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Efficient ELM Model with Parameter Optimization Using PSO Algorithms in the Prediction of Combustion Pressure Parameters of DSI Engine Using Ethanol-Gasoline Blends

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Abstract

The present study focused mainly on developing PSO based ELM model to predict cylinder pressure associated parameters. Performance of PSO-ELM model then compared with ELM model to obtain its credential. For training and testing the models, data has been acquired through experiments on a Twin Spark Ignition (TSI) gasoline engine using EGB as fuel. The various operating variables are treated as input data whereas cylinder pressure associated parameters are treated as output data for the model. The result of the proposed modelling study indicated that PSO-ELM model has obtained the best performance with lowest value of MSE, MAPE (%) and hidden layer size as compared to ELM model. Hence PSO-ELM results in an efficient model structure with great generalization performance. Further, it is also observed that PSO-ELM takes more time as it calls for an iterative procedure for searching the optimal solution as compared to ELM, which takes only a single epoch.

Keywords: *ANN, ELM, PSO-ELM, TSI*

1.0 Introduction

With the ever-increasing prices of conventional fuels due to lack of reserves and rapid rate of consumption, there has been a greater tendency towards the search for environmentally friendly renewable fuels in the recent years. From the last two decades, the Indian union government is adding ethanol to the gasoline in small percentage. They increased ethanol percentage from 1.5% in 2014 to 10% in 2022 and aims to mix 20% ethanol by 2030. They also stressed on the point that petrol engines need to be compliant with 20% ethanol by 2025 five years sooner than the deadline of 2030[1]. Therefore, it is necessary to carry out studies to determine the usability of ethanol gasoline blends at various operating conditions. It costs money and time to perform engine studies under different operating modes and fuels. The adoption of Artificial Neural Networks (ANN) can reduce costs and save time. In recent years, there has been many modelling works involving various learning algorithms in this domain and has shown significant success. Kiani *et al.,*[2] developed prediction model using standard backpropagation (BP) algorithm for the performance and emission parameters in SI engine operated with ethanol gasoline blends. It was shown that an ANN model with BP algorithm makes prediction model fast, accurate and

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reliable, particularly in case of failure of numerical and mathematical methods. Mostafa Kiani Deh Kiani *et al.,*[3] developed an ANN model with BP algorithm to predict Spark Ignition (SI) engine thermal balance under different engine speeds, loads and ethanol gasoline blends. The correlation coefficient of 0.997, 0.998, 0.996 and 0.992 were observed for work utilized, heat lost through the engine exhaust, heat lost through engine cooling water and unaccounted losses respectively. The Back Propagation (BP) algorithm is the most popular and extensively used algorithm which can deal more rapidly with complicated nonlinear systems. However, it has many drawbacks. Most importantly, it takes more processing time because of its iterative characteristics. The algorithm often has a tendency to converge to local minima. A large difference between the global minimum and the local minimum clearly makes this factor highly undesirable. Since the difficulty in stopping the iteration in this error reduction technique, there might be the network over trained with reduction in generalization performance[4,5]. Further, the optimum values of the learning rate and momentum rate parameters significantly contributes to the convergence and overall performance of the network, and determination of their optimal value are absolutely specific problem[6].

An ELM algorithm developed by G. B. Haung[7] is a fast learning algorithm. It is a powerful modeling technique employed for solving problem particularly in large data sets. A.H. Sebayang *et al.,*[8] developed engine performance prediction model using ELM. They predicted different performance and emission parameters of the engine with a value of 0.980–1.000 for R^2 and 0.411%−2.782% for MAPE. Weiying Zeng *et al.,*[9] performed an accurate model using ELM to predict gasoline engine's output torque. This model showed its ability in predicting the engine torque with high accuracy with RMSE was about 9 N-m, which is about 2.7% mean torque. It is also demonstrated that performance of progressive ELM is similar to that of LM algorithm while having higher accuracy and superior generalization. A.S. Silitonga *et al.,*[10] used K-ELM technique for the development of prediction model for engine performance and emission parameters of biodiesel-bioethanol-diesel blends. They obtained a prediction value with MAPE between 1.363–4.597% and R^2 values approximately equal to 1. Zhao Y *et al.,*[11] reviewed prediction models of carbon emissions on machine learning basis. They made a comparative analysis of five types of prediction models of carbon emissions based on BP, SVM, LSTM, RF and ELM. Based on the comparison they summarized that SVM and ELM perform better with a lower Mean Square Error (MSE) and MAPE than BP and LSTM models. Viviana Cocco, *et al.,*[12] developed optimized prediction ELM models for the IMEP of a SI engine. It is noticed from their study that the proposed optimized ELM and its variations optimized by BBO techniques have potential for IMEP prediction, that exhibited some degree of consistency with the experimental data. Pak Kin Wong a *et al.,*[13] developed prediction model using K-ELM and LS-SVM and then compared the performance of these two models. The comparative results showed that K-ELM performs better regarding prediction error, training time and executing time. Mortaza Aghbashlo *et al.,*[14] developed ELM-WT, ELM, GP and BP model and also compared the model performance. This model development was carried out for obtaining prediction performance of CI engine when operated with diesel and biodiesel blends containing polymer waste. The result showed that ELM-WT model yielded better performance compared to the other models and also noticed that this model is much faster along with smaller error in training. Wang Y, and Heydari H *et al.,*[16] established an ELM based prediction model for isothermal compressibility of long-chain fatty acid esters. The developed ELM model predicted isothermal compressibility at high accuracy with R^2 equal to 1 and RMSE equal to 0.0018714.

