-ICA hybrid has found its way in numerous fields such as oil flow rate to asphaltene precipitation prediction [10].The objective of current study is to apply novel ANN-ICA methodology to optimize ANN modeling in prediction of output results. Experimental results were obtained from engine tests for four cases of different composition of fuels crucial

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parameters in engine were used to predict Engine power and emission.

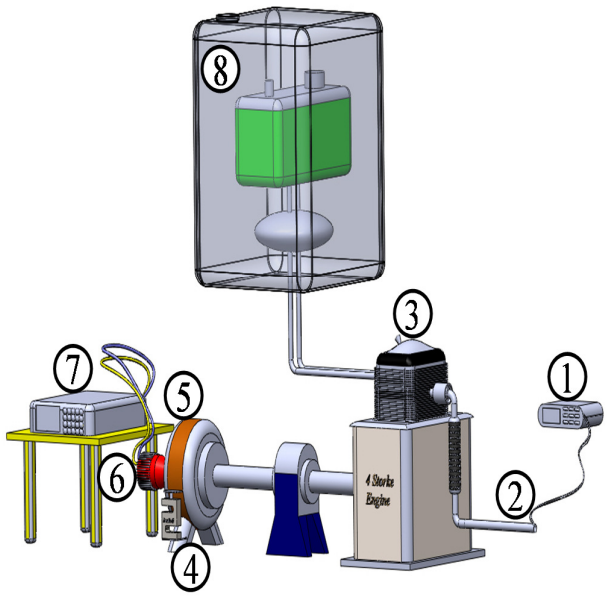

Fig1. Schematics of diesel test engine and setup: 1) exhaust gas analyzer, 2) exhaust gas analyzing probe, 3) diesel engine, 4) load cell, 5) dynamometer, 6) tachometer, 7) control unit, 8) fuel container.

Table 1. Engine specifications

Engine model	OM314LA EUll
Induction system	Turbocharged
Maximum power	81kW@2800rpm
Maximum torque	340N.m@1400-2000 rpm
Bore	97 mm
stroke	128 mm
Compression ratio	17:1
Combustion system	4 stroke Direct injection
Number of cylinders	4. in line, vertical
Number of valves per cylinder	2
Fuel	Diesel

2. Experimental Setup and Procedure

The experiments were conducted on a four cylinder; four-stroke, turbocharged direct injection diesel engine located in IDEM Co. (Tabriz, Iran). Engine test performed with 13 mode test cycle. The

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schematic picture of the engine test set-up is shown in Fig. 1. The engine specifications are detailed in Table 1. An AVL DiCom4000 gas analyzer was used to measure NOx, CO, and CO2 using non-dispersive infrared gas analysis (NDIR). Oxygen (O2) concentration was evaluated through the exhaust manifold using an electrochemical method. The sensor of the analyzer was exposed to the exhaust gas and the observations were recorded. Smoke was measured using an AVL 415S smoke meter. Table 2 shows the measurement accuracy of the instruments involved in the experiment for various parameters.

Biodiesel was produced from pre-treated SBE oil with methanol and an alkali catalyst (KOH) in a stirred tank reactor at 60 ℃ for 1 h. The pretreatment process was carried out with the methanol-to-oil ratio of 0.3 (v/v) in the presence of 1% H2SO4 (v/v) as an acid catalyst for 1 hour at 60 °C. After the reaction, the mixture was allowed to settle for 1h and the methanol–water fraction separated at the top was removed. The acid value of the bottom phase was determined and if the value was above 0.5 mgKOH/g, the pretreatment step was repeated before proceeding to the trans esterification reaction.

Four different levels of waste polystyrene used in building materials (i.e. 0, 2.5, 5, 7.5 gr) that were dissolved in 100 ml of the produced biodiesel. At lower temperatures, dissolution of polystyrene in biodiesel may be incomplete leading to reversible reactions. As a consequence, using Commercial acetone was used as a co-solvent for dissolution of polystyrene in biodiesel. In order to process provided samples, of polystyrene content were dissolved in of biodiesel accompanied with a heating treatment (60°C). These samples were blended with diesel fuel to make 5% blends. The produced B5 blends from polystyrene-biodiesel-diesel along with B5 without polystyrene blends were tested in a diesel engine.

