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PREDICTION OF PERFORMANCE AND SMOKE EMISSION USING ARTIFICIAL NEURAL NETWORK IN A DIESEL ENGINE

Yakup Sekmen [a] , Mustafa Gölcü [b] , Perihan Erduranlı [c], Yaşar Pancar[d]

[a] Department of Automotive, Karabuk Vocational College, Zonguldak Karaelmas University, Karabuk, Turkey. ysekmen@yahoo.com
[b] Department of Mechanical Education, Technical Education Faculty, Pamukkale University, Kinikli, Denizli, Turkey
[c] Department of Mechanical Education, Technical Education Faculty, Zonguldak Karaelmas University, Karabuk, Turkey
[d] Department of Mechanical Engineering, Engineering Faculty, Osmangazi University, Bati Meselik, Eskisehir, Turkey

Abstract- The fuel injection pressure is one of the significant operating parameters affects atomization of fuel and mixture formation; therefore, it determines the performance and emissions of a diesel engine. Increasing the fuel injection pressure decrease the particle diameter and caused the diesel fuel spray to vaporize quickly. However, with decreasing fuel particles their inertia will also decrease and for this reason fuel can not penetrate deeply into the combustion chamber. In this study, artificial neural-networks (ANNs) are used to determine the effects of injection pressure on smoke emissions and engine performance in a diesel engine. Experimental studies were used to obtain training and test data. Injection pressure was changed from 100bar to 300bar in experiment (standard injection pressure of test engine is 150bar). Injection pressure and engine speed have been used as the input layer; smoke emission, engine torque and specific fuel consumption have been used as the output layer. Two different training algorithms were studied. The best results were obtained from Levenberg-Marquardt (LM) and Scaled Conjugate gradient (SCG) algorithms with 11 neurons. However, The LM algorithm is faster than the SCG algorithm, and its error values are smaller than those of the SCGs. For the torque with LM algorithm, fraction of variance (R^2) and mean absolute percentage error (MAPE) were found to be 0.9927 and 7.2108%, respectively. Similarly, for the specific fuel consumption (SFC), R^2 and MAPE were calculated as 0.9872 and 6.0261%, respectively. For the torque with SCG algorithm, R^2 and MAPE were found to be 0.9879 and 9.0026%, respectively. Similarly, for the specific fuel consumption (SFC), R^2 and MAPE were calculated as 0.9793 and 8.7974%, respectively. So, these ANN predicted results can be considered within acceptable limits and the results show good agreement between predicted and experimental values.

Keywords- Artificial neural-network, Diesel engine, Injection pressure

1. INTRODUCTION

There are several factors that the engine designer considers to provide both current and future low emission levels and high performance with a good fuel economy. Some of these factors are the shape of the combustion chamber, inlet port, injection rate, nozzle geometry, spray pattern, injection timing and pressure. Combustion and emission characteristics are greatly influenced by quality of atomization in diesel engines. The fuel injection pressure is one of the significant operating parameters affects atomization of fuel and mixture formation; therefore, it determines the performance and emissions of a diesel engine. Increasing the fuel injection pressure decrease the particle diameter and caused the diesel fuel spray to vaporize quickly. However, with decreasing fuel particles their inertia will also decrease and for this reason fuel can not penetrate deeply into the combustion chamber. Higher injection pressures initially generate faster combustion rates, resulting in higher cylinder gas temperatures. However, initial combustion with the spray was restricted to a small region near the injector and the flame spreads around the chamber through slow propagation. The combustion may worsen as the air near the surfaces of the cylinder is not used. This caused an inefficient conversion process of heat to work. The inefficient combustion results in more reduction in torque and power. On the other hand, decreasing the fuel injection pressure increase the particle diameter and caused the diesel fuel spray to vaporize needs more time. The longer ignition delay results in an inefficient conversion process of heat to work. Thus, smoke formation increase due to no having time to complete combustion of carbon particles [1-7].

Nitrogen oxides (NO_x), carbon monoxide (CO), unburned hydrocarbons (HC), sulphure dioxides (SO_2) and smoke are the most important pollutants in diesel engine. Among these components, Smoke is caused by accumulation of unburned carbon particulates result in incomplete combustion. Because the smoke is exhausted unburned fuel it affects fuel economy negatively and accelerate the wear of cylinder surface and piston rings. In addition, residual smoke particulates on valve seat surfaces may cause compression leakage [8].

