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Optimization and study of performance parameters in an engine fueled with hydrogen

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HIGHLIGHTS

- Effect of hydrogen fuel in direct injection engine was studied.
- Use of HCNG fuel can improve engine performance and exhaust emissions.
- The SVM model could predict the engine performance and CO with error of less than 4%.
- Ignition timing, injection timing and hydrogen volume fraction at different engine speeds.

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ABSTRACT

Engine performance parameters, including fuel conversion efficiency (FCE), power, torque and specific fuel consumption (SFC), can be affected by variables such as ignition timing (IGT), injection timing (IT) and hydrogen volume fraction (H2%). In this paper an engine fueled with different H2/CNG blend rations from 0 to 50% volume under ignition and injection timing at different speeds were investigated. For model validation, the engine operating conditions were simulated using the AVL fire software and compared with experimental results. The statistical comparison showed that there was no significant difference between them. Also, a support vector machine (SVM) was used to study the engine's behavior according to the variables studied. The SVM model predicted the FCE, power, torque, SFC and CO with error of less than 4%. The Genetic Algorithm (GA) was used to find optimal IGT, IT and H2% values to achieve optimum engine performance. Therefore, the results showed that the optimum engine operating conditions depend on the engine speed. Also, the results showed that independent variables (IT, IGT and H2%) maximize the engine performance and minimize SFC and CO emission. So that the optimum use of hydrogen in this research at different engine speeds was between 20% and 30%.

Introduction

Hydrogen fuel due to its favorable physicochemical properties could be as sustainable fuel in future and proper alternative fuel for internal combustion engines [1,2]. In recent years because of emission regulations especially in big cities, the high price of fossil fuels led to a promotion in using alternative fuels such as natural gas and hydrogen fuel. Natural gas is with abundant resources and clean nature for using in automotive engines [3–7]. Enhancing hydrogen energy share in a compression ignition engine improved marginally with retarded injection timing mode [8]. An experimental study by Khandal and colleagues showed that add hydrogen in a dual fuel engine powered with renewable fuels has yielded better and NOx emission decrease about 26–28% when injection

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Nomenclature

FCE	Fuel conversion efficiency
SFC	Specific fuel consumption
IGT	Ignition timing
SVM	Support vector machine
GA	Genetic Algorithm
CVCB	Constant volume combustion bomb
BTDC	Before top dead center
LHV	Lower heating value
CFD	Computation fluid dynamics
IT	Injection timing
CNGDI	Compressed natural gas direct injection
ANN	Artificial neural network
LS-SVM	least square support vector machine
RBF	radial basis function
RMSE	Root mean squared error
MAPE	Mean absolute percentage error
MOGA	Multi-objective genetic algorithm
NSGA-II	Non-dominated and crowding algorithm II

timing is 27° BTDC [9]. Retarding ignition timing in a hydrogen-enriched n-butanol rotary engine (3%–25% hydrogen) cause that HC and NOx emissions were reduced and CO emission decrease a little whereas with the increase of ignition timing, peak chamber pressure and temperature increased and brake thermal efficiency initially went up and then declined [10–13]. A H2NG blends ranging in 0%–30% vol. of hydrogen fraction are built in a conventional and condensing boilers and investigate the effects of alternative fuel on combustion performance and exhaust emissions in a diesel engine that showed combustion efficiency increase and hydrocarbon (HC), carbon monoxide (CO) emissions have decreased [14,15].

Design of model and it's implemented is one of the most commonly used methods for studying and evaluating engine behavior and performance versus design changes and the use of fuel combinations. A lot of research has been done in this regard [16–19]. Most of them were modeled based on two methods: black-box and experimental-mathematical. Most scholars tend to use black-box modeling techniques such as the artificial neural network (ANN) and support vector machine (SVM). Because these methods find the relationships between the variables with the acceptable precision without evaluating statistical assumptions and with the aid of experimental examples. In the present study, the SVM method is used to study and optimize engine behavior. SVM's success in modeling engine behavior has been considered in various study situations [20–22]. Also for modeling complex systems can use of function approximation and regression [23]. The results of Xiao et al. relate to the prediction of the marine diesel engine performance showed that the accuracy of the prediction and generalization capability of the SVM model is more acceptable than ANN [20]. Against, ANN model may face the overfitting problem and local minima. With the aid of the generated model, it is possible to examine the effect of each parameter changes on the engine performance and plotting the response levels. Neural network in the adaptive neuro-fuzzy inference system adjusts parameters of membership function in the fuzzy logic of the fuzzy inference system. And learning algorithm is used for training this network using the simulation show the effectiveness of the developed method [24,25]. Also, the design of a novel intelligent controller based on the adaptive neuro-fuzzy inference system is confirmed by simulation results and the effectiveness of the proposed controllers was verified [26,27]. It should also be noted that neuro-fuzzy technique was applied to the fractal data because of high nonlinearity of the data. The neuro-fuzzy approach is used to detect the most important variables to the fractal dimensions [28].

Therefore, to achieve optimal operating conditions, the optimization techniques should be used. Genetic Algorithm (GA) is one of the most common methods for finding optimal parameter values in a model to maximize and minimize response variables. Based on the Darwinian Theory, GA locates and finds the best solutions in the variable definition space. Various studies have been used in the GA model to optimize the engine. Zhang and colleagues optimized NOx, PM, HC, CO and BSFC variables in a diesel engine with fueled soy biodiesel. Bertram and colleagues with the GA model have been able to optimize the BSFC and pollutants of a diesel engine. Lotfan et al. also utilized GA to optimize the emissions of a diesel engine fueled by CNG and diesel [29]. Other Similar studies have been done to optimize with GA on internal combustion engines [30].

Resource surveys showed that most studies have sought to add hydrogen to fuel. Also, in other studies, the modeling of all independent variables including the percentage of hydrogen fuel, injection timing (IT) and ignition timing (IGT) at different engine speeds has been discussed. Therefore, in this paper, we seek to investigate the motor's behavior against H2% variations, IT, IGT and speed using the SVM model. Besides, with the use of single-objective and multi-objective genetic algorithms, we examined the conditions of the optimum parameters for different engine speeds. The structure of the paper will be as follows: in the materials and methods section, the procedure of the simulation with AVL fire and experimental setup, SVM modeling, and optimization with the genetics algorithm will be paid. In the results and discussion section, also, first, the different SVM settings will be checked to achieve the desired response. Then the SVM surface response graph is studied. To help the genetic algorithm, optimizing the engine conditions at various speeds are examined. And finally, the conclusion of this investigation will be presented. The purpose of this study is to investigate the effect and optimization of IGT, IT and H2% variables on engine performance and exhaust emissions. Also, in this paper, the optimization of engine performance at different engine speeds was considered as the main scope due to different behavior at various speeds.

Materials and methods

For this research, first, a single-cylinder gasoline engine designed with CATIA software and simulated with AVL fire. Then, with the help of real data obtained from testing, the modeling precision was checked and confirmed. The SVM model is also used to estimate engine variables in terms of engine speed, H2%, IT and IGT. Eventually the engine optimization conditions at different speeds investigated by the SVM model and single-objective and multi-objective genetic algorithm.

The operation condition and mesh generation

As showed in Fig. 1a a typical CNGDI engine with a single cylinder and two exhaust and intake valves is used. Fig. 1b shows two different shapes of the piston that is used for examining pattern and behavior of turbulence tumble and swirl intensity field inside the cylinder to obtain suitable piston shape for the combustion process. The piston B is deeper from piston A but it was not positioned in the crown center. Gambit software was used for generation mesh and hexahedral cells.