3. Artificial Neural Network

A network structure is consisted of inter-connected elements called neurons. Each neuron has input and output that performs a simple, local function. Neural network structure learns its function through a learning process. A feed-forward with back-propagation algorithm was selected as the network function in the assessments due to its documented ability for dealing with great deal of stochastic problems. For deletion of the effect of randomly choosing the weights and biases of neurons by the network, implementation of each set was carried out fifty times and then the developed network with the minimum of quality criterion of MSE was considered. MSE obtained as following.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(Y_i - Y_j)^2 \quad (1)$$

Where Yi and Yj are output variables of actual and predicted by ANN, respectively, $\bar{Y}$ is the average over n number samples. Furthermore, to achieve fast convergence to low error and also to ensure that each input variable provides an equal contribution in the ANN, each of input variables was normalized in the range of -1 to 1. The activation function for hidden layer was selected to be the tangent-sigmoid transfer function since the output of this function falls into (-1, 1) range. This range is in compliance with the range of utilized activation function, tangent-sigmoid. In this paper, ANN approach was adopted to predict engine power and emission concentration based on experimental data acquired from naturally aspirated engine.

Table 2. Measurement accuracy

NO_X (AVL DiCom4000)	1 ppm
Smoke (AVL 415S smoke meter)	0.1%
CO (AVL Digas4000)	0.01%
Inlet & exhaust CO_2 (AVL Digas4000 Light)	0.01%

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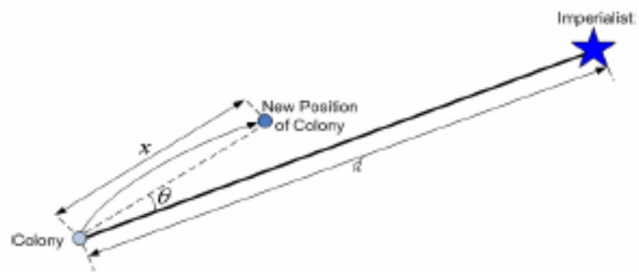

Fig2. Movement of colonies toward the imperialist[8]

4. Imperialist Competitive Algorithm

The ICA is a newly developed algorithm based on the basis of socio-political trend proposed by Atashpaz-Gargari and Lucas [8]. This algorithm initializes with primitive population referred to as countries. Countries fall into two types; imperialist and colony which together form empire. For optimization purpose with N dimension, a country is defined by 1*N arrays as following:

$$\text{country}=\left[P_1,P_2,P_3,...,P_{N_{\text{variable}}}\right] \quad (2)$$

Cost function of any country is assessed by:

$$\cos t_i=f(\text{country})=f\left(P_1,P_2,P_3,...,P_{N_{\text{variable}}}\right) \quad (3)$$

Several parameters such as number of countries (N) and number of imperialist (Nimp) with the most minimized costs were assigned to begin imperialist competitive algorithm. In order to distribute colonies proportionally between imperialists, the normalized cost of an imperialist is presented as:

$$C_n=\max_i\{c_i\}-c_n \quad (4)$$

Where cn is the cost of n-th imperialist, maxi{ci} is the highest cost among imperialists and Cn is the normalized cost of imperialists. The power of every imperialist is denoted as Pn and is defined based on its normalized cost function as following:

$$P_n=\left|\frac{C_n}{\sum_{i=1}^{N_{\text{imperialist}}} C_i}\right| \quad (5)$$

Hence the initial number of each imperialist can be determined by:

$$N.C._n=\text{round}\{P_n.N_{col}\} \quad (6)$$

Where N.Cn is the number of subjugated colonies of n-th empire and Ncol is the number of overall colonies. The colonies along with imperialists constitute the n-th empire.

Second stage of ICA procedure is colonies movement toward the imperialist. The imperialists draw colonies in an effort to make them part of their territory. Fig. 2 depicts colony's movement toward imperialist in direction of a vector which its size is d and colonies new location is shown by x unit from colony's former position. x distance is defined by following formula:

$$x \square U(0,\beta\times d) \quad (7)$$

B is a number that is greater than 1. During colony movement, it may reach to the position where its cost function would be lower than that of imperialist. In such circumstance, colony and imperialist exchange their position. Algorithm then proceeds with new imperialist with colonies attracted to new imperialist.

The next step involves determination of the total power of an empire. This power relies on both the power of imperialist country and its colonies. Total cost of an empire can be achieved by:

$$T.C._n=Cost(imperialist_n)+\xi mean\{Cost(\text{colonies of empire}_n)\} \quad (8)$$

In the aforementioned expression, T.Cn is the overall cost of the n-th empire. ζ is a positive numberless than 1.the lower number of ζ increase the role of colonies in total power while higher value dentes prime imperialist role in determination of total power. Recommended value for ζ in most practical cases is 0.1.

The final stage is revolved around imperialistic competition. To this effect, all empires are set on occupying colonies of other empires as to control them. The competition between imperialists is resulted in the decrease of weaker empires and the increase of powerful empires. This trend goes on until a convergence is established or the range of iteration is being acquired. All empires topple but one empire stand as the most powerful empire and all countries are ruled under single empire.