Fuel injection systems are designed to provide higher injection pressure (>130MPa, common rail injection) in today's diesel engine. In recent years, a number of studies have been conducted on injection pressure and atomization to improve combustion and engine performance and to reduce exhaust emissions in diesel engines [3, 9-13]. Can et al. [2] were investigated to determine the effect of ethanol addition on the engine performance and emissions of a turbocharged IDI Diesel engine running at different injection pressure. It was found that increasing the injection pressure decreased CO and smoke emissions. Celikten [9] conducted experiments to investigate effects of injection pressure on engine performance and exhaust emissions in a four-stroke, four cylinder indirect injection turbocharger diesel engine. High injection pressure for O_2, SO_2, CO_2 and smoke emissions, low injection pressure for NO_x should be preferred. Choi and Reitz [14] found that high injection pressure reduce particulate emissions while did not change HC emissions. They found that high injection pressure increase NO_x emissions slightly. Increasing injection pressure to a value higher than a certain value may contribute adverse effect on engine performance in diesel engine. The influence of fuel composition parameters (aromatic content, cetane index, gross heat power and nitrogen and sulfur content) on particulate emissions was studied and was fitted along with operation conditions using neural Networks. The mathematical reproduces experimental data within 87-90% of confidence and allows for the simulations of emissions at steady conditions for any value of parameters in experimental range [15].

Modeling of complex and ill-defined problems, engineering analysis and prediction can be done using ANN. There are different network types like cascade-forward back-propagation, feed-forward back-propagation, competitive, generalized regression, and radial basis. The back-propagation algorithm is the most popular learning algorithm with different variants. ANNs have been successfully used in modeling complex physical phenomena in various fields [16-21].

In this paper, two different training algorithms are used to predict the effects of injection pressure on smoke emissions and engine performance. The first one is a LM algorithm; the second is a SCG algorithm. In both algorithms, a logarithmic sigmoid and purelin functions were used as the activation function in the hidden and output layers, respectively. A computer program has been performed under Matlab 6.5. To obtain the best prediction values, the number of neurons was increased step-by step from 8 to 15 in a single hidden-layer.

2. ANN APPROACH

The activation function is chosen by the designer in the modeling. Choosing the appropriate number of hidden neuron and the activation function are very important to obtain an accurate ANN model. Back-propagation neural networks use the logarithmic sigmoid, the hyperbolic tangent sigmoid, or the purelin activation functions. Some statistical methods, RMSE, R^2, and MAPE values have been used for comparison in the sensitive analysis. The more detailed information and calculations, formulas, etc. about the method can be found in [18, 19, 22-27].

ANNs were used to predict the effect of injection pressure on smoke emissions and engine performance in a diesel engine. In order to train an ANN, 42 patterns obtained from the experiments have been used. Nine patterns have been randomly selected and used as the test data. It has been shown selected some sample data sets used for training and testing the network in Table.1. Main parameters for the experiments are the injection pressure, engine speed, torque, specific fuel consumption, and smoke density. In the selected ANN model, inputs were the injection pressure and engine speed while the outputs were torque, specific fuel consumption, and smoke density. A network consisting of one input layer, one hidden layer, and one output layer by definition is called two-layer network. The selected ANN model of a multi-layer with 2 inputs, 11 hidden neurons and 3 outputs has been shown in Fig. 1.

