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Prediction and optimization of hydrogen yield and energy conversion efficiency in a non-catalytic filtration combustion reactor for jet A and butanol fuels

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Abstract−Hydrogen production is one of main subjects in fuel cells. The traditional method of synthesis gas production is based on fuel reforming using catalysts. The main problem of these methods is sensitivity and fast degradation of catalysts especially when fuels with high sulfur content are used. A new technique for hydrogen production is fuel-reforming using non-catalytic filtration combustion in porous media reactors. Various experimental works have been carried out to increase hydrogen production under different operating conditions such as inlet fuel velocity and equivalence ratio. First, we investigated the ability of adaptive neuro fuzzy inference system (ANFIS) for predicting the filtration combustion characteristics. Four distinct ANFIS models were developed for estimating the hydrogen yield and energy conversion efficiency for fuels of jet A and butanol. Eight different membership functions of dsigmf, gauss2mf, gaussmf, gbellmf, pimf, psigmf, trapmf and trimf were tested for training of the ANFIS networks. The results showed that the RMSE of the best developed ANFIS models for estimating of the hydrogen yield of jet fuel, hydrogen yield of butanol, conversion efficiency of jet fuel and conversion efficiency of butanol were 1.399, 1.213, 0.508 and 2.191, respectively. Moreover the R^2 values of 0.998, 0.998, 0.999 and 0.999 were obtained for predicting the above mentioned variables, respectively. In the second step, a novel algorithm based on imperialist competitive algorithm (ICA) was used for optimization of hydrogen yield and energy efficiency. The maximum value of hydrogen yield and energy efficiency was 50.46% and 67.88% for jet A and 47.27% and 96.93% for butanol, respectively. The results showed that the imperialist competitive algorithm is an efficient and powerful algorithm to optimize combustion processes.

Keywords: Optimization, ICA, ANFIS, Hydrogen Yield, Energy Conversion Efficiency, Jet Fuel, Butanol

INTRODUCTION

Hydrogen is a chemical compound widely used in refining processes, such as hydrocracking, hydrogenation and as a feed in ammonia production units in petrochemical industries. It has high energy per unit mass and low-emissions during combustion compared to other fuels. Hydrogen can be produced from many fuels such as methanol [1], ethanol [2], butanol, jet fuel [3], gasoline, ISO-octane, methane [4], and heptane [5]. Numerous studies on reforming of fuels to syngas using catalysts have been performed [6,7]. Bharadwaj et al. [7] used Rh as a catalyst to reform natural gas to syngas. The main problem of this method is that the catalysts are often disposed to deactivate or degrade [8-10]. Without catalysts, these reactions are too slow for practical applications. and so the initial temperature needs to be increased to enhance the reaction rates. Another way to produce hydrogen is non-catalytic filtration combustion inside a stationary inert porous medium. Several studies have been based on this method. Dhamrat et al. [4] used filtration combustion to convert methane to hydrogen. They found that conversion percentage increases with an increase in the inlet velocity and is primarily due to the increase in the peak gas temperature. Dixon et al. [5] studied the conversion of liquid heptane to syngas in a porous media reactor. Their results showed that the hydrogen concentration in the exhaust gas increases with raising equivalence ratio. Smith et al. [2] studied conversion of ethanol to syngas via filtration combustion and concluded that the conversion of ethanol is similar to conversion of heptane and methane in terms of combustion behavior. Smith et al. [3] investigated the conversion of jet fuel (Jet-A) and butanol to syngas by partial oxidation in a porous media reactor. The authors concluded that H_2 yield increases with φ for jet fuel, whereas for butanol both yields of H_2 and CO reach peaks within the tested operating ranges [3]. Araya et al. examined the effect of adding steam during filtration combustion of natural gas-air mixtures [11]. The results showed that hydrogen yield increases when steam content in the natural gas-air mixtures is increased. Different foams and beads can be used in filtration combustion reactors as a porous matrix. Alumina foam, alumina bead, cordierite foam [1], YZA (yttria stabilized zirconia/alumina) [5,12], ZTM (zirconia toughened mullite) [12] are some examples of porous media. Both gaseous and liquid fossil fuels have been converted to syngas successfully by filtration combustion [1, 5,13]. Combustion of different fuels of LPG, butane, propane, diesel fuel and heavy fuel oil in a porous media reactor was investigated experimentally by Toledo et al. [14]. Their results revealed that the tested heavy fuels have the potential to produce syngas in significant volumes. Rich combustion of n-heptane and diesel in a two layer porous matrix reactor was studied experimentally by Pastore and Mastorakos [15]. The experimental runs for n-heptane were performed at equivalence ratio of 2 and various inlet velocities. Results demonstrated that the concentrations of H_2 and CO

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in the outlet gas of n-heptane reforming reactor are 12.6% and 15%, respectively. In another study [16], they performed an experimental work on reforming of n-heptane, diesel oil, kerosene and bio-diesel in a two-layer porous bed reactor. The effects of equivalence ratio and porous material were investigated. They concluded that a working condition with equivalence ratio around 2 and thermal load of 7 kW give a stable flame with high conversion efficiency and low soot emission. The rapid progress of numerical algorithms and software, such as ANN and CFD codes, has enhanced the capability of engineers to solve complex engineering problems [17,18]. A numerical study on combustion of methane in porous media reactor was carried out by Guoneng et al. [19]. The results revealed that the combination of CFD model with chemical mechanism of Glarborg et al. [20] generates a reasonable prediction of H_2 concentration, but the model cannot capture CO concentration. The ICA optimization method has been employed extensively in various chemical engineering applications, such as prediction of hydrate formation temperature, prediction of various petroleum fluid properties and operational optimization of distillation column [21-27]. This method has potential superiority over other well-known optimization techniques, such as the genetic algorithm (GA) and particle swarm optimization (PSO) in terms of its convergence rate and global optima achievement [26-30,40]. Maroufmashat et al. applied the ICA algorithm to determine the optimum condition of the PV/EL system to maximize the hydrogen production and minimize the energy transfer loss [31]. They concluded that the ICA algorithm has the ability to quickly converge in both hydrogen production maximization and energy transfer loss minimization. Justesen et al. developed an ANFIS model for predicting the gas composition in a reformed methanol fuel cell [32]. They found that the proposed model has the required ability for an accurate prediction of reformed gas flow rates. Justesen and Andreasenet developed a hybrid model for obtaining the temperature which gives the best efficiency for reformed methanol fuel cell [33]. Yaïci and Entchev performed a modeling work for performance prediction of solar thermal energy system [34]. They compared the ANFIS and ANN predicted performance results and concluded that the ANFIS gives more precise results with respect to ANN; however, the computing speed of the ANFIS model was less than ANN model. Although several numerical models have been developed for describing the filtration combustion process [35-37], few studies employed the soft computing algorithms for modeling of these processes [38]. In this study, we used three powerful intelligent algorithms of ANFIS, ICA and GA for prediction and optimization of the filtration combustion systems. The parameters of hydrogen production and energy conversion efficiency for two fuels of Jet A and butanol were investigated. The required experimental data were collected from work of Smith et al. [3,12,39]. The proposed methods were developed using MATLAB functions.