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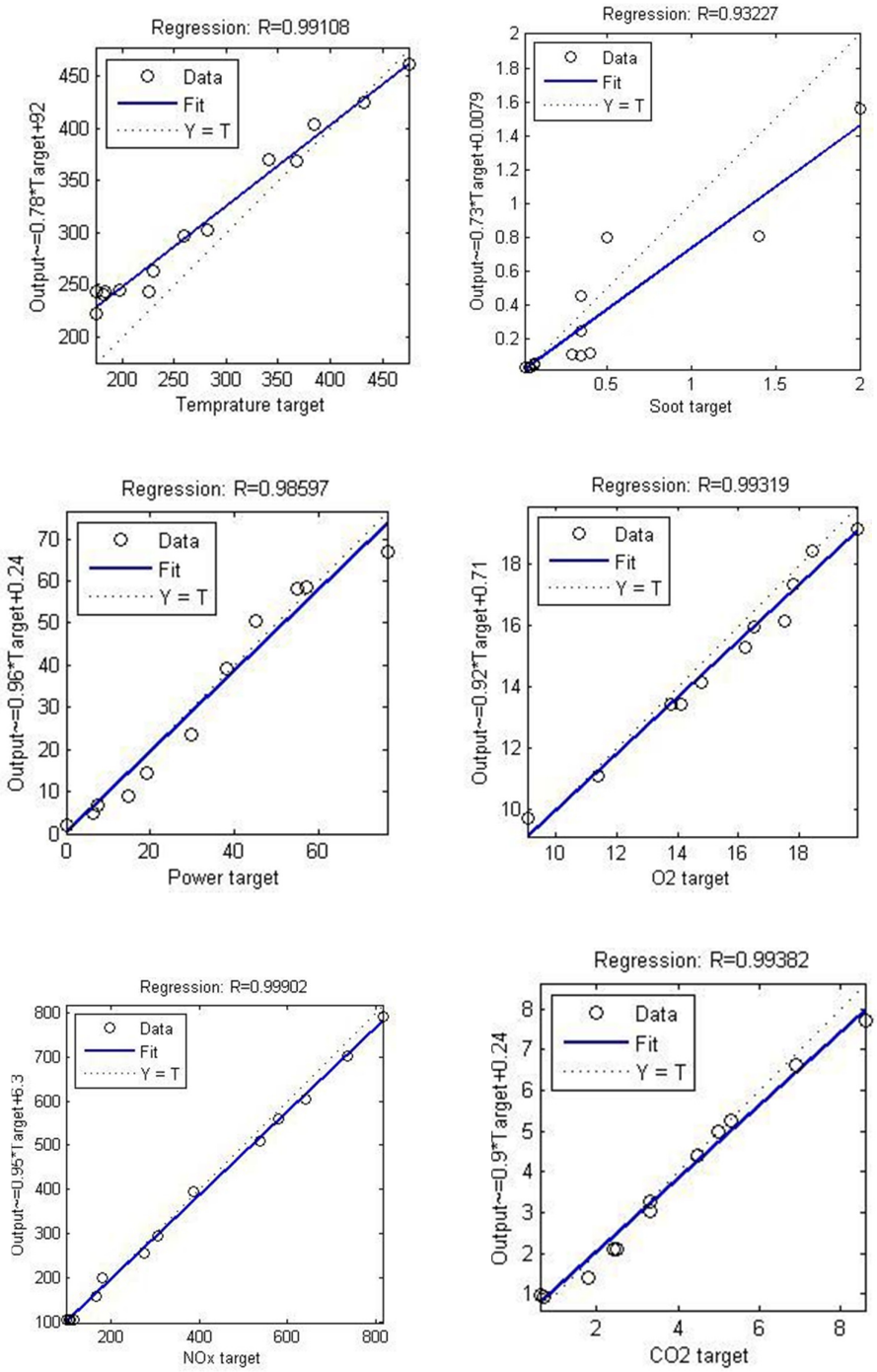

Fig3.. Regression plot of ICA-ANN.