Mesh

Computation fluid dynamics (CFD) is an engineering tool used to simulate the action of thermo-fluids in a system. It is used by many industries in their development work to analyze, optimize and verify the performance of designs before costly prototypes and physical tests. In the CFD calculation, the finite volume method is used. Mesh in 3D models which include nodes, faces and volumes and numerical values for desired quantities in node positions are calculated. In Fig. 2 is the example of 2D mesh which represents nozzle (a nozzle included some cell) and the mesh properties are shown. Blue surfaces represent the calculation mesh and black lines walls.

The engine operating conditions for the baseline condition of CFD simulation were chosen at a fixed speed at 2000, 3000, 4000, 5000 and 6000 rpm. The investigated engine operating conditions covered certain variations in the intake temperature, injection timing, injection duration, and spark ignition timing. The obtained engine operating conditions from the experimental data of a single-cylinder research engine (SCRE) are listed in Table 1.

The CFD simulation was executed by defining the events for the engine cycle and it is started from the crank angle degree of 0ºCA by defining the value of initial pressure and temperature. The simulation finished at the crank angle degree of top dead center, where the exhaust valves will be opening. The measured intake temperature from the experimental work has been implemented to the engine computational mesh, as the piezo static pressure boundary condition. Injection and ignition timings were adjusted appropriately according to increasing engine speeds. Engine operating conditions are shown in Table 2.

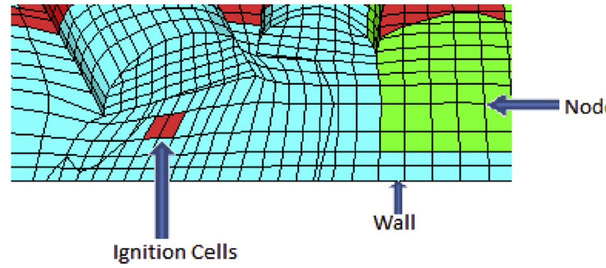

Fig. 2 – Mesh properties.

Table 3 shows some properties of compressed natural gas and hydrogen fuel combinations from 10% hydrogen added to fuel (HCNG10%) to 50%(HCNG50%) under stoichiometric conditions as can be seen with the increase of hydrogen to natural gas, LHV of the mixture increased.

Experimental setup

A 1.6 L, 4-cylinder spark ignition engine direct injection filled with natural gas and hydrogen were installed to control the HCNG (a mixture of hydrogen and natural gas) operation. The substantial advantage that CNG has in antiknock quality is related to higher auto-ignition temperature and higher-octane number. An engine control system and portable exhaust gas analyzer were used for controlling engine operations and recording engine performance and emissions data.

The engine was converted to computer integrated CNG-hydrogen fuel operation by installing a direct injection engine. As shown in Fig. 3 and Fig. 4. The result was recorded in steady-state condition. So ambient pressure, temperature, and humidity were noted to estimate air inlet density. All tests have been done at WOT (throttle position) and each test was conducted several times.

The fuel used in this study is natural gas and hydrogen which stored at 200 bar pressures and 250 bar pressures respectively and was reduced by a pressure regulator.

Support vector machine (SVM)

In this study, SVM modeling technique was used to investigate the effects of four-engine control variables including IGT, IT, H2% and speed on engine performance parameters including FCE, power, torque, SFC, and CO (Fig. 5). With the assistance of the SVM model, the response surface of each of the engine's

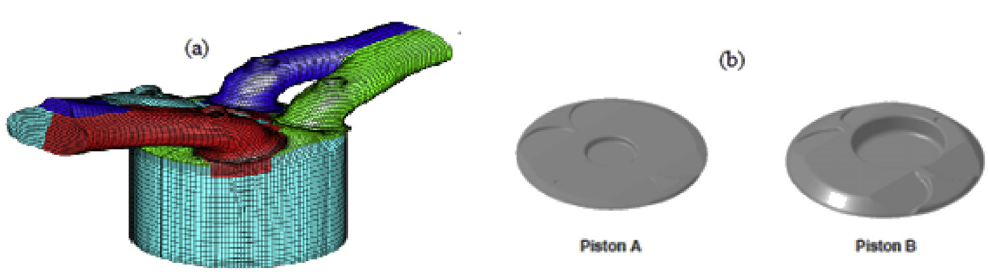

Fig. 1 – The computational domain of the engine model (a) and geometry of the combustion chambers on piston(b).

Table 1 – Specification of the CNG-DI engine.

Engine parameter	Value	Unit	Engine parameter	Value	Unit
Maximum rated power (kW/rpm)	82/6000	kW/rpm	Intake valve opening	12	bTDC
Maximum rated torque (Nm/rpm)	148/4000	Nm/rpm	Intake valve closing	48	aBDC
Stroke	84	mm	Exhaust valve opening	45	bBDC
Connecting rod length	131	mm	Exhaust valve closing	10	aTDC
Crank radius	44	mm	Maximum intake valve lift	8.1	mm
Compression ratio	14	–	Maximum exhaust valve lift	7.5	mm
Fuel	CNG + Hydrogen				

Table 2 – Baseline engine operating conditions.

Engine Parameters and Unit	Value				
Engine Speed (rpm)	2000	3000	4000	5000	6000
CNG mass(mg)	5.2	5.2	5.2	5.2	5.2
Equivalence Ratio	1.0	1.0	1.0	1.0	1.0
Intake Port Temperature (K)	305	305	305	305	306
Intake Port Pressure (bar)	1.04	1.03	1.02	1.01	0.9
Start of Injection Timing (bTDC)	130	150	170	190	210
End of Injection Timing (bTDC)	80	100	120	140	160
Spark Ignition Timing (bTDC)	19	21	23	25	28
Injection pressure(bar)	20	20	20	20	20

variables was plotted and the effects of independent variables were studied. It was also used as the fitness function in the genetic algorithm. The reasons for encouraging us to use SVM model include high computational speed, good generalization [31], quadratic programming approach to problem-solving [32] and its transparency feature [33]. In this paper, the least square support vector machine (LS-SVM) was used. This method is based on the least -squares cost function. SVM model considers the nonlinear function (equation (1)) for the training data set [34]. In this way, the relationship between dependent variables can be obtained in terms of independent variables. The steps of SVM diagram will be described in Fig. 5. The purpose of the SVM model is to estimate $\hat{y}$ (the dependent variables) studied in terms of x.

$$\hat{y} = \sum_{k=1}^{m} \overline{\alpha}_k . K(\mathbf{x}, \mathbf{x}_k) + b \tag{1}$$

where, $\overline{\alpha}_k = (\alpha_k - \alpha_k^*)$, $K(x, x_k)$ is the inner product of input vector (x) and support vector (x_k) and b is the bias term.

To calculate $\alpha^* = (\alpha_1^*, \alpha_2^*, \ldots, \alpha_k^*)^T$ and $\alpha = (\alpha_1, \alpha_2, \ldots, \alpha_k)^T$ the optimization equation (2) needs to be solved.

Table 3 – Energy and Mass Composition of H_2-NG fuel.

	CNG	HCNG10	HCNG20	HCNG30	HCNG40	HCNG50
H2(% Mass)	0	1.21	2.69	4.52	6.72	9.02
H2(% energy)	0	3.09	6.68	10.49	15.59	20.93
LHV(MJ/kg)	46.28	47.17	48.26	49.61	51.41	53.294
LHV stoich. mixture(MJ/NM^3)	3.376	3.359	3.353	3.349	3.344	3.340
CNG mass(mg)	5.2	5.13708	5.06012	4.96496	4.855	4.7474
Hydrogen mass(mg)	0	0.06292	0.13988	0.23504	0.3450	0.4526

Fig. 3 – The engine test-bed.

Fig. 4 – High pressure regulator panel.