EXPERIMENTAL WORK

The experimental apparatus, shown in Fig. 1 [3], consists of the reactor, fuel vaporization, reactant delivery, and data acquisition systems. The reactor was a quartz cylinder, 5 cm in diameter, 30 cm in length and filled with 99.5% pure alumina spheres. It was surrounded by an insulating sleeve of alumina. The fuel and water flows were vaporized and mixed with air before entering the reactor. A thermocouple was placed before the entrance of the reactor for measuring temperature. The temperature of the inlet mixture was always between 150 °C and 200 °C. The fuel was pumped by a peristaltic pump. The vaporization system consisted of an air-atomizing nozzle and the quartz chamber for mixing. Dry air was supplied by the laboratory's compressor. The oxidation reactions of vaporized fuel-air mixture occurred in the porous matrix, and the products exiting the burner passed through a filter to remove particulates. Then the outlet gas was dried and injected into a gas chromatograph. Further details about the experiments can be found in [3].

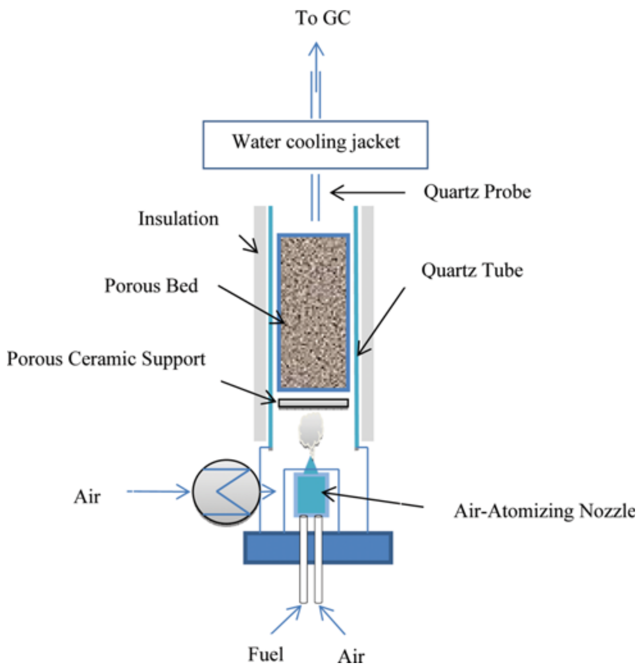

Fig. 1. Schematic diagram of the filtration combustion reactor [3].

IMPERIALIST COMPETITIVE ALGORITHM (ICA)

ICA, first presented by Esmaeil Atashpaz-Gargari [40], is an evolutionary approach that imitates the competition between imperialist countries in order to strengthen their empires. The main principles of this algorithm are assimilation, imperialistic competition and revolution. This algorithm considers the solutions of optimization problems as countries and tries to gradually improve them during the iterative process. Like other evolutionary algorithms, the suggested algorithm starts with an initial population. Population members called country are categorized in two classes, colonies and imperialists, that all together establish some empires. Imperialistic competition between these empires constitutes the basis of the suggested evolutionary algorithm. During this competition, weak empires collapse and powerful ones take possession of their colonies. Imperialistic competition confidently converges to a state in which there exists only one empire and its colonies are in the same situation and have the same cost as the imperialist. Using this approach, one can find the optimum condition for most functions. In this connection, the suggested model is then placed into the ICA to optimize the objective function. To find the optimal solution, an array of variable values, called "country," is constituted. In an N_{var}-dimensional problem, a country is a $1*N_{var}$ array. This array is presented by:

$$country=[p_1, p_2, ..., p_{Nvar}] \quad (1)$$

The cost of a country is obtained by assessing the cost function at the variables (P_1, P_2, P_3, …, P_{NVAR}). Then:

$$cost=f\,(country)=f\,(P_1, P_2, P_3, \ldots, P_{NVAR}) \quad (2)$$

The flowchart of the ICA algorithm is shown in Fig. 2. In the starting step, the initial population with size of N_{pop} is formed. The N_{imp} of the most dominant countries is chosen to generate the empires. The remaining N_{col} of the population are the colonies, each of which is placed within an empire. To generate the initial empires, the colonies are allocated between the imperialists, based on their powers according to fitness function. The normalized power of each imperialist, which is used as a criterion for distributing the colonies among the imperialists, is calculated by

$$P_n=\left|\frac{c_n}{\sum_{i=1}^{Nimp} c_i}\right| \quad (3)$$

where

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

In the above equations, c_n, C_n and P_n are the cost, normalized cost and normalized power of nth imperialist, respectively.

The initial number of colonies held by each empire is determined as follows:

$$N.\,C._n=round\{P_n.\,N_{col}\} \quad (5)$$

where N. $C._n$ and N_{col} are the initial number of colonies belong to n_{th} empire and the number of all colonies, respectively.