ELM algorithm performs operation in single epoch and it provides good generalisation performance with lesser simulation parameters with compact model architecture and it overcomes difficulties of overfitting, underfitting and local minima problems. When developing an ANN model, fixing the network parameters requires some prior knowledge. Because the performance of the model is sensitive to its simulation parameters factors, it takes considerable effort as well as time for fixing it through trial and error technique[17]. Kaloop MR, *et al.,*[18] developed prediction model using PSO-ELM for estimating the performance of the stabilized aggregate bases and then they made a comparison between performance of this model with PSO-ANN and K-ELM. Compared to other models, the PSO-ELM yields better prediction performance in terms of the RMSE, MAPE and coefficient of determination (R^2) and also PSO-ELM yields prediction values distribution trend as same as that of observed data. Liu B *et al.,*[19] developed PSO-ELM that predict carbon particle emissions in china at Chongqing. They noticed that PSO-ELM model obtains better prediction performance by giving greatest accuracy compared to BP and WOA-BP with minimum MSE, RMSE and MAPE. Wong KI *et al.,*[20] developed ELM, LS-SVM and RBF models for biodiesel engine performance. they also employed two optimization algorithm SA and PSO to decide about the optimum biodiesel ratio. The results showed that ELM based on LT performs much better than LS-SVM and RBFNN with/without LT. Also, PSO performs better than SA in respect of fitness as well as standard deviation with sufficient data processing time.

From the review of the previous studies, it can be noticed that some efforts have been made in the development of ELM models with PSO as the optimization technique. However, the use of ELM with PSO in the SI engine performance and combustion studies are found to be limited. Therefore, this study was undertaken to develop PSO-ELM hybrid ANN model for the prediction of combustion pressure related parameters in the DSI engine particularly in the usage of EGB as the fuel.

2.0 Materials and Methods

2.1 Fuel Preparation and Properties

In the present work, a twin spark plug mounted SI engine has been used for acquiring data to train and test the model. The experiment has been carried out in the laboratory using EGB as fuel. A Gasoline (REC-90) and ethanol (99.9% pure) was purchased from a local supplier and are mixed in appropriate proportions to obtain EGB fuel. Ethanol is mixed with gasoline in the ratio of 0:100, 5:95, 10:90, 15:85 and 20:80 by volume to obtain Pure gasoline, EGB5, EGB10, EGB15 and EGB20 respectively. To obtain uniform concentration of ethanol and gasoline in the mixture, it is agitated by a magnetic stirrer, which is rotating at 500-600 rpm for about 5-7 minutes. The below Table 1 shows some of the physical, chemical and thermal properties all EGBs which have been obtained from the literature[21].

Table 1. Properties of EGB

Properties	Gasoline	EGB5	EGB10	EGB15	EGB20
Relative density	0.772	0.773	0.775	0.776	0.777
C (% mass)	87.4	87.7	86.7	87.6	87.6
H_2 (% mass)	13.3	12.2	13.2	12.3	12.3
O (% mass)	0	1.89	3.97	5.86	7.89
Vapour Pressure (Reid) at 37.8^{0}C (kPa)	53.4	59.3	59.6	58.8	58.3
RON	92	92.8	93.6	95.3	105.6
MON	82	82.4	82.7	83.4	87.9
Stoichiometric AFR	14.57	14.26	13.96	13.36	13
LCV (KJ/kg)	42.61	40.57	39.82	39.41	39
Laminar Burning speed (cm/s)	34	34.42	34.88	35.32	35.74
Latent Heat of Vaporization (KJ/kg)	305	-	-	-	-
Auto Ignition Temperature (^{0}C)	442.8	265	271	281	290

2.2 Experimental Setup and Procedure

The data for training and test the model has been obtained by conducting experiment on a single cylinder twin spark plug mounted gasoline engine. The engine has been coupled to water-cooled eddy current type dynamometer with crank angle encoder. The simplified layout of the engine test rig is presented in the Figure 1 and its technical specifications are listed in the Table 2.