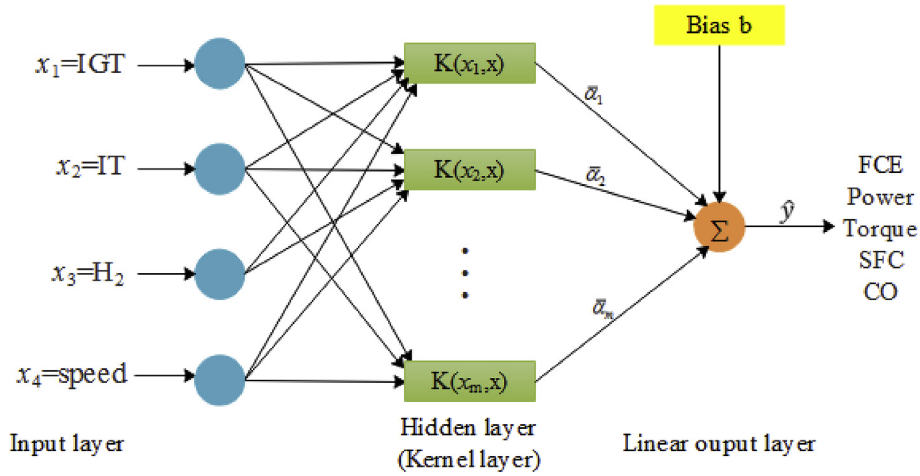

Fig. 5 – SVM model structure.

$$\begin{cases} \sum_{i,k}(\alpha_i-\alpha_i^*)(\alpha_k-\alpha_k^*)K(x_i,x_k)+\varepsilon\sum_{i=1}^{k}(\alpha_i+\alpha_i^*)-d\sum_{i=1}^{k}(\alpha_i-\alpha_i^*) \\ \text{sunbject to} \\ \sum_{i=1}^{k}(\alpha_i-\alpha_i^*)=0 \ \text{and} \ \ \alpha_i,\alpha_i^*\in[0,C] \end{cases} \tag{2}$$

where ε and C are the hyper-parameters.

Two types of kernel functions, including the function of the Gaussian (radial basis function (RBF)) and polynomial, were used.

$$K(x_i,x)=\exp\left(\frac{\|x-x_i\|^2}{\sigma^2}\right) \tag{3}$$

$$K(x_i,x)=[(x^*x_i)+1]^d \tag{4}$$

where $\sigma > 0$ is kernel's width, d is the polynomial degree (d = 1,2,3).

In this study, four types of kernel functions including polynomial degree 1 (Poly1), polynomial degree 2 (Poly2), polynomial degree 3 (Poly3) and RBF were used. The most suitable kernel function was selected based on the size of the R^2 model in the training and testing phase.

As can be seen in the diagram below, the independent variables include speed, IGT, IT and H_2% and the dependent variables are include power, torque, FCE, SFC and CO.

SVM assessment criteria

To evaluate the SVM model in the estimation of the response surface of the engine parameters in terms of independent parameters, the error criteria including RMSE, MAPE and the model's capability criteria including the efficiency of the model (EF) and the coefficient of determination (R^2), were used.

$$MAPE=\frac{1}{n}\sum_{j=1}^{n}\left|\frac{d_j-p_j}{d_j}\right|\times 100 \tag{5}$$

$$RMSE=\sqrt{\frac{\sum_{j=1}^{n}\left(d_j-p_j\right)^2}{n}} \tag{6}$$

$$EF=\frac{\sum_{j=1}^{n}\left(d_j-\bar{d}\right)^2-\sum_{j=1}^{n}\left(p_j-d_j\right)^2}{\sum_{j=1}^{n}\left(d_j-\bar{d}\right)^2} \tag{7}$$

$$R^2=\left[\frac{\sum_{j=1}^{n}\left(d_j-\bar{d}\right)\left(p_j-\bar{p}\right)}{\sum_{j=1}^{n}\left(d_j-\bar{d}\right)\times\sum_{j=1}^{n}\left(p_j-\bar{p}\right)}\right]^2 \tag{8}$$

where d and p, are the actual and predicted values of the engine parameters respectively, and $\bar{d}$ and $\bar{p}$ are also average values. The SVM's reliability will increase as much as SVM can estimate engine parameters with less RMSE and MAPE, and more R^2 and EF in both stages of training and testing. Also, to further assess and ensure the validity of SVM results, statistical evaluation including mean comparison, variance, and statistical distribution of two real and predicted data sets were also used. Thus,

Table 4 – The result of the comparison of the CVCB experimental and simulated values.

H2 (%)		Average	Variance	Skewness	Kurtosis	*Pm*	Pv	Pt
0	Simulated	1.48	1.08	0.37	1.42	0.94	0.95	0.88
	Experimental	1.44	1.04	0.31	1.28			
3	Simulated	1.47	0.98	0.31	1.37	0.98	0.93	0.88
	Experimental	1.46	1.05	0.27	1.23			
6	Simulated	1.53	1.05	0.21	1.32	0.93	0.98	0.88
	Experimental	1.48	1.07	0.21	1.17			
15	Simulated	1.65	1.14	0.005	2.75	0.93	0.92	0.88
	Experimental	1.60	1.05	0.008	2.71			

Pm, Pv, and Pt are equal to P-value of the mean test, variance and statistical distribution of two simulated and predicted data sets at a probability level of 5% in respectively.

the null hypothesis implies the similarity of the two actual and predicted data sets. The p-value statistic was used to evaluate the statistical tests. If p-value> 0.05, then the two sets of data do not have a significant difference between each other. Therefore, the predictions of the model can be assured.

Optimization with genetic algorithm (GA)

After validation of the SVM model was confirmed in the engine performance estimation. It was used as a fitness function in the genetic algorithm. The genetic algorithm was used to obtain the best engine operating conditions. Optimum conditions in this paper include achieving the highest level of power, torque, and fuel conversion efficiency, and minimizing carbon monoxide emissions and specific fuel consumption. With the use of GA, the optimal levels of each of the independent variables IT, IGT and H2% in different engine speeds are obtained. Because the engine in different working conditions needs to different speeds conditions, optimization was done in different runs. The