To allocate the colonies for each imperialist, N. $C._n$ of the colonies is selected randomly and is given then to the imperialist. These colonies accompanied by the imperialist will generate n_{th} empire. Fig. 3 shows the initial population of each empire. As can be seen,

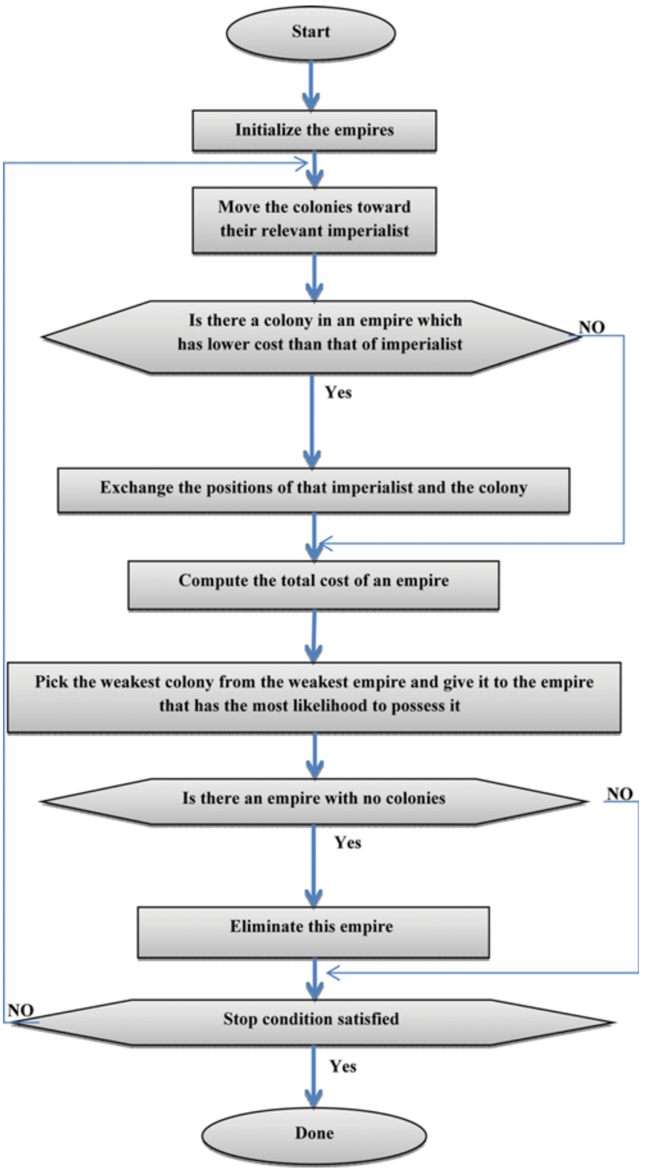

Fig. 2. flowchart of the ICA algorithm [40].

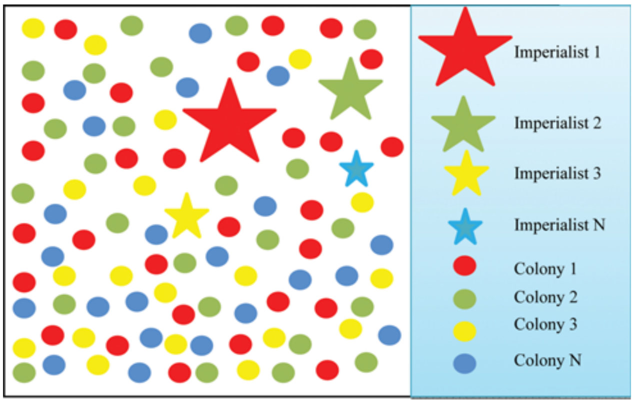

Fig. 3. Generating the initial empires [40].

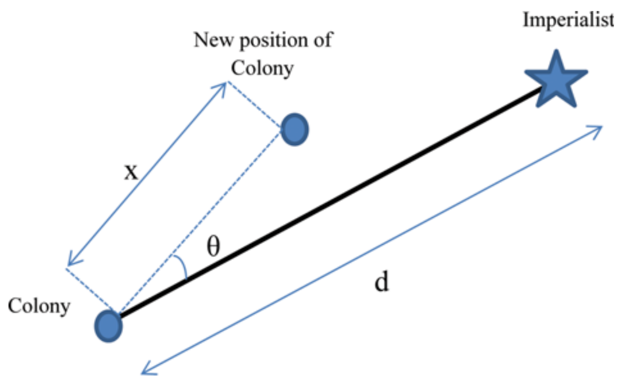

Fig. 4. Movement of colonies toward their relevant imperialist [40].

the more powerful imperialists have more colonies.

Trying to improve their powers, imperialist countries will increase their colonies by applying an assimilation strategy so that these colonies will start moving toward their pertinent imperialist. Fig. 4 shows the movement of a colony towards the imperialist. In this figure, θ and x are random numbers with uniform distribution and d is the distance between colony and the imperialist.

$$x \sim U(0, \beta \times d) \tag{6}$$

$$\theta \sim U(-\gamma, \gamma) \tag{7}$$

β and γ are the parameters with arbitrary values that adjust the zone which colonies randomly search around the imperialist. In this work, values of 2 and are considered for β and γ, respectively.