A water-cooled piezo-electric transducer is mounted in the cylinder which is meant for the cylinder pressure measurement. The setup provided with necessary arrangement to change the CR of the engine. A crank angle encoder of high precision is fitted on the on the dynamometer to record the crank angle in degrees. The sensors for measuring the temperature of inlet air, inlet and outlet of engine cooling water, exhaust gas, inlet and outlet of calorimeter water are also incorporated in the setup. The test rig is also incorporated with instruments for measuring the air flow rate, fuel flow rate, engine cooling water flow rate and calorimeter water flow rate. A programmable Open Electronic Control Unit (ECU) regulates throttle position sensor, fuel pump, fuel injector, ignition coil, fuel spray nozzle, and trigger sensor etc. and generates signals according to the engine operating environment. The signals are then made to transmit to the software via a high-speed data acquisition device. A software called Enginesoft is used for data analysis and evaluation.

Water circulation for dynamometer, Piezo electric transducer, engine and calorimeter has been provided. Engine has been set to 8:1 compression ratio and 240-240 bTDC spark timing. Switch on the set up and run the engine at 1800rpm for 4-5 minutes with no load. Turn 'on' the computer and run Enginesoft. Load the engine at 60%, 80% and 100% of full load by gradually opening the throttle all the way while keeping the speed at 1800rpm. Wait for some time to reach the steady state by observing the engine cooling water temperature at each load point and log the data in the Enginesoft. Repeat the same procedure for other compression ratio 9:1 and 10:1, and

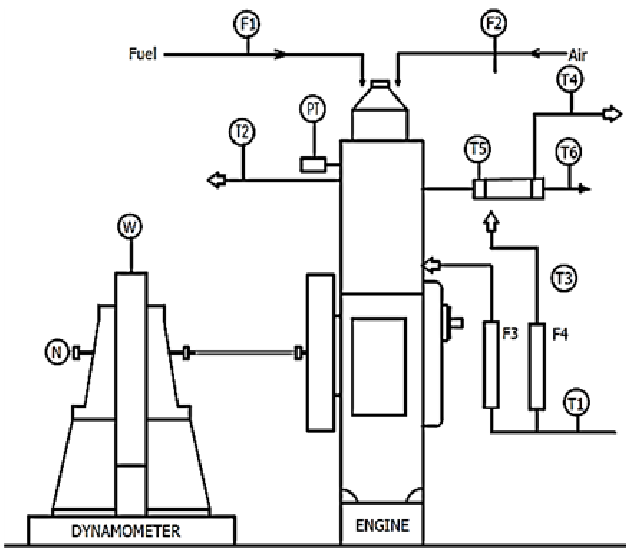


Figure 1. Simplified layout of engine set-up.

PT= Pressure transducer

T1= Temperature of cooling liquid at Inlet of the engine

T2 = Temperature of cooling liquid at exit of the engine

T3 = Temperature of liquid at the Inlet of the calorimeter

T4 = Temperature of liquid at the exit of the calorimeter

T5 = EGT at the Calorimeter inlet

T6 = EGT at the Calorimeter exit

F1= EGB flow rate

F2 = Air flow rate

F3 = Engine cooling liquid flow rate

F4 = calorimeter liquid flow rate

N = Crank angle encoder

Table 2. Engine specifications

Engine type	Computerized 4- stroke, dual fuel VCR with open ECU
Number of cylinders	one
Power output	4.5kW@ 1500rpm
Engine cooling fluid	Liquid water
Cylinder size	87.5mm X 110mm
Compression ratio	6:1 to10:1
Piston displacement volume	661 cc
Dynamometer characteristics	liquid cooled, eddy current type, 185 mm arm length
Engine ignition	Battery ignition with Twin Spark plug

other spark timing of 280-280 bTDC and 200-200 bTDC. After the experiment, data has been extracted from the Enginesoft and the mean value $(\bar{X})$ and Coefficient Of Variation (COV) has been calculated using equation (1) and (2) respectively.

$$\bar{X} = \frac{\sum_{i=1}^{N} X_i}{N} \tag{1}$$

$$\sigma = \sqrt{\left(\sum_{i=1}^{N} (X_i - \bar{X})^2 / N\right)}$$

$$COV = \frac{\sigma}{\bar{X}} \tag{2}$$

2.3 Test Conditions

This section lists the different operating conditions at which the data from the engine was collected. To collect large set of data, it is necessary to carry out the engine experiment at larger scale under different operating variables *i.e* blend, load, CR and spark timings. All these operating variables has been regulated through open ECU. The experiment was done in the laboratory at constant speed of 1800rpm. In engine operating condition, accuracy of engine data depends on the conditions at which data has been collected. Therefore, the data was collected under each operating condition when the engine operation reached steady state. The steady state of the engine operation was observed by maintaining the constant engine cooling water temperature. The operating conditions are presented in Table 3.