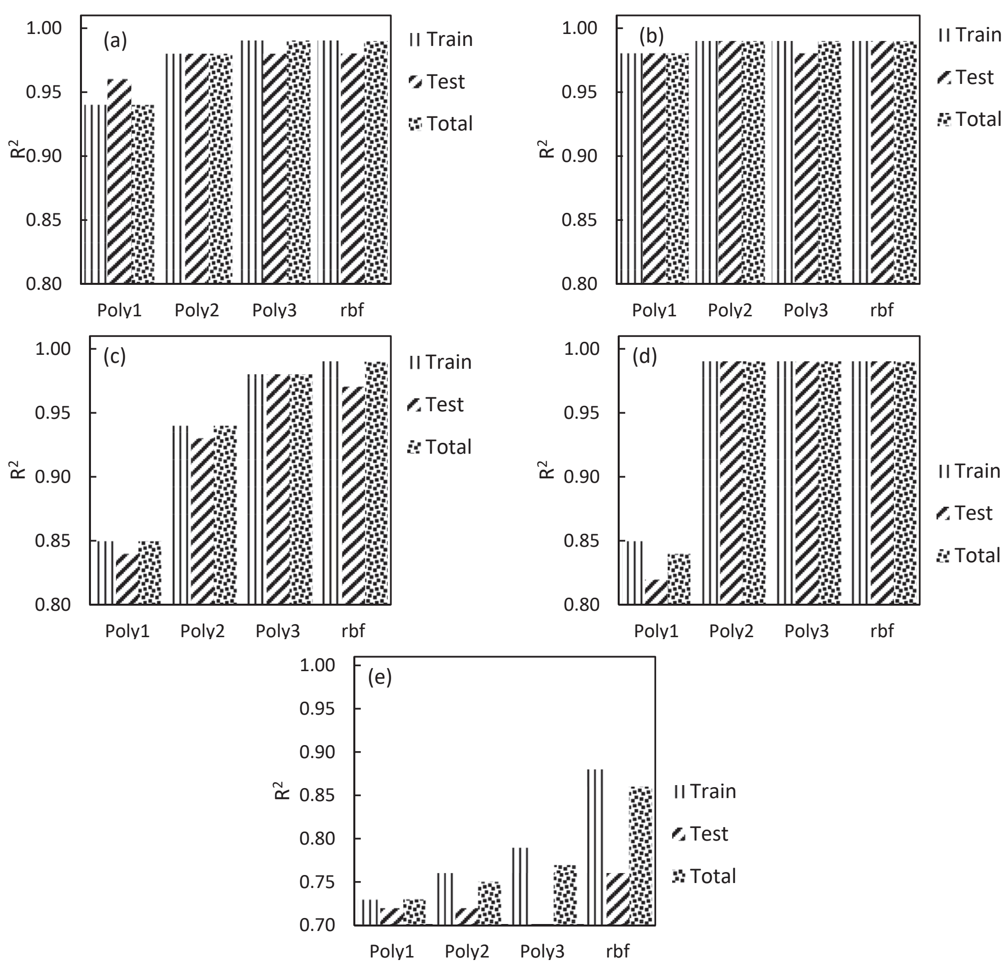

Fig. 6 – R^2 values of the SVM model in the estimation FCE (a), power (b), torque (c), SFC (d) and CO (e).

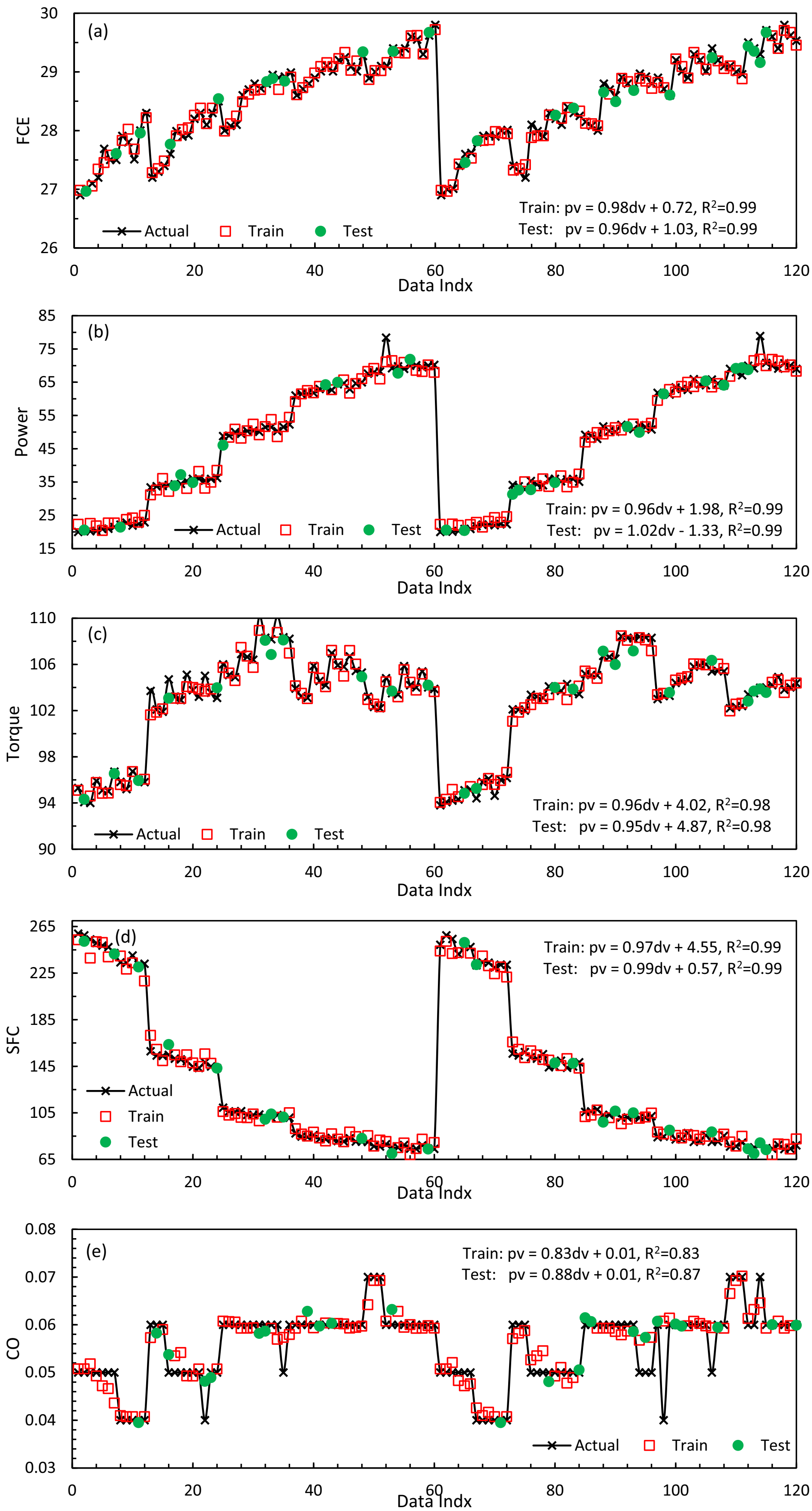

Fig. 7 — The real and predicted values of the engine performance parameters by SVM model for FCE (a), power (b), torque (c), SFC (d), and CO (e).

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Table 5 – The SVM model error values for estimating engine performance parameters and the statistical comparison between simulated and predicted values.

	FCE			Power			Torque		
	Train	Test	Total	Train	Test	Total	Train	Test	Total
RMSE	0.09	0.09	0.09	1.90	1.57	1.84	0.53	0.64	0.55
MAPE	0.24	0.26	0.89	3.88	2.99	3.72	0.37	0.47	0.39
EF	0.99	0.99	0.99	0.99	0.99	0.99	0.98	0.98	0.98
Pm	0.96	0.92	0.99	0.96	0.96	0.98	0.90	0.99	0.91
Pv	0.85	0.88	0.81	0.74	0.91	0.81	0.72	0.67	0.63
Pt	0.95	0.99	0.88	0.53	0.99	0.67	0.95	0.99	0.95
	SFC			CO					
RMSE	5.06	3.72	4.82	0.00	0.00	0.00			
MAPE	3.17	2.61	3.06	3.64	3.35	3.58			
EF	0.99	0.99	0.99	0.83	0.86	0.83			
Pm	0.99	0.99	0.99	0.79	0.72	0.69			
Pv	0.76	0.99	0.79	0.37	0.77	0.35			
Pt	0.65	0.62	0.56	0.00	0.11	0.00			

Pm, Pv, and Pt are equal to P-value of the mean test, variance and statistical distribution of two simulated and predicted data sets at a probability level of 5% in respectively.

engine Optimum conditions were investigated in two single-objective and multi-objective situations. The purpose of a single objective is to achieve an optimal point without considering other goals. For example, just maximize power. Also, the purpose of multi-objectives is to optimize engine conditions at different speeds to achieve all goals together (Equation (9)). For this purpose, a multi-objective genetic algorithm (MOGA) based on Pareto-dominance and the non-dominated and crowding algorithm II (NSGA-II) was used in MOGA.

$$\begin{cases} \max f_{svm}(\text{Power}) \\ \max f_{svm}(Torque) \\ \max f_{svm}(FCE) \\ \min f_{svm}(SFC) \\ \min f_{svm}(CO) \end{cases} \tag{9}$$