ADAPTIVE NEURO-FUZZY INFERENCE SYSTEM

The Adaptive network based fuzzy inference system (ANFIS) [41-43] is a class of estimation algorithms that are based on two approaches of neural network and Takagi-Sugeno fuzzy inference system. The ANFIS model has the ability to capture the benefits of both fuzzy logic and ANN approaches. The structure of Sugeno type ANFIS with two inputs (x1 and x2), two fuzzy rules and one output (f) is shown in Fig. 5. The relations between two inputs and one output are given as follow:

$$\text{Rule 1: If } (x_1 \text{ is } A_1) \text{ and } (x_2 \text{ is } B_1) \text{ then } f_1=p_1x_1+q_1x_2+r_1 \tag{8}$$

$$\text{Rule 2: If } (x_1 \text{ is } A_2) \text{ and } (x_2 \text{ is } B_2) \text{ then } f_2=p_2x_1+q_2x_2+r_2 \tag{9}$$

where A and B are the fuzzy sets, p, q and r are adjustable parameters determined during the training process. As can be seen from Fig. 5, ANFIS structure consists of five layers which are known as fuzzy layer, product layer, normalized layer, defuzzy layer, and total output layer. The layers and relationship between the input and output of the layers are described in detail elsewhere [44]. The ANFIS can utilize two methods (back propagation or hybrid) in the learning process for updating the parameters of membership functions. Dataset A is employed to train the model, and the forecasting ability of ANFIS is verified on dataset B. However, attaining the best architecture in conventional ANFIS for estimation of output parameters is time consuming and boring. To overcome these problems,

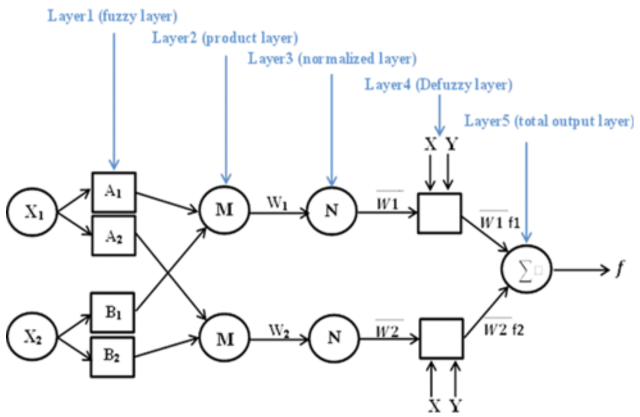

Fig. 5. The ANFIS structure [41].

the optimization algorithms such as genetic algorithm (GA), imperialist competitive algorithm (ICA) and particle swarm optimization (PSO) can be utilized for obtaining the parameters of membership functions in ANFIS model. These optimization algorithms are extensively used to optimize different engineering problems. In this study, we used the ICA and GA algorithms for optimization of hydrogen production and energy conversion efficiency.

HYDROGEN YIELD AND ENERGY CONVERSION EFFICIENCY

Main factors for a hydrogen production process are hydrogen yield and the total energy conversion efficiency. The first one is defined as follows:

$$\text{yield}=100 * \frac{2 * \dot{N}_{H2}}{N_H * \dot{N}_{fuel}} \tag{10}$$

where the units of $\dot{N}_{fuel}$ and $\dot{N}_{H2}$ are moles per second. The values of N_H for butanol and jet fuel are 10 and 21, respectively. This factor explains how the hydrogen bound in the fuel is converted to diatomic hydrogen.

The second parameter, the total energy conversion efficiency, is defined as the percentage of the whole chemical energy of inlet fuel that is transferred to flue gas species. This factor is represented by the following equation:

$$\text{total energy conversion efficiency}=100 * \frac{\Sigma \dot{N}_i * LHV_i}{LHV_{Fuel} * \dot{N}_{Fuel}} \tag{11}$$

where LHVs (Low Heating Value) are in units of kJ per mole.

RESULTS AND DISCUSSION

1. Prediction of Parameters Using ANFIS

In this section, hydrogen yield and energy conversion efficiency of combustion of two different fuels (jet A and butanol) in a porous media reactor are estimated using four distinct Sugeno-type ANFIS models. The output parameters depend on two input parameters: the inlet fuel/air mixture velocity and the equivalence ratio. The data set was divided randomly into two parts. Two-thirds of the data set was considered for training the networks and the remaining data was employed for validation of the ANFIS networks. The criteria for evaluating the performance of the ANFIS network were the root mean square errors (RMSE) and absolute fraction of variance (R^2), which are defined as follows:

$$\text{RMSE}=\sqrt{\left(\frac{1}{N}\Sigma_{i=1}^{N}(t_i-y_i)^2\right)} \tag{12}$$

$$R^2=1-\frac{\Sigma_{i=1}^{N}(t_i-y_i)^2}{\Sigma_{i=1}^{N}(t_i)^2} \tag{13}$$

where N is the number of data points, t and y are the actual and predicted values, respectively. Eight algorithms were employed for training the ANFIS networks and the accuracy of predictions for each algorithm was evaluated based on RMSE and R^2. The training algorithms were dsigmf (Difference of two sigmoid membership

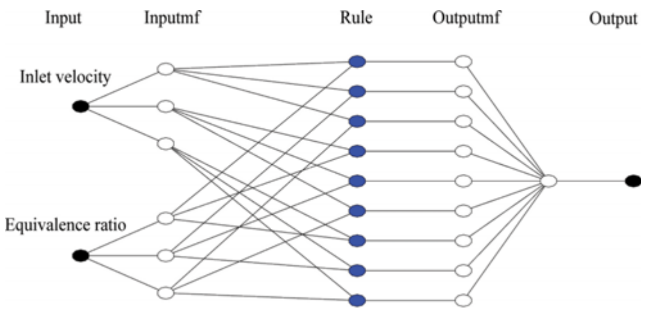

Fig. 6. Structure of desirable ANFIS model for predicting of hydrogen yield and energy conversion efficiency.

functions), gauss2mf (Two-sided Gaussian curve membership function), gaussmf (Gaussian curve membership function), gbellmf (Generalized bell curve membership function), pimf (Pi-shaped curve membership function), psigmf (Product of two sigmoidal membership functions), trapmf (Trapezoidal membership function) and trimf (Triangular membership function). The optimum method was hybrid and the structure of best ANFIS network was obtained by trial and error method. The chosen structures were the same for the four studied cases. The desired structure, which is shown in Fig. 6, has three membership functions for each input. Increasing the number of MFs may lead to overfitting, which usually occurs in complicated networks. The operators employed automatically in the training process were AND method is 'prod', OR method is 'probor', defuzz Method is 'wtaver', imp Method is 'prod' and agg method is 'sum'.