Table 3. Engine variables

Fuel	**0% [Pure gasoline], 5% [EGB5], 10% [EGB10], 15% [EGB15] and 20%[EGB20]**
Spark timings [^{0}bTDC]	24^0-24^0, 28^0-28^0 and 20^0-20^0.
Compression ratio	8:1.9:1 and 10:1
Load (% of full load)	60%, 80% and 100%
Speed	Constant 1800rpm

3.0 Modeling Study

An Artificial Neural Network (ANN) is a computational framework that draws inspiration from the intricate organization and operation of neural networks in the human brain. Extreme Learning Machine (ELM) is a machine learning algorithm enabling efficient training and high-speed predictions. Metaheuristic optimization algorithms are intelligent search techniques designed to solve complex optimization problems by iteratively exploring and navigating the solution space.

3.1 Extreme Learning Machine (ELM) Algorithm

ELM is a simple and powerful algorithm which is extremely fast as it eliminates the iterative procedure in comparison to gradient descent method, which uses a time-consuming iterative procedure[7,24]. It finds its applications in large scale computing and in real-time due to its superior prediction accuracy, very fast learning speed, high reliability, controllability and good generalization capability[22,23]. ELM algorithm, when compared to traditional algorithm, overcomes the difficulties of slow training speed, underfitting, overfitting and local minima problems. It is based on Empirical Risk Minimization (ERM) theory and requires single iteration for completing the training program. This algorithm uses generalized inverse (Moore- Penrose) operation on the hidden layers output matrix for obtaining the output weight matrix. This algorithm requires a smaller number of simulation parameters which results in less involvement of human being to set these parameters. This algorithm finds its applications in variety of fields such as system identification, control and robotics, computer vision, biomedical engineering, etc.[25].

The working of ELM algorithm was as follows:

1. A set of input and output features $\{x_i^\mu, y_k^\mu\}$ were taken from the training patterns.
   where, $\mu = 1, 2\ldots N$ represented the number of patterns
   i = 1, 2...p, denoted the size of input features
   k = 1, 2...r, denoted the size of output features
2. The values of weights and bias i.e. w_{ji}, b_{jk} were initialized randomly .

3. The hidden layer output was determined using equation (3) for Q number of hidden nodes.

$$H(w_1, \dots w_N, b_1, \dots . b_N, x_1, \dots .. x_N) =$$

$$\begin{bmatrix} g(w_1 x_1 + b_1) & \dots & g(w_Q x_1 + b_Q) \\ . & & . \\ . & \dots & . \\ . & & . \\ g(w_1 x_N + b_1) & \dots & g(w_Q x_N + b_Q) \end{bmatrix}_{NXQ} \quad (3)$$

Where g(x) is usually a sigmoidal activation function.

4. The output weight matrix was obtained w_{kj} : $w_{kj} = H^{\dagger}T$,

where $H^{\dagger}$ is the Moore-Penrose generalized inverse of the H, and T is the actual output matrix as given in equation (4)[5].

$$T = \begin{bmatrix} t_1^T \\ . \\ . \\ . \\ t_N^T \end{bmatrix}_{NXk} \quad (4)$$

3.2 Optimization Algorithm

For soving real world complicated problems, meta-heuristic optimisation algorithm becomes a popular adaption over traditional algorithms, which are nature inspired. Over conventional and deterministic methods, the methods of this type have several notable advantages. For example, it works efficiently in multi objective problems and insufficient or incomplete data that require less processing power[26]. These algorithms use an effective integration of exploration and exploitation of the search space to arrive intelligently to the best solution. Those governing mechanisms are studied from social behavior, evolutionary mechanisms and physical phenomena.