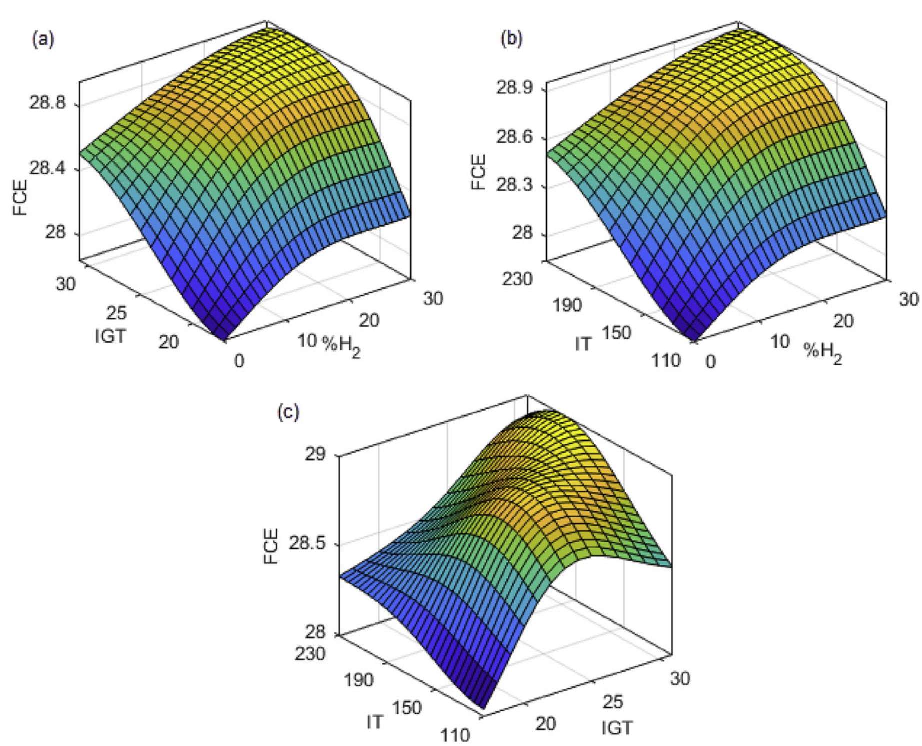

Fig. 8 – The FCE response level graph between the independent variables H2%, IT and IGT at 4000 rpm for IT = 170°(a), IGT = 28°(b) and H2 = 30%(c).

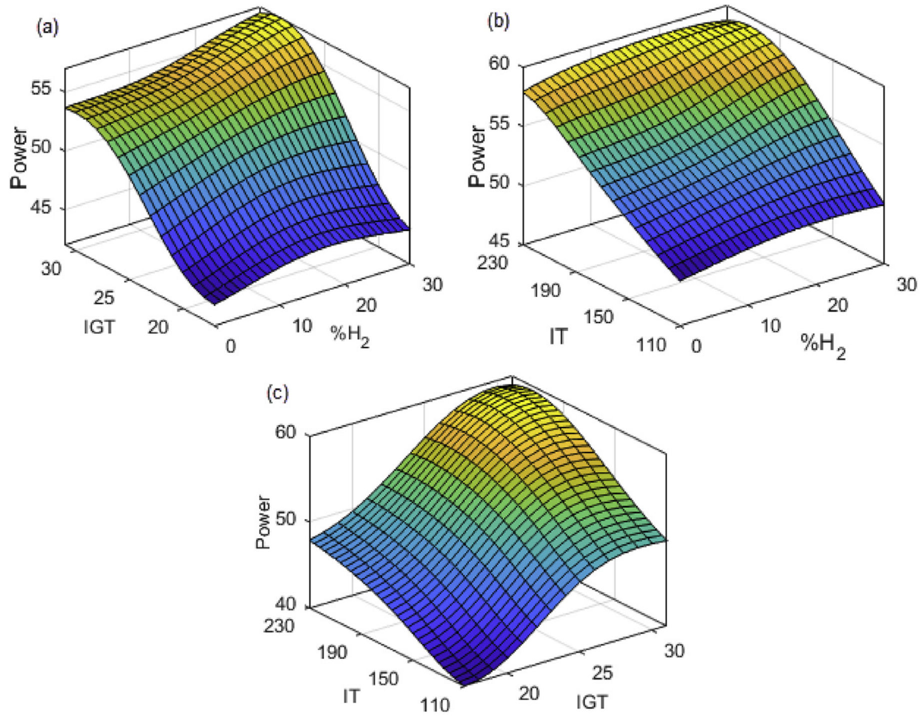

Fig. 9 – The curves of the power response level versus the independent variables H2%, IT and IGT at 4000 rpm for IT = 170°(a), IGT = 28°(b) and H2 = 30%(c).

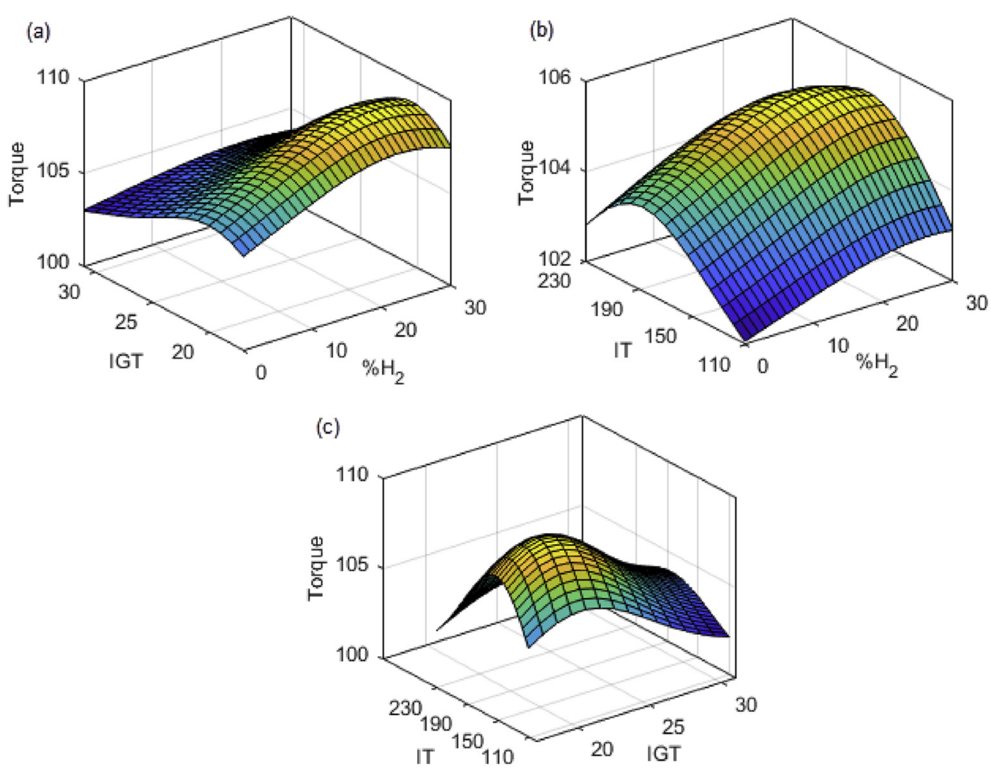

Fig. 10 – The curves of the torque response level versus the independent variables H2%, IT and IGT at 4000 rpm for IT = 170°(a), IGT = 28°(b) and H2 = 30%(c).

The optimal GA solutions are based on the principle of natural selection and genetic theories. First, GA provides random solutions to the definition of independent variables. Then, next generations generate the possible solutions after the evaluation of fitness function with the help of selection, crossover and mutation operators. The generation of different generations of solutions continues to the point where there is no longer any way to achieve new solutions. MATLAB software was used for SVM modeling and GA optimization.