Table 1 shows the RMSE and R^2 values of different algorithms for each case. As can be seen from the table, gauss2mf, gbellmf, gaussmf and dsigmf membership functions give the most precise predictions of hydrogen yield of jet fuel, hydrogen yield of butanol, conversion efficiency of jet fuel and conversion efficiency of butanol, respectively. The RMSE of the best algorithm for the hydrogen yield of jet fuel, hydrogen yield of butanol, conversion efficiency of jet fuel and conversion efficiency of butanol are 1.399, 1.213, 0.508 and 2.191, respectively.

Details of the best ANFIS models for prediction of the aforementioned output variables are presented in Table 2.

Fig. 7 presents the ANFIS predicted values versus experimental values for both mentioned parameters. As is evident, the predicted results are in reasonable agreement with measured values for all four cases, and the ANFIS model of jet fuel efficiency is the most precise compared to other ANFIS models.

2. Optimization of Process Using ICA

2-1. Hydrogen Yield Optimization

In optimization by ICA algorithm, the input variable, output variable and cost function must be determined. In this section, inlet velocity and equivalence ratio are the input variables, and hydrogen yield is output variable. Table 3 shows the experimental data ranges used in this work for the optimization of hydrogen yield.

For the cost function, the hydrogen yield can be considered as a function of two independent variables of inlet velocity and equivalence ratio. The yield function was developed by using Excel nonlinear regression.

Table 1. Deviations of different algorithms for the predictions of hydrogen yield and energy conversion efficiency

Algorithm	Hydrogen yield (jet fuel)		Hydrogen yield (butanol)		Energy conversion efficiency (jet fuel)		Energy conversion efficiency (butanol)	
	RMSE	R^2	RMSE	R^2	RMSE	R^2	RMSE	R^2
dsigmf	2.5112	0.99486	3.0729	0.99259	0.90164	0.99970	**2.1918**	**0.99907**
gauss2mf	**1.3998**	**0.99840**	2.1344	0.99643	0.68671	0.99983	3.6653	0.99739
gaussmf	8.4425	0.94187	2.1518	0.99637	**0.5089**	**0.99990**	2.5494	0.99874
gbellmf	4.5695	0.98297	**1.2137**	**0.99884**	0.52686	0.99989	3.6151	0.99746
pimf	2.1340	0.99629	1.9304	0.99708	1.2303	0.99944	3.5962	0.99748
psigmf	2.4799	0.99498	3.0729	0.99259	0.90106	0.99970	2.1980	0.99906
trapmf	2.1460	0.99624	4.5591	0.98369	1.1460	0.99952	5.4278	0.99427
trimf	4.8151	0.98109	4.1897	0.98623	1.9003	0.99867	3.0470	0.99819

Table 2. Details of developed ANFIS models with best results

Variable	Hydrogen yield (jet fuel)	Hydrogen yield (butanol)	Energy conversion efficiency (jet fuel)	Energy conversion efficiency (butanol)
	gauss2mf model	gbellmf model	gaussmf model	Dsigmf model
Number of MFs to each input	3	3	3	3
Number of nodes	35	35	35	35
Number of linear parameters	27	9	27	9
Number of nonlinear parameters	24	18	12	24
Total number of parameters	51	27	39	33
Number of fuzzy rules	9	9	9	9

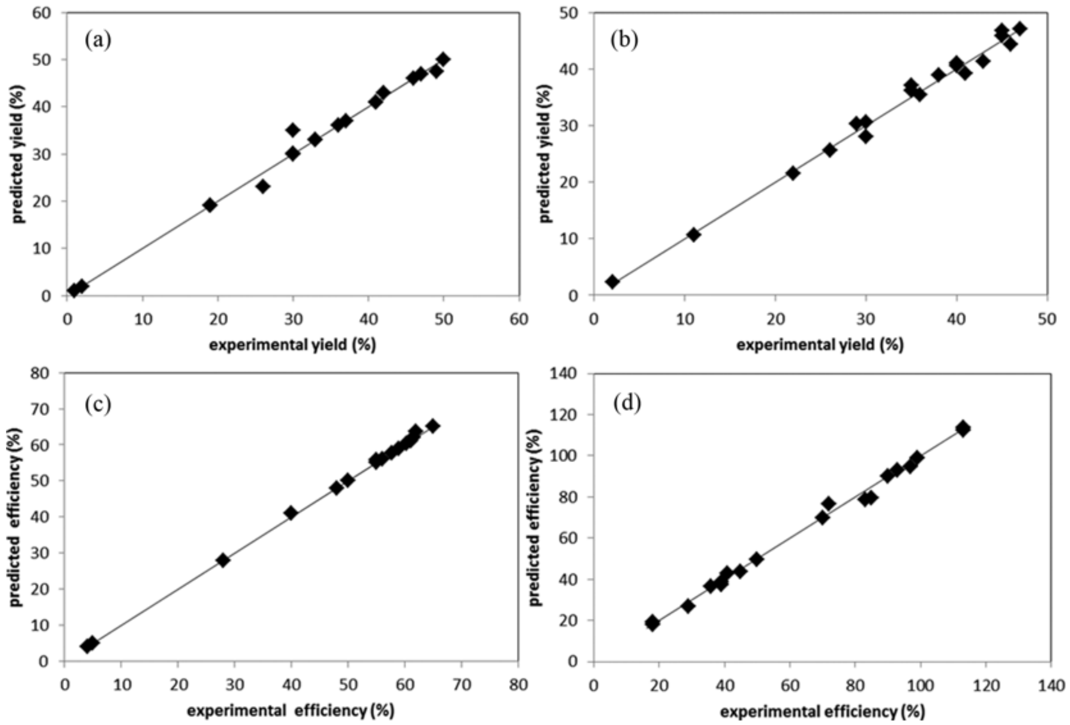

Fig. 7. ANFIS Predicted versus experimental data points. (a) hydrogen yield of jet fuel, (b) hydrogen yield of butanol, (c) energy conversion efficiency of jet fuel, and (d) energy conversion efficiency of butanol.