$$s1 = W1 \cdot u + b1 \quad (1)$$

$$y1 = f1(s1) = f1(W1 \cdot u + b1) \quad (2)$$

$$s2 = W2 \cdot y1 + b2 \quad (3)$$

$$y2 = f2(s2) = f2(W2 \cdot f1(W1 \cdot u + b1) + b2) \quad (4)$$

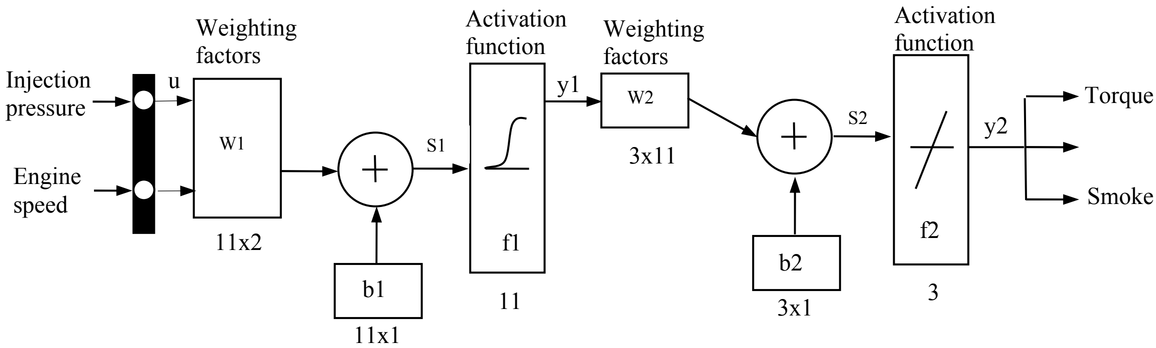

Fig. 1. The selected ANN model

Table 1 Samples for input and output

Input data		Output data		
Engine speed (rpm)	Injection pressure (bar)	Torque (Nm)	Smoke (%N)	Specific fuel consumption (g/kWh)
900	175	31.44	32.8	250.665
900	225	33.90	18.4	261.514
1100	100	28.87	61.3	340.117
1300	150	38.69	34.2	254.960
1300	225	41.16	15.8	216.498
1500	100	36.30	58.4	294.860
1500	300	41.16	39.6	252.150
1500	200	41.11	30.2	227.210
1700	125	33.90	74.3	316.314
1900	175	31.44	66.7	299.227

In the Fig. 1, u is the input vector of length 2, W1 and W2 are 11x2 and 3x11 matrix containing weighting factors for input layer and hidden layer, respectively. y1 and y2 are output vector for hidden layer and output vector containing the torque, specific fuel consumption, and smoke, respectively. b1 and b2 are also bias vector for input layer and hidden layer, respectively. Generally the functional relationship for this output can be written as above [20].

3. EXPERIMENTAL APPARATUS AND PROCEDURE

The experimental set up consists of a direct injection diesel engine, engine test bed with a Leclasrege Electriou brand electrical dynamometer and a smoke meter. The schematic view of the experimental set up is shown in Fig. 2. The basic specifications of the test engine are given in Table 2. The smoke emissions were measured using VLT 2600 gas analyzer with ±0.01% accuracy and recorded manually. The calibration of smoke meter was controlled regularly. Fuel flow measurement was performed as in mass. Air flow rate was measured using capacity damping tank and interchangeable orifice plates. Optical tachometer was used in engine speed measurement. Fuel injection nozzle was adjusted by injection pressure device controlled manually. Experiments were performed with five different injection pressure (100-300bar) at full load after the engine working temperature of 80ºC. Engine speed was changed from 900 rpm to 1900 rpm with 200 rpm increments. During the experiments, the average ambient temperature and atmospheric pressure were recorded as 22^{o}C and 752 mm-Hg, respectively. The accuracies of the measurements and the uncertainties in the calculated results are shown in Table 3.

Table 2 Specification of the test engine

Type	Superstar 7710, four-stroke, DI diesel engine, Water cooled
Number of cylinder	1
Bore / stroke	98 / 100 mm
Volume	754 cm^3
Compression ratio	17:1
Maximum power	7kW at 1700 rpm
Type of injection pump	Unit
Injection pressure	175 bar
Injection advance	27° CA (before TDC)

Table 3 Accuracies of the measurements and the uncertainties in the calculated results

Measurements	*Accuracy*
Load	± 0.1%
Speed	±1 rpm
Time	±0.5%
Smoke meter	± 0.01%
Specific gravity	±1%
Temperatures	±1 °C
Calculated results	*Uncertainty*
Torque	±0.1%
Power	±1%
FC	±1.1%
SFC	±1.5%