Results and discussion

The experimental methods ratio to simulation methods requires costing and adequate time. So, the AVL fire software used for engine simulation. To validation and reliability of the simulation model, the experimental and simulation results of constant volume combustion bomb (CVCB) compared [35].

In the present study as the meshing procedures and sub-models used in CNG-DI engine, combustion simulation was also used in the CVCB combustion simulation. As the validation was done for 100% natural gas combustion as well as different blends of hydrogen-natural gas in CVCB.

Statistical comparisons were used to compare the experimental and simulated results. The average, variance, skewness, and kurtosis values of experimental and simulated results with the percentage of hydrogen in the blend are presented in Table 4. For statistical comparison of the mean value, variance and statistical distribution of two real and simulated data sets, *t*-test, F-test and Kolmogorov-Smirnov tests were used at 5% probability level. The p-value of each of these tests is shown in Table 4, with the *Pm*, Pv, and Pt, respectively. As the results show, the values p-value are greater than 5%, so no significant differences were found between experimental values and simulations. Therefore, the results simulated by AVL fire can be trusted.

The best choice of the kernel function for SVM

For modeling of engine parameters, four types of kernel functions in SVM are used: polynomial degree 1 (Poly1), polynomial degree 2 (Poly2), polynomial degree 3 (Poly3) and RBF function. The results of three stages of training, testing, and total (both training and testing) indicate that the RBF function is considered to be the most suitable type of kernel function in SVM to evaluate engine parameters (Fig. 6).

Comparative evaluation of SVM model predictive validity

In Fig. 7, the result of the validation of the SVM model prediction is shown on five performance parameters of the engine in the training and testing stages. As the results show,

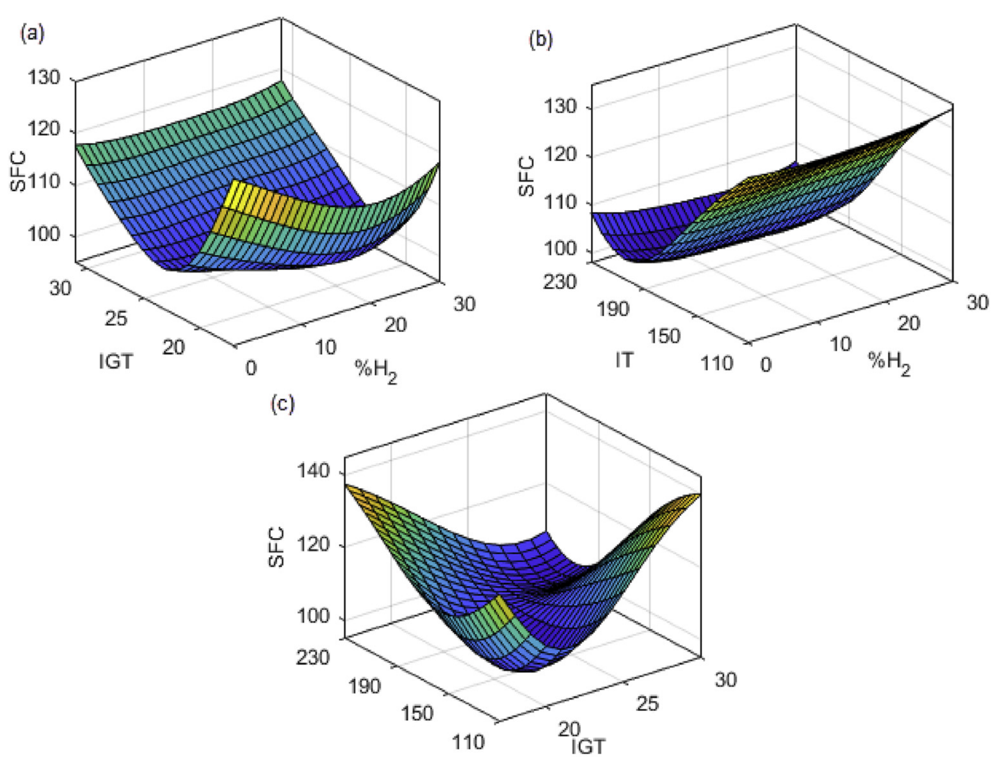

Fig. 11 – The curves of The SFC response level versus the independent variables H2%, IT and IGT at 4000 rpm for IT = 170°(a), IGT = 28°(b) and H2 = 30%(c).

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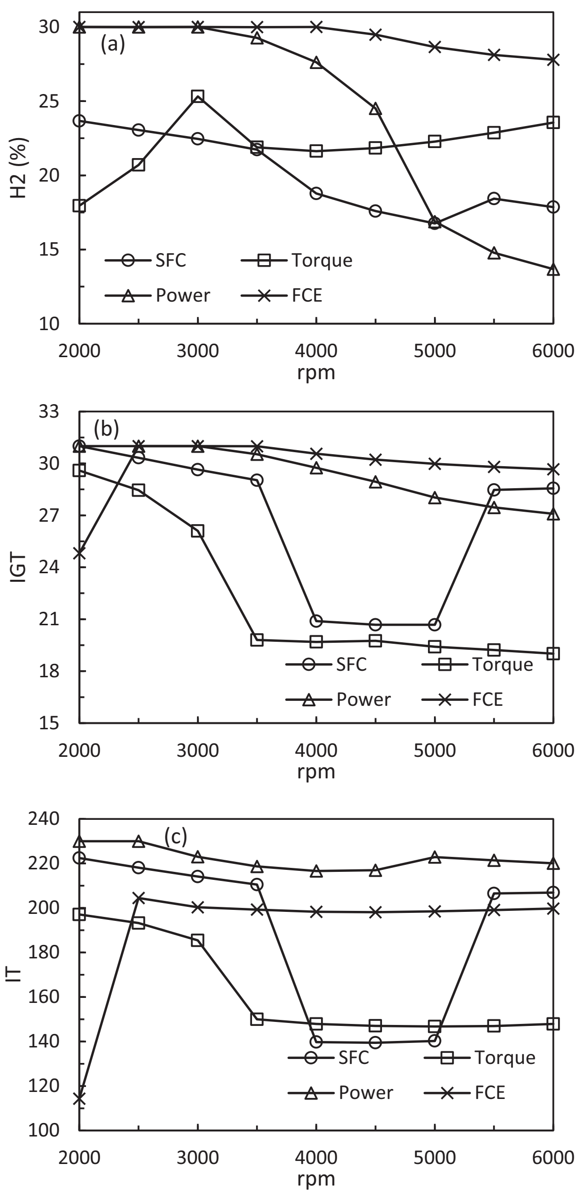

Fig. 12 – The optimal values of three independent variables H2% (a), IT and IGT to obtain the maximum FCE, Torque and power and the minimum values of SFC at different engine speeds using a single-objective genetic algorithm.

there is a good agreement between actual and predicted values of engine performance parameters other than CO (in all cases, R^2 is greater than 0.98). Therefore, the SVM model can well provide the relationship between independent variables (H2%, RPM, IGT and IT) and dependent variables including engine performance parameters.

In Table 5, the error values of the model (RMSE and MAPE), the efficiency of the model (EF) and the similarity and equality results of the statistical assessment including mean value, variance and statistical distribution of the simulated data sets and predicted by the SVM model is presented in three stages: training, testing, and both stages of total. As the results show, the SVM model has been able to predict FCE, Power, Torque, and SFC with a greater EF of 98% and less than 4% error. Also, the statistical test between two simulated and predicted datasets by SVM model showed that the maximum significant difference between them is in the 5% probability level (in all cases p-value> 0.05). Besides, the SVM model was able to predict CO with a maximum error of 3.58 with a predicted EF of more than 83%. Two simulated and predicted datasets of CO emission did not have a significant difference in terms of mean values and variance. According to all the results, it can be stated here that the SVM model has a good ability to predict the performance parameters of the engine in terms of independent variables. So that the results will be useable and can predict.