Table 3. Range of data employed for optimization of the hydrogen yield

Variable	Range
Inlet velocity (cm/s)	20-60
Equivalence ratio	1-5
Hydrogen yield	1-50

Hydrogen yield of Jet A:

$$y(\text{jet A})=-696.516+43.02302v-0.90575v^2+20.69659\varphi^2 +0.968197\varphi v+4.917378\varphi^3+0.004813v^3 -1.81654\varphi^2 v+0.079272v^2\varphi \quad (14)$$

Hydrogen yield of butanol:

$$y(\text{butanol})=366.73737535-39.8499v+0.825888v^2 -43.2737\varphi^2+12.13992v\varphi+3.686734\varphi^3 -0.00029v^3+0.112678\varphi^2 v-0.25893v^2\varphi \quad (15)$$

The absolute fraction of variance (R^2) of jet A and butanol correlations is 0.97583 and 0.982245, respectively. In Fig. 8, hydrogen yield is plotted as a function of inlet velocity and equivalence ratio for both fuels. Hydrogen yield, especially at middle inlet velocities, increases as equivalence ratio is increased, and this parameter reaches its maximum value. Then, the yield profile reveals a decreasing trend, which ultimately reaches a constant value.

The cost function is $-$Y and the country is a vector of input variables, $Xi=[{V \atop \varphi}]$.

The countries compete internally to minimize their costs in order to become the imperialist and represent the optimum level of input variables. After this stage, the external competition between imperialists is started and continued until one with the lowest cost function occupies the others. In this section, the winner imperialist is equivalent to maximum hydrogen yield. Table 4 shows the results of optimization.

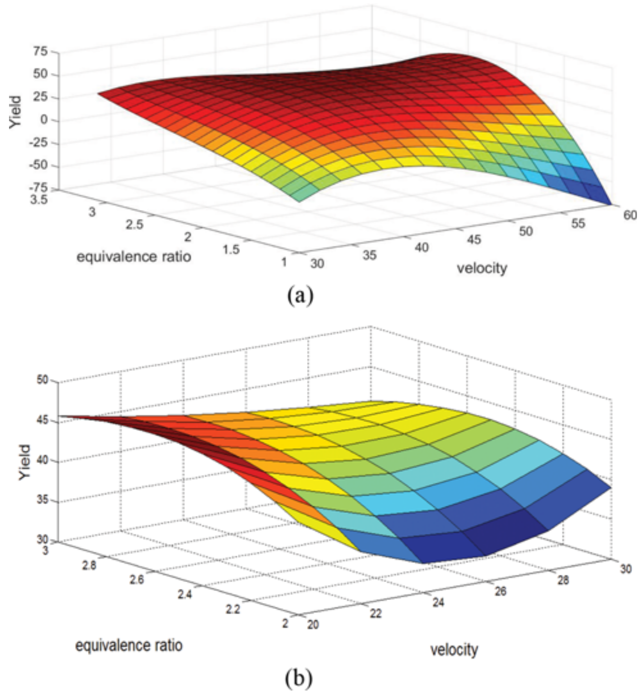

Fig. 8. Hydrogen yield as a function of inlet velocity and equivalence ratio for (a) jet A and (b) butanol.

Table 4. Results of optimization

Number of total countries	100
Number of initial imperialist countries	8
Number of iterations (epochs)	30
Revolution rate	0.3
Assimilation coefficient	2
Assimilation angle	0.5
Cost function	(−Y) or (−E)

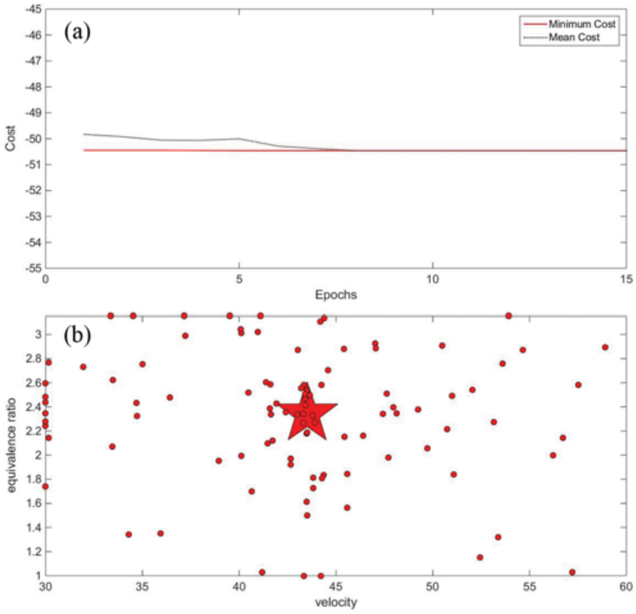

Fig. 9. (a) Mean and minimum cost of all imperialists versus epochs for the hydrogen yields of jet fuel. (b) Demonstration of winner imperialist in the search space including inlet velocity and equivalence ratio for yield of jet fuel.

Fig. 9(a) shows the minimum and mean cost of all imperialist for jet fuel. The figure illustrates that the target function could reach to minimum value of −50.46 after eight iterations.

Fig. 9(b) shows that at equivalence ratio of 2.35 and velocity of 43.35 cm/s, the imperialist with the lowest target function could occupy other imperialists and generate its empire and the relevant colonies. The results also show that the maximum hydrogen yield of 50.46 was obtained at equivalence ratio of 2.35 and velocity of 43.35 cm/s.

Fig. 10(a) depicts the mean and minimum cost of all imperialists versus iteration for butanol. It shows the minimum of the function (−47.27) is found at the third iteration. Fig. 10(b) reveals that the minimum of cost function occurs at inlet velocity of 20 cm/s and equivalence ratio of 2.63 for butanol fuel.

2-2. Energy Conversion Efficiency Optimization

The total energy conversion efficiency is an important parameter in filtration combustion processes. The main factors which have direct effect on the energy conversion efficiency are inlet velocity and equivalence ratio. In optimization by ICA, the inlet velocity and the equivalence ratio are considered as input variables and the energy conversion efficiency is taken as output variable. Table 5 depicts the experimental data ranges used in this study for the optimization of energy conversion efficiency.