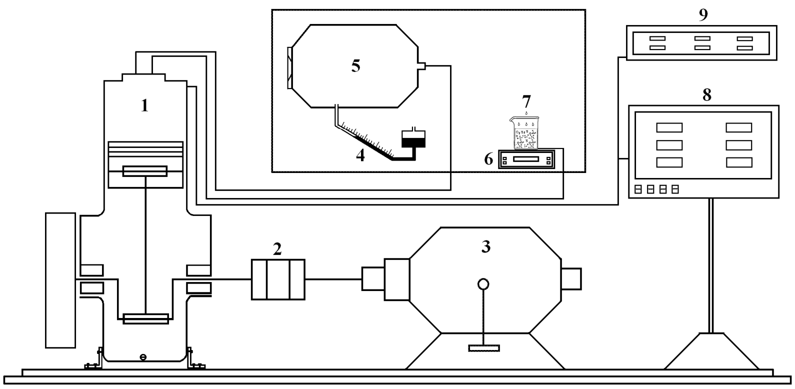

Fig. 2. Schematic view of the engine test bed (1- Engine, 2- Clutch, 3- Dynamometer, 4- Manometer, 5- Air tank, 6- Digital scale, 7- Fuel tank, 8- Exhaust gas analyzer, 9- Smoke meter).

4. RESULTS AND DISCUSSION

The selected ANN model consists of one hidden layer of logarithmic sigmoid function and output layer of purelin transfer function. Two applications of neural networks to the prediction of diesel engine performance have been performed and used successfully. To predict the engine performance parameters and emission from the diesel engine, back-propagation neural network was used and following results were obtained. The network applied is a two-layer network. The statistical values such as R^2, RMSE, and MAPE (%) of ANN approach and the best algorithmic results have been shown in Table 4 for training and testing. To obtain the best prediction values, the number of neurons was increased step-by step from 8 to 15 in a single hidden-layer. The results for other neurons haven't been presented in this paper.

As shown in the Table 4, the best results have been obtained from the LM algorithm and the best number of neurons is eleven for both of torque and specific fuel consumption, and these results have been used for generating the graphical outputs. In addition to this, the error values of smoke emission are bigger than the other output error values. Of all the training that we have studied, for smoke emission; the lowest MAPE, R^2, and RMSE are about 18%, 0.9553, and 10.0152 in the testing, respectively. The smoke emission predicted using neural network is not considered with in the acceptable range.

Table 4 Error values of predicted engine performance at the best hidden number of neurons with different algorithms.

Algorithms	Outputs	Training			Testing		
		Torque (Nm)	SFC (g/kWh)	Smoke (%N)	Torque (Nm)	SFC (g/kWh)	Smoke (%N)
LM	Number of neurons	11	11	11	11	11	11
	MAPE	5.2907	3.0019	15.5065	7.2108	6.0261	18.3533
	R^2	0.9954	0.9977	0.9753	0.9927	0.9872	0.9553
	RMSE	2.3712	0.0133	7.7936	3.0328	0.0314	10.0152
SCG	Number of neurons	11	11	11	11	11	11
	MAPE	7.7359	7.2797	23.3291	9.0026	8.7974	20.6060
	R^2	0.9910	0.9906	0.9495	0.9879	0.9793	0.9349
	RMSE	3.3126	0.0273	11.0114	3.8260	0.0405	12.0761

It shows that the MAPE values for torque and specific fuel consumption are 7.2108% and 6.0261%, respectively. Similarly, R^2 values are 0.9927 and 0.9872, RMSE values are 3.0328 and 0.0314 for LM algorithm. For also SCG algorithm, MAPE values for torque and specific fuel consumption are 9.0026% and 8.7974%, respectively. Similarly, R^2 values are 0.9879 and 0.9793, RMSE values are 3.8260 and 0.0405. As shown these results, error values in the LM algorithm is lower than those of the SCGs. Effect of the number of neurons in the hidden layer on the mean absolute percentage error has been shown in Fig. 3 for torque and specific fuel consumption. The training epoch for each neural network is 20000. For both of them, it is shown that the training error is minimized when 11 neurons are used for LM and SCG algorithms, respectively. The actual and the predicted torque, specific fuel consumption, fuel consumption, and power values of the test data have been shown in Fig. 4. As shown in the figure, the values predicted by ANN are very close to actual values. Comparison of experimental and predicted values for the torque and fuel consumption with 11 neurons in the hidden layer have been shown in Fig. 5. The developed ANN gives a very accurate representation of the R^2 values over all the range of working conditions.