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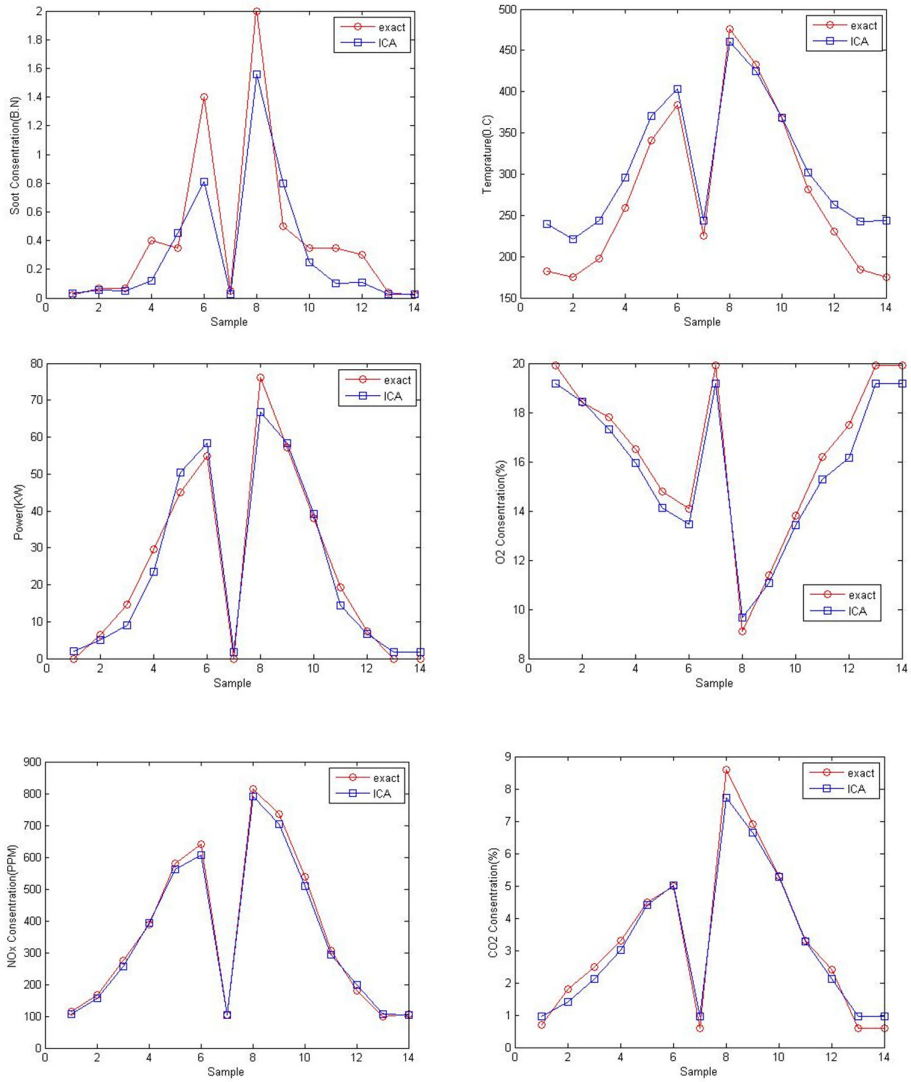

Fig4. Comparison of estimated values of ICA-ANN modeling vs. experimental results

Table 3. ICA-ANN performance indexes.

	Metrics	TEMP	POWER	CO2	O2	SOOT	NOx
ICA-	MSE	0.0073	0.0111	0.0049	0.0061	0.0257	0.0014
ANN	R	0.99108	0.98597	0.99382	0.99319	0.93227	0.99902

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5. Results and Discussion

ICA is used as a method to optimize neural network modeling to predict engine performance and emitted pollution. MSE metric is used as cost function with the aim of possible cost function minimization by ICA approach. Input dataset qualify all requisite parameters regarding emission determination such as excess air factor, fuel mass, engine speed, and torque. Number of countries are 1500 and 300 imperialists were used for simulation implementation. It should be noted that β is chosen to be equal to 2.For measuring accuracy and error estimation, two important criteria were taken into account; mean squared error(MSE) and error correlation coefficient(R). the target of modeling is obtaining the highest value of R (which is indicator of maximum predictability of simulation)and the least amount of MSE. ICA-ANN hybrid was succeeded in modeling, since all R values are well above 0.9 and low MSE was achieved. Fig.3 demonstrates regression plot of ICA-ANN for different parameters of output results where experimental values of engine power and emissions are depicted versus estimated values of modeling. As Fig. 3 suggests extent of variance between measured and evaluated data are so negligible, therefore ICA-ANN reveals excellent accuracy and efficiency in simulation of output forecasting. Fig. 4 shows comparison between experimental values gained from engine test and predicted values of ICA-ANN simulation. MSE and correlation coefficient(R) for six outputs were reported in Table 3. According to Table 3 the best modeling performance is recognized for NOx, since the least error of 0.0014 and high amount of R by 0.99902 was achieved by applying hybrid to experimental data

6. Conclusion

A hybridization of imperialist competitive algorithm and artificial neural network was implemented successfully on experimental dataset. Hybridization is performed to exploit ANN's local searching capability with ICA's global searching capacity in order to strengthen modeling prediction. Experiments were carried out on naturally aspirated engine while different characteristics were changed so that engine power and emissions could be analyzed. ICA has the potential to optimize connection weights of neural network thereby introducing more efficient method for simulation practice. According to simulation results, all parameters present acceptable R values near unity. MSE values are very low representing the least error on modeling process. The best modeling of hybridization method is pertinent to NOx output that is well predicted by ICA-ANN approach.

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