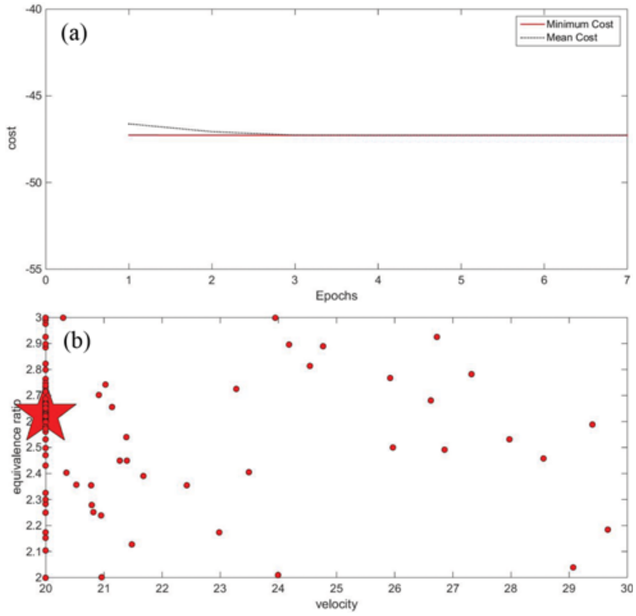

Fig. 10. (a) Mean and minimum cost of all imperialists versus epochs for hydrogen yield of butanol. (b) Demonstration of winner imperialist in the search space including inlet velocity and equivalence ratio for yield of butanol.

Table 5. Range of data employed for optimization of the energy conversion efficiency

Variable	Range
Inlet velocity (cm/s)	20-60
Equivalence ratio	1-5
Total energy conversion efficiency (%)	4-99

The cost function for the total energy conversion efficiency (E) optimization is (−E), where E is a function of inlet velocity and equivalence ratio as described by the following equations:

Energy conversion efficiency of jet A:

$$E(\text{jet A})=966.5363-80.7877v+2.047981v^2-5.29736\varphi^2+4.330258\varphi v+5.735415\varphi^3-0.01787v^3-1.34227\varphi^2 v+0.010183v^2\varphi \tag{16}$$

Energy conversion efficiency of butanol:

$$E(\text{butanol})=-227.25+19.90809v-0.50665v^2-2.8879\varphi^2+1.056686\varphi v+0.273314\varphi^3+0.003109v^3-0.08878\varphi^2 v+0.014069v^2\varphi \tag{17}$$

The absolute fraction of variance (R^2) of the above equations is 0.995 for both jet fuel and butanol. In Fig. 11, the efficiency is plotted versus the inlet velocity and equivalence ratio for (a) jet fuel and (b) butanol. According to this figure, the efficiency increases as equivalence ratio is increased excluding jet fuel, for which the efficiency firstly increases and then decreases at high velocities.

The results of the efficiency optimization are summarized in Table 4. Fig. 12(a) demonstrates the variation of the minimum and mean

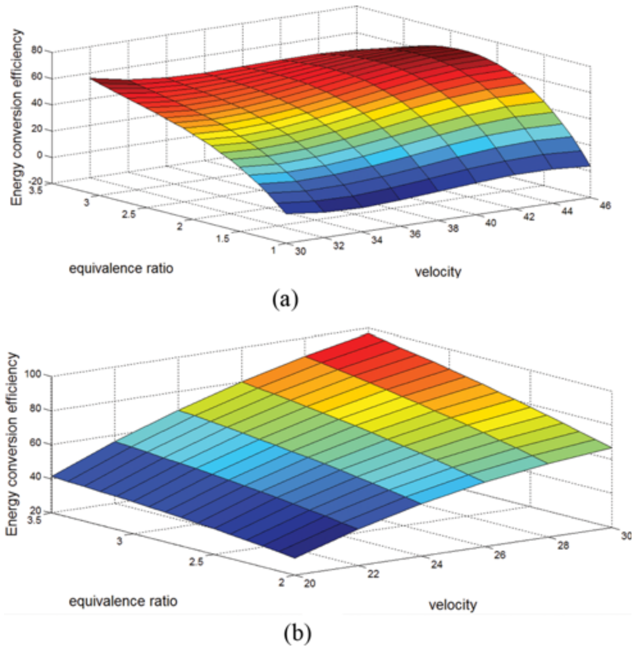

Fig. 11. Energy conversion efficiency as a function of inlet velocity and equivalence ratio for (a) jet A and (b) butanol.

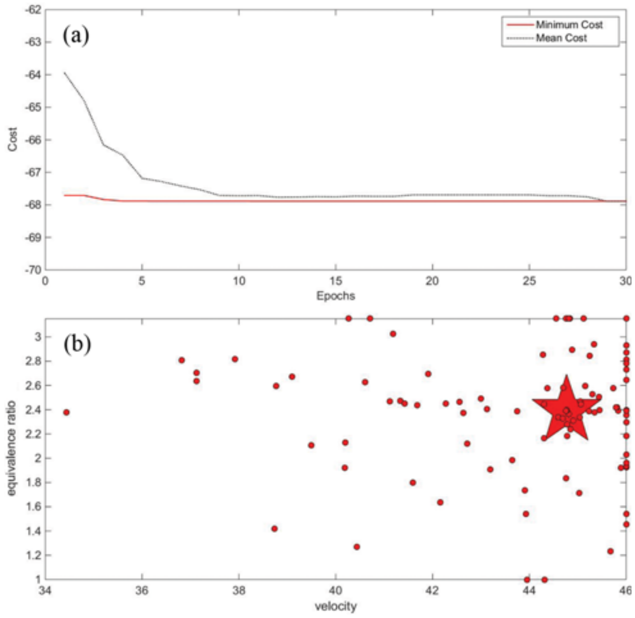

Fig. 12. (a) Mean and minimum cost of all imperialists versus epochs for the energy conversion efficiency of jet fuel. (b) Demonstration of winner imperialist in the search space including inlet velocity and equivalence ratio for efficiency of jet fuel.

cost function during the iteration process. It can be observed that the lowest target function is found to be −67.88 after 28 decades.