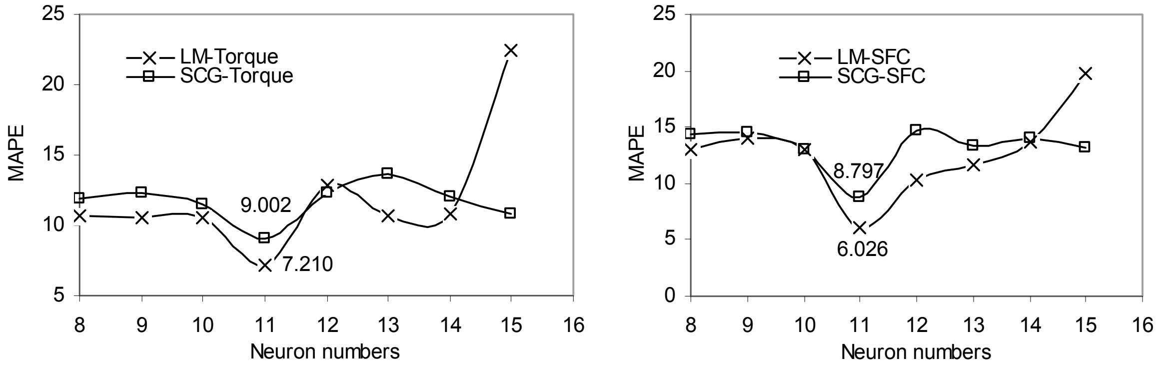

Fig. 3. The effects of the neuron numbers in the hidden layer on the mean absolute percentage error

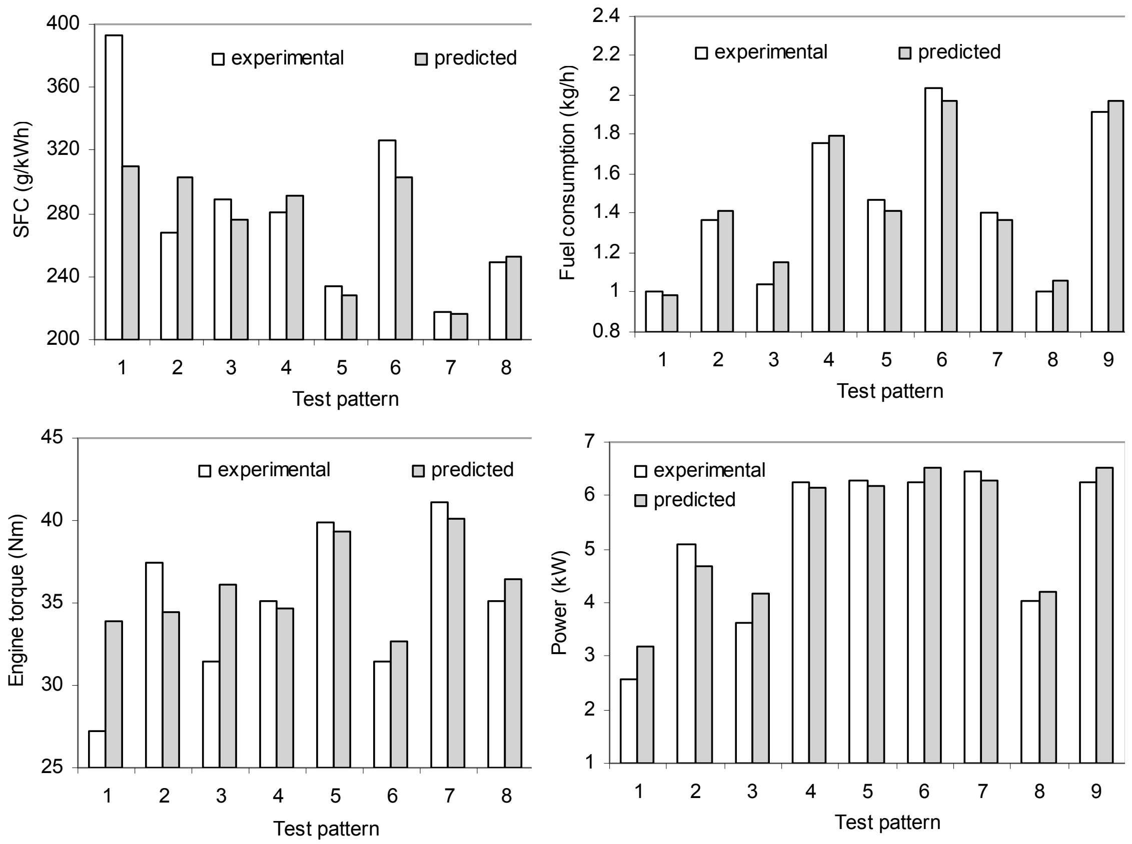

Fig. 4. Experimental and ANN predicted results of engine performance.