Optimization algorithms randomly initializes populations, evaluates each generated population for fitness, creates a new set of population using an evolutionary procedure. These steps are repeated until stopping criterion is reached. Many algorithms of such type are developed such as Particle Swarm Optimization (PSO), Genetic Algorithm (GA), Artificial Bee Colony (ABC) etc. James Kennedy and Russel Eberhart[27] originated PSO algorithm and it attracted researcher's attention because of its simple theory, computational effectiveness, and ease of implementation. This algorithm makes use of a batch of randomly created particles. These particles are set into motion with some velocity and tend to approach optimum using multi-dimensional search by moving according to simple rule. Every individual particle defines its motion by regulating its position relative to best global and local positions, denoted respectively by gbest and pbest. All particles in the end of each cycle, move towards the best solutions by noticing objective function.

Let u and s be the velocity and positions of every particle respectively. The velocity and position of every particle 'i' in iteration t+1 can be reconditioned using equations (5) and (6)

$$u_i^{t+1} = w * u_i^t + C_1 \text{rand1}(\text{pbest}_i - s_i^t) +$$
$$C_2 \text{ rand2}(\text{gbest} - s_i^t) \quad (5)$$

$$s_i^{t+1} = s_i^t + u_i^{t+1} \quad (6)$$

where

u_i^t = velocity in iteration t

u_i^{t+1} = velocity in iteration t+1.

s_i^t = position in iteration t.

s_i^{t+1} = position in iteration t+1.

r and 1 and rand 2 are the uniformly distributed random variables.

C1 and C2 are the acceleration factors.

p best be the best local position.

g best be the best global position

w be the inertia weight.

3.3 Exploring Data Characteristics and Pre-processing Techniques

The large set of data collected from the experiment that has been utilized for network training and model testing. From the experimental data, nearly randomly selected 80% data has been used for the purpose of training and the rest has been used to test the developed model. Normalizing the data within the range of 0 to 1 using equation (7) was necessary to guarantee that all inputs have an equivalent influence on the development of the ANN model.

$$X' = \frac{X}{X_{Max}} \quad (7)$$

Where

X' - Data was normalized

X - Original data

X_{Max} - Data sets maximum data.

3.4 Model Development Details

In the present study, total six models were developed for predicting the cylinder pressure associated parameters. The engine operating variables *i.e* % load, % EGB, CR and IGN are considered as the input parameters of the model.

Three set of models are developed to predict three sets of parameters as shown in Figures 2. % Load, % blend, Compression Ratio (CR) and Spark Timing (IGN) are considered as the input parameters for each of the model. Model-1 and Model-2 were developed for predicting P_{IMEP} and COV_{IMEP} parameters using ELM and PSO-ELM respectively and the architecture is depicted in Figure 2a. Model-3 and Model-4 were developed for predicting $P_{MCP,}$ COV_{MCP} and θ_{MCP} using ELM and PSO-ELM respectively and the architecture is depicted in Figure 2b. Model-5 and

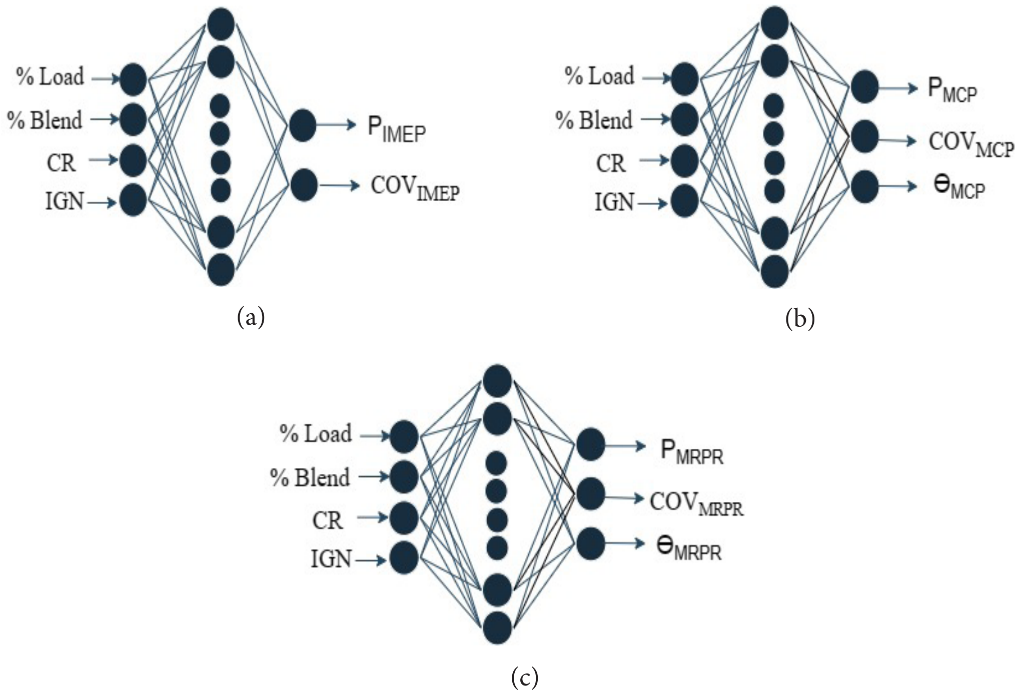


Figure 2. Network structure of models to predict a) IMEP b) MCP c) MRPR parameters.