Fig. 12(b) depicts that the minimum cost function corresponding to the maximum energy conversion efficiency occurs at inlet velocity of 44.75 cm/s and equivalence ratio of 2.4.

The convergence of the ICA algorithm versus epoch number for energy conversion efficiency of butanol is presented in Fig. 13(a).

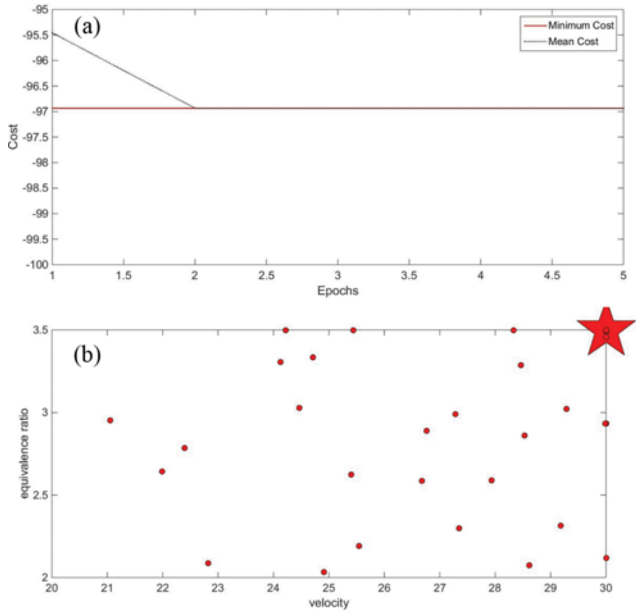

Fig. 13. (a) Mean and minimum cost of all imperialists versus epochs for the energy conversion efficiency of butanol. (b) Demonstration of winner imperialist in the search space including inlet velocity and equivalence ratio for efficiency of butanol.

This figure illustrates that the ICA has fast performance due to finding global minimum just after two iterations. The maximum efficiency of 96.93 for butanol is obtained in the optimization process.

Fig. 13(b) reveals that at inlet velocity of 30 cm/s and equivalence ratio of 3.5, the imperialist with lowest cost function generate its empire and the related colonies.

3. Comparison between ICA and GA

Genetic algorithm (GA), one of main tools in optimization, is based on the Darwinian biological evolution principle. The GA optimization method starts with an initial set of random solutions (population) and evolves through successive iterations (generations) toward better solutions. The genetic algorithms include fitness evaluation, parent selection, elitism, crossover, and mutation operators [45]. More details about genetic algorithm are described in Ref. [45-47]. In the present work, the GA tool is also employed for optimizing the energy conversion efficiency and hydrogen yield. The equivalence ratio and inlet velocity were considered as input parameters. Similar to ICA, the regression equations of 14 to 17 were embedded into GA for optimization. The computational parameters used in the GA model are given in Table 6, and the results of optimization are shown in Table 7. The results show excellent agreement between the proposed GA and ICA optimized values. The main difference between two algorithms is the time of convergence, which is shorter for ICA algorithm.

CONCLUSION

This study presents a hybrid intelligent modeling work on hydrogen yield and energy conversion efficiency of a non-catalytic partial oxidation reactor for jet A and butanol fuels. Three models of ANFIS, ICA and GA were used for predicting and optimizing

Table 6. The parameter values for the GA optimization

Population type	Double vector	Crossover function	Scattered
Population size	300	Time limit	Inf
Selection function	Tournament	Stall time limit	Inf
Tournament size	4	Stall generation	50
Crossover fraction	0.8	Function tolerance	1e-6
Mutation function	Constraint dependent	Objective function	(−Y) or (−E)
Fitness limit	−Inf		

Table 7. Optimization results

Optimized parameters		Equivalence ratio	Inlet velocity (cm/s)	Hydrogen yield of jet fuel
Optimized values	ICA	2.35	43.35	50.46
	GA	2.34	43.52	50.46
		Equivalence ratio	Inlet velocity (cm/s)	Hydrogen yield of butanol
	ICA	2.63	20	47.27
	GA	2.63	20	47.27
		Equivalence ratio	Inlet velocity (cm/s)	Energy conversion efficiency of jet fuel
	ICA	2.4	44.75	67.88
	GA	2.39	44.76	67.88
		Equivalence ratio	Inlet velocity (cm/s)	Energy conversion efficiency of butanol
	ICA	3.5	30	96.93
	GA	3.5	30	96.93

the mentioned parameters. The hydrogen yield and conversion efficiency were modeled as a function of equivalence ratio and inlet velocity. In ANFIS modeling, the best predictions of hydrogen yield of jet fuel, hydrogen yield of butanol, energy conversion efficiency of jet fuel and energy conversion efficiency of butanol were obtained with gauss2mf, gbellmf, gaussmf and dsigmf, respectively. The RMSE values of best models related to four mentioned parameters were 1.399, 1.213, 0.508 and 2.191, and the R^2 values were 0.998, 998, 0.999 and 0.999, respectively. In ICA modeling, the yield and efficiency parameters for both fuels were optimized. The results showed that the maximum values of hydrogen yield and energy efficiency were 50.46% and 67.88% for jet A and 47.27% and 96.93% for butanol, respectively. The equivalence ratios and inlet velocities which give the maximum values were 2.35 and 43.35 cm/s for hydrogen yield of jet fuel, 2.63 and 20 cm/s for hydrogen yield of butanol, 2.4 and 44.75 cm/s for efficiency of jet fuel and, 3.5 and 30 cm/s for efficiency of butanol. Comparison between the suggested optimization strategies shows that there is an excellent agreement between the results of GA and ICA. Also, ICA has higher computation speed in comparison to GA. This study showed that the imperialist competitive algorithm and genetic algorithm are efficient and powerful algorithms to optimize combustion processes.

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