The response surface graphs of engine performance parameters using the SVM model

After that, the research results were proven that can rely on the results of the prediction of the SVM model, by which the response surface graphs of dependent variables were plotted in terms of independent variables. In Fig. 8, the FCE response level of the engine is shown at 4000 rpm against H2%, IGT, and IT. As shown in Fig. 8 (a), with assuming IT = 170, increasing of H2% as well as increasing the IGT, the functional parameter FCE has an upward trend. In this situation, the highest amount of FCE obtained at 30% of hydrogen and with IGT at 28°. In Fig. 8 (b), the FCE changes in terms of hydrogen and IT were plotted with the assumption of IGT = 28°. In this case, the FCE increased with an increase in both parameters of H2 and IT simultaneously. The highest FCE was obtained at IT = 204 and H2 = 30%. The effect of the changes in the two independent parameters of IT and IGT in H2 = 30% on FCE can be seen in Fig. 8 (c). As the results show, the two parameters of IT and IGT have significant interaction with FCE changes. The effect of IGT on FCE variations is dependent on the amount of IT. So that the opposite of this subject is true. However, the highest FCE value is obtained at IGT = 31 and IT = 200.

In Fig. 9, the relation between the power response level and independent variables studied at 4000 rpm is shown. As can be seen, the effect of IGT on power increase is much higher than that of H2 (Fig. 9 (a)). Because the slope of power changes versus the increase of IGT at different levels of hydrogen is higher. Besides, the highest power levels were obtained at IGT = 29° and 30% H2. The same process of change can also be seen for IT (Fig. 9 (b)). Therefore can reach to the highest power by taking IT = 221° and H2 = 26%. Therefore, the impact of IGT and IT on increasing power is greater than H2. Also, based on Fig. 9 (c) can say that the two parameters of IT and IGT have a significant interaction effect on power changes. Also, IGT's impact on power increase is more than IT. Of course, the highest amount of power is available when IGT = 30° and IT = 214°.

Fig. 10 illustrate variations of torque versus three independent variables H2, IGT and it at 4000 rpm. The results showed that at each level of H2, with a decrease of IGT, the variation of torque is upward (Fig. 10 (a)). But the highest torque is achievable in IGT = 20° and the use of 24%H2. In terms of torque variations in terms of IT and H2, it can be said that with increasing H2 the torque is always increased. In terms of torque variations against IT and H2, it can be said that with increasing H2 the torque is always increased. Nevertheless, the amount of IT effects on these changes. As with

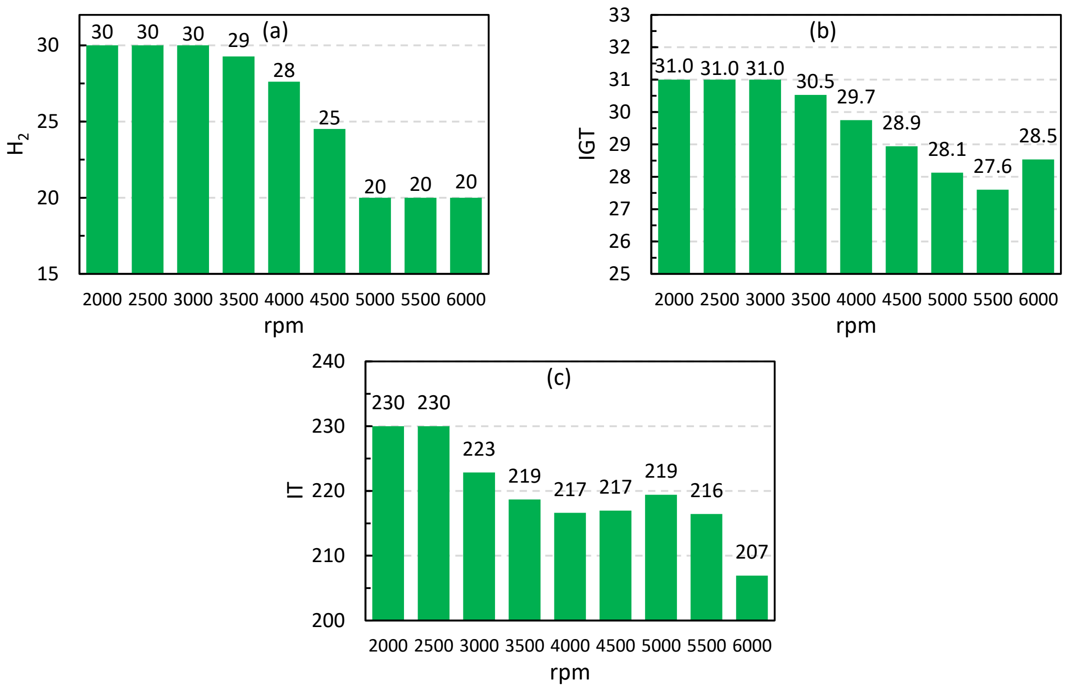

Fig. 13 – The optimal values of three independent variables H2%, IT and IGT to obtain the maximum FCE, Torque and power and the minimum values of SFC at different engine speeds using a multi-objective genetic algorithm.

increasing IT to 160° BTDC, the trend of torque is upward and then decreasing. But the effect of torque changes due to IT is much more than the percentage of hydrogen (Fig. 10b). In this case, the highest torque is obtained at IT = 178° and 25%H2. The trend of torque changes in terms of changes the two variables of IT and IGT can be seen in Fig. 10 (c).

In Fig. 11 the SFC response level can be seen in terms of the three variables H2, IT and IGT at 4000 rpm. Increasing the IGT to 21° before top dead center reduced the SFC, and then the trend of SFC was upward. The lowest amount of SFC is obtained at 22% H2 and IGT at 21° (Fig. 11 (a)). As shown in Fig. 11 (b), the increase in IT will reduce SFC. Also, the effect of going up IT on SFC reduction is much more than adding hydrogen percentage. Similar to the previous results, the two IT and IGT variables have a very significant interaction effect on the SFC variations. The lowest SFC values are also available in the combination of IGT = 21° and IT = 146°. The results also showed that the CO response surface graph is similar to the changes in the engine's performance parameters and is affected by four independent engine, IT, IGT, and H2 variables.

Optimization of engine performance parameters using a genetic algorithm

As the response level results indicate, each of the engine's performance parameters varies according to the value of the independent variables. But our studies showed that the optimal value of the three independent variables of IT, IGT and H2% varies at different engine speeds and this subject can be seen in Fig. 12. Using the single-objective genetic algorithm and the SVM model, the optimal values of IT, IGT and H2 were calculated to obtain the maximum power, torque, and FCE, and the minimum SFC at different speeds (Fig. 12). As the results show, the optimal amount of H2 varies at different speeds. To reach a maximum FCE at 4000 rpm, it needs to 30% H2 fuel. But then, with increasing engine speed, the percentage of hydrogen to reach the maximum FCE should be reduced. Similarly, in order to achieve the highest possible power, the consumption ratio of hydrogen fuel should be reduced. But in order to maximize torque over different engine speeds, hydrogen should be used up to 3000 rpm, and the consumption of hydrogen should be at a constant rate. And similarly, the optimal amount of other variables, including IT and IGT, varies at different speeds (Fig. 12 b and c). Therefore, these results confirm the fact that it is necessary to use independent variables to achieve the best-operating conditions of the engine at different speeds from different optimal values. On the other hand, the results of this section are obtained using a single-objective genetic algorithm. In other words, here the optimal values of the variables are obtained only by considering one of the goals. But in reality, all goals must be considered together. For this purpose, the multi-objective genetic algorithm was used.