Table 4. The model details

Model name	Learning algorithm	Output parameter	Optimum configuration
Model-1	ELM	P_{IMEP} and COV_{IMEP}	4:25:2
Model-2	PSO-ELM	P_{IMEP} and COV_{IMEP}	4:19:2
Model-3	ELM	$P_{MCP,}$ COV_{MCP} and θ_{MCP}	4:20:3
Model-4	PSO-ELM	$P_{MCP,}$ COV_{MCP} and θ_{MCP}	4:16:3
Model-5	ELM	$P_{MRPR,}$ COV_{MRPR} and θ_{MRPR}	4:25:3
Model-6	PSO-ELM	$P_{MRPR,}$ COV_{MRPR} and θ_{MRPR}	4:22:3

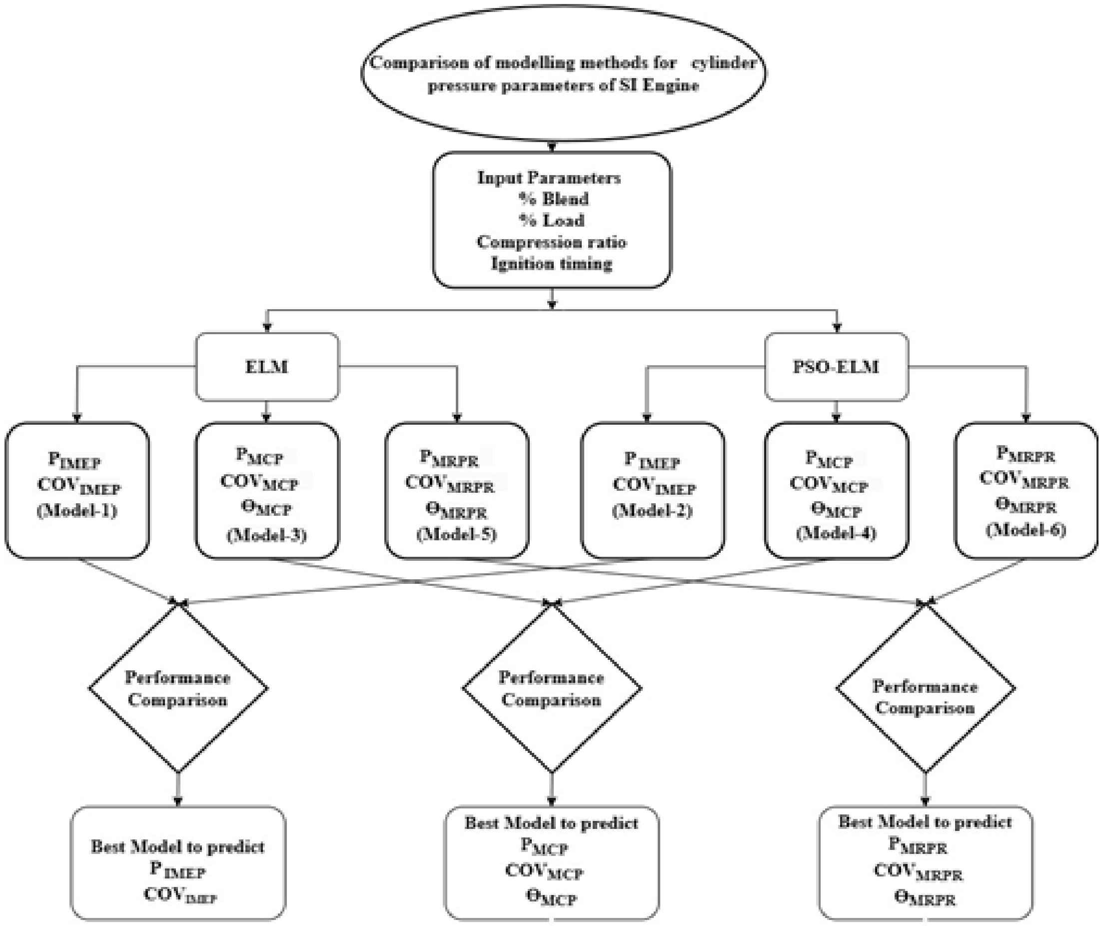


Figure 3. Methodology.