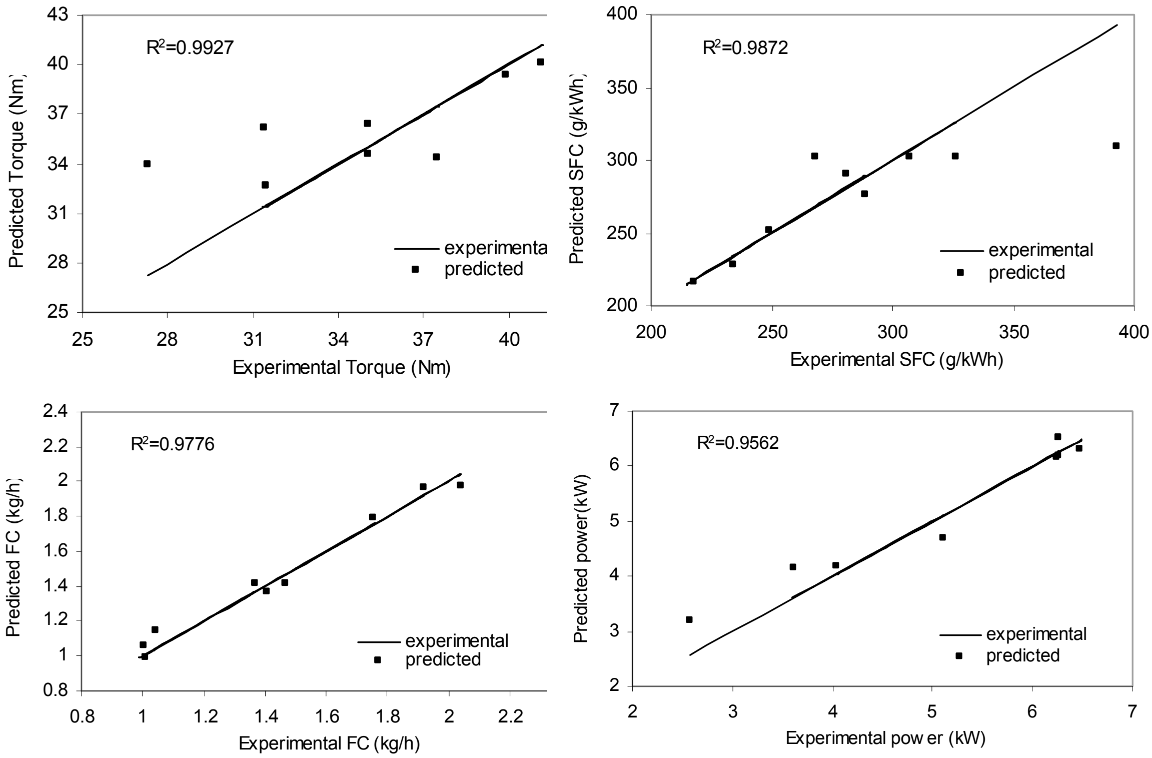

Fig. 5. Comparison of experimental and predicted results for engine performance parameters

5. CONCLUSION

In this paper, two back-propagation learning algorithms are used to predict of the torque, power, specific fuel consumption, and smoke emission of diesel engine using different injection pressure and engine speed. Injection pressure and engine speed have been used as the input layer; engine torque, specific fuel consumption, and smoke emission have also been used as the output layer. The performance of these models is evaluated and the results compared with experimental values. The LM algorithm with 11 neurons has produced the best results and for the torque the mean absolute percentage errors are limited to about 7-9% both algorithms. For also the specific fuel consumption the mean absolute percentage errors are limited to 6-8.8% both algorithms. The smoke emission predicted using neural network is not considered with in the acceptable range. With these results, it is believed that the ANN can be used for prediction of torque and specific fuel consumption as an appropriate method in diesel engine.

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