According to the previous results of a single-objective genetic algorithm, it cannot be performed separately for obtaining all goals, because each of the optimization goals of the engine performance parameters is in contradiction with each other especially in various engine speeds. So, we optimize the engine performance parameters at each speed by the multi-objective model (Figs. 13 and 14). Here at each speed of the engine, we simultaneously sought to find levels of independent variables including IT, IGT, and H2 to maximize power, torque and fuel conversion efficiency, as well as minimize SFC and CO. Fig. 13. Show the results of

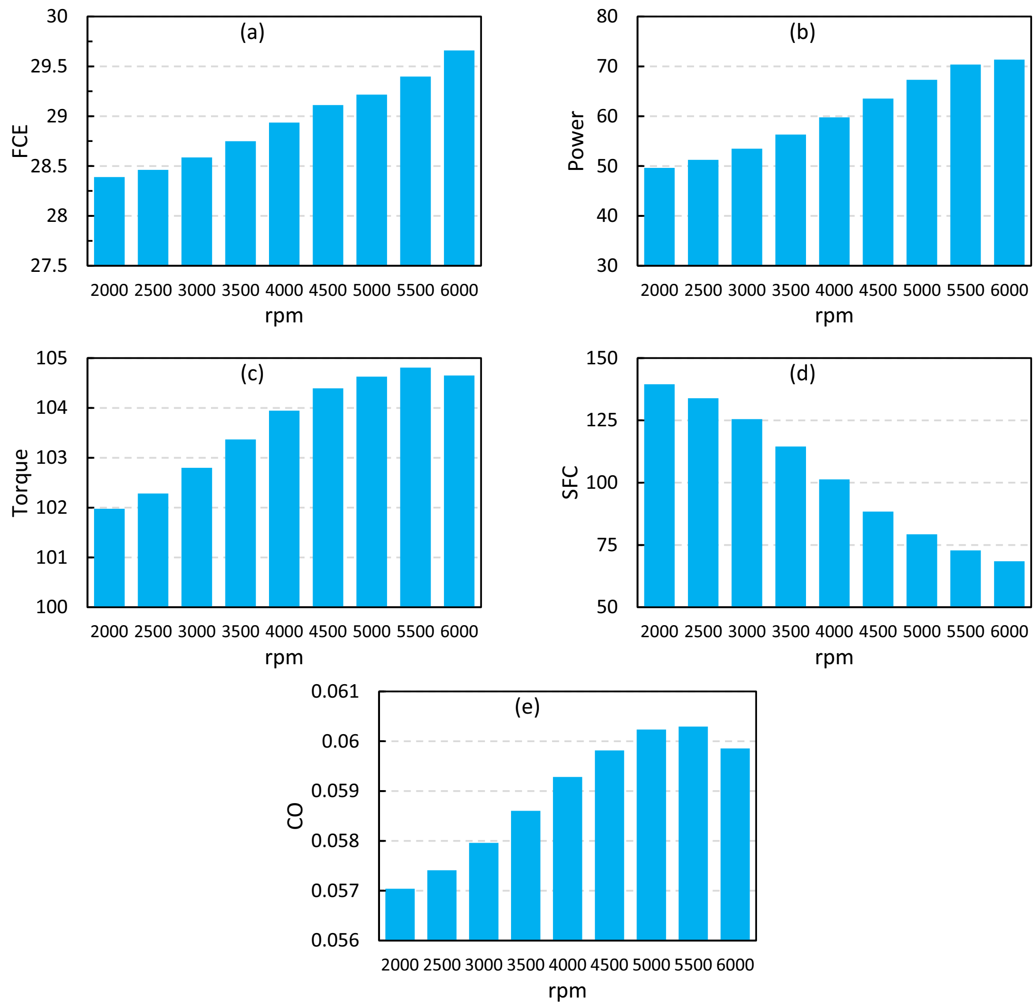

Fig. 14 – The optimal values of the engine performance parameters including FCE, Torque and power and the minimum values of SFC at different engine speeds.

optimization of independent variables in different speeds. As the results confirm, in order to achieve the three goals of maximization and two goals of minimization, it is necessary to use 30% hydrogen in the blend of fuel to 3000 rpm. Subsequently, the amount of hydrogen was reduced by a gentle gradient to reach to 20% until 5000 rpm and up. In order to keep the engine in optimal condition, the hydrogen percentage in the blend of fuel should be controlled in proportion to the engine speed. The need to high levels of hydrogen in the low speed is due to incomplete combustion and low speed of combustion but in the higher speeds, the hydrogen consumption should be reduced due to the complete combustion process. But in any case, the results indicate that the optimum use of hydrogen in the various engine speeds is between 20% and 30%. The optimization result of the two variables, IGT and IT shows that their optimal values vary at different speeds (Fig. 13 b and c). Fig. 14 Shows the results of applying independent variables at optimal levels for the five targets considered in different engine speeds. As can see, the FCE decrease with an increase of engine speed and keeping independent variables in optimal condition (Fig. 14a).this is due to the higher power and more efficiency at high speed.

Conclusions

In this paper, the SVM model was used to estimate the engine performance parameters including FCE, power, torque, SFC, and CO. The results of the SVM prediction showed that there is no significant difference between the actual and the predicted values and the maximum predicted model error is approximately 4% also, SVM model response levels were plotted to independent variables including rpm, H2%, IT and IGT.

1. Investigating the level of FCE response showed that the effects of three independent variables including IT, IGT and H2% on FCE are significant.
2. The power response level obtained by the SVM model showed that the IGT's impact on power is much higher than that of H2%. The impact of IGT and IT on increasing power is higher than H2. The two parameters of IT and IGT have a significant interaction effect on power changes. Also, IGT's impact on power increase is more than IT.
3. Investigation on the torque changes in terms of IT, IGT and H2% showed that torque increases with decreasing IGT. Also, with increasing H2, torque is always increased.

But IT effects on these changes. As the impact of torque changes due to IT is much higher than the percentage of hydrogen.

4. The response level of the SFC in terms of the three variables H2%, IT and IGT showed that with increasing the IGT to 21° BTDC, the SFC decreases and then increases. The results also indicated that increment of IT decreased SFC parameter. Also, the effect of the increase of IT on SFC reduction is much higher than adding hydrogen percentage in the blended fuel.
5. The results of optimizing the engine performance parameters using a single-objective genetic algorithm showed that the optimal values of the independent variables vary in different speeds. Therefore, in order to keep the engine in optimal condition, it is necessary to use different variable regimes in each engine. Our investigations also showed that if only one goal was considered, contradictory levels of variables were obtained. Therefore, to achieve a comprehensive result for each speed, a multi-objective genetic algorithm should be used.
6. In a multi-objective genetic algorithm for each engine speed, it simultaneously sought to find levels of independent variables including IT, IGT and H2% to maximize power, torque and fuel conversion efficiency as well as minimize SFC, and CO. The results confirmed that in order to achieve the three goals of maximization and two minimization goals, and keeping the engine condition in the optimal case, the hydrogen percentage in the blend should be controlled in proportion to the engine speed. But in any case, the results indicate that the optimum use of hydrogen in the various engine speeds is between 20% and 30%. The result of optimizing the two variables, IGT and IT, also shows that their optimal values vary in different speeds. In overall, for this engine, it can be concluded that converting a port injection engine into a direct injection and adding hydrogen fuel between 20% and 30% to CNG at different speeds according to changing IGT and IT has the best achievement.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ijhydene.2019.10.250.

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