Mdel-6 were developed for predicting $P_{MRPR,}$ COV_{MRPR} and θ_{MRPR} using ELM and PSO-ELM respectively and the architecture is depicted in Figure 2c. The details of the model with optimum configurations are provided in the Table 4. The methodology employed in the present work with sequential steps is illustrated in the Figure 3. All the simulations were executed on a personal computer in MATLAB R2014a environment using customized codes with an Intel i5-6200U, 2.3 GHz CPU and 4 GB RAM.

Out of six models, three models were trained by using ELM algorithm. *i.e.* Model-1, Model-3 and Model-5. One of the most attractive characteristic features of ELM is it requires single epoch to learn and demand fewer simulation parameters. The ELM model's sole simulation parameter is the neurons present in the hidden layer. This number has been determined through a trial-and-error approach, taking into account the highest training error. Remaining three models are hybrid models *i.e.* Model-2, Model-4 and Model-6. These are developed by PSO for the selection of optimal neurons present in the hidden layer of an ELM model. Otherwise this might be selected using trial and error basis which demands the experience of the model developer. The objective function for PSO optimisation is to minimize percentage of MAPE in the training data. In this work, the simulation parameters of PSO algorithm *i.e.* 'C1' and 'C2' acceleration parameters, 'w' inertia weights and population size are set as 1.5, 1.5, 0.9 and 10 respectively are fixed on the basis of trial and error. 100 iterations are set as the stopping criterion for PSO algorithm.

All six models with learning algorithm, output parameters and optimum configurations are shown in Table 4. The model performance was checked during training for varying number of neurons in the hidden layer and for other simulation parameters of the model. Model-1 and Model-2 were developed using ELM and

PSO-ELM algorithm respectively to predict P_{IMEP} and COV_{IMEP} parameters along with optimum configurations as given in Table 4. It is noticed that from the Table 4 that Model-1 and Model-2 showed their best performance with neurons in the hidden layer 25 and 19 respectively. The Model-3 and Model-4 were developed using ELM and PSO-ELM algorithm respectively to predict $P_{MCP,}$ COV_{MCP} and θ_{MCP} parameters with optimum configurations as given in Table 4. It was found that the best performance of Model-3 and Model-4 were obtained with optimum neurons in the hidden layers 20 and 18 respectively. The Model-5 and Model-6 were developed using ELM and PSO-ELM respectively to predict $P_{MRPR,}$ COV_{MRPR} and θ_{MRPR} parameters with optimum configurations as given in Table 4. It is seen that the performance of Model-5 and Model-6 were achieved best with neurons in the hidden layer 25 and 22 respectively. It is important to remember that PSO has been used in Model-2, Model-4 and Model-6 to optimize the number of neurons in the hidden layers significantly saving designers effort and time.

4.0 Results and Discussions

The prime objective function of this study was that developing a hybrid ANN model by combining PSO with ELM and then results this model was compared with ELM Model. These models were developed for different set of output parameters and for the same set of input parameters. % MAPE and MSE were used as the performance metrics which were obtained by the equation (8) and equation (9) respectively.

$$\mathrm{MAPE}\ (\%) = \frac{1}{\mathrm{N}}\sum_{\mathrm{i}=1}^{\mathrm{N}} \frac{|\mathrm{y_p(i)} - \mathrm{y_a(i)}|}{\mathrm{y_a(i)}} \times 100 \tag{8}$$

$$MSE = \frac{1}{N}\sum_{I=1}^{N} \left(y_p(i) - y_a(i)\right)^2 \tag{9}$$

Where

y_p (i) is the predicted values of output parameter at i^{th} data point.

ya (i) is the actual values of output parameter at i^{th} data point.

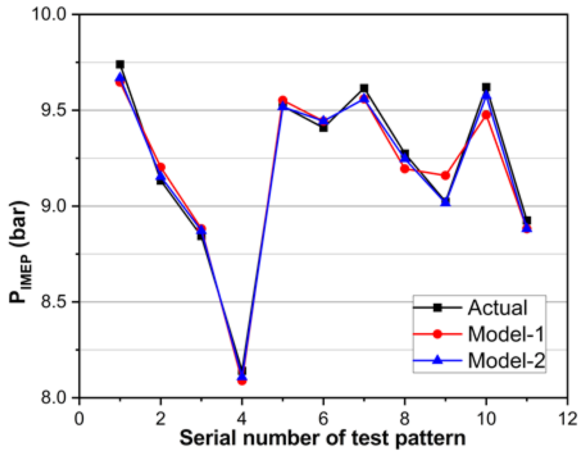
N represents the size of data points used.

4.1 IMEP Prediction Model

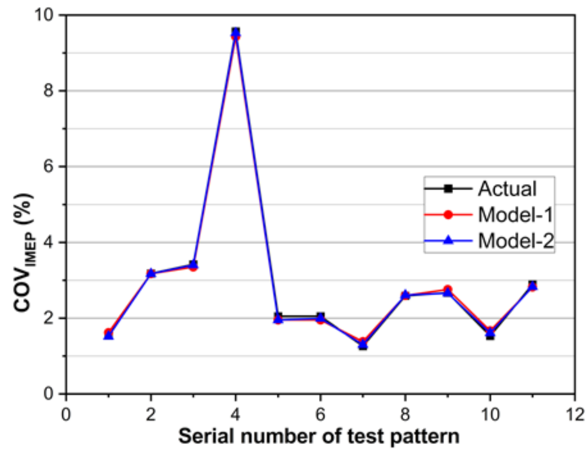
Model-1 and Model-2 were developed using ELM and PSL-ELM to predict P_{IMEP} and COV_{IMEP} respectively. The Table 5 and Table 6 presents the performance of Model-1 and Model-2 respectively. The results of Model-1 were obtained for varying neurons in the hidden layers because the neurons in the hidden layer was set by manually. From the Table 5, It is seen that Model-1 obtained performance best at 25 neurons in the hidden layer with a least MAPE of 2.33% on the test data using a CPU time of 0.004095 seconds. From the Table 6, It is seen that Model-2 obtained least MAPE value of 2.24% on the test data using a CPU time of 0.986012 seconds with 19 neurons in the hidden layers which was selected optimally by PSO. By comparing the performance of Model-1and Model-2, Model-2 resulted lowest MSE as well as MAPE for both training and testing data. Model-1 resulted extremely fast as it takes single epoch for training. Using PSO in Model-2, much minimises the dependence of designer's experience and hence minimises the human effort involved in the model development. Using PSO in Model-2, it has resulted compact model network structure with high degree of accuracy.

Table 5. Model-1 Performance

Neurons in the hidden layer	15	20	25	30	35	40
MSE Training data	0.00065	0.00050	**0.00020**	0.00031	0.00045	0.00055
MSE Test data	0.00078	0.00072	**0.00033**	0.00042	0.00056	0.00061
MAPE % Training data	4.92	3.54	**1.77**	2.80	3.12	4.95
MAPE % Test data	7.98	6.31	**2.33**	3.95	4.80	6.46
Executed Time (s)	0.003945	0.004061	**0.004095**	0.004207	0.004431	0.004662



(a)



(b)

Figure 4. Comparison of prediction performance of Model-1 and Model-2 for a) P_{IMEP} and b) $COV_{IMEP.}$

Table 6. Model-1 Performance

Hidden neurons sample size	**19**
MSE Training data	0.00016
MSE Test data	0.00024
MAPE % Training data	1.002
MAPE % Test data	2.24
Execution Time (s)	0.986012

The predicted values obtained from Model-1 using ELM and Model-2 using PSO-ELM were compared with actual values of P_{IMEP} in Figure 4 (a) and COV_{IMEP} in Figure 4 (b). From both the figures, it is seen that the values predicted by Model-2 are much closer to the actual values compared to Model-1. This proves that Model-2 is superior in developing ANN model for predicting P_{IMEP} and COV_{IMEP} parameters.

4.2 MCP Prediction Model

Two models Model-3 and Model-4 were developed using ELM and PSO-ELM respectively to predict three parameters i.e. $P_{MCP,}$ COV_{MCP} and θ_{MCP}. The Table 7 and Table 8 presents the performance results of Model-3 and Model-4 respectively. It is seen from Table 7 that for Model-3, MSE and MAPE both on training and test data were decreased with increase in the neurons in the hidden layers and were found to be least at 20 neurons

Table 7. Model-3 Performance

Neurons in the hidden layer	5	10	15	**20**	25	30
MSE Training data	0.00028	0.00021	0.00016	**0.00013**	0.00011	0.00025
MSE Test data	0.00040	0.00037	0.00032	**0.00022**	0.00029	0.00034
MAPE % Training data	5.21	5.11	4.48	**1.93**	3.66	4.38
MAPE % Test data	9.42	8.79	6.88	**3.24**	4.94	6.18
Executed time (s)	0.004746	0.004711	0.006950	**0.008585**	0.006908	0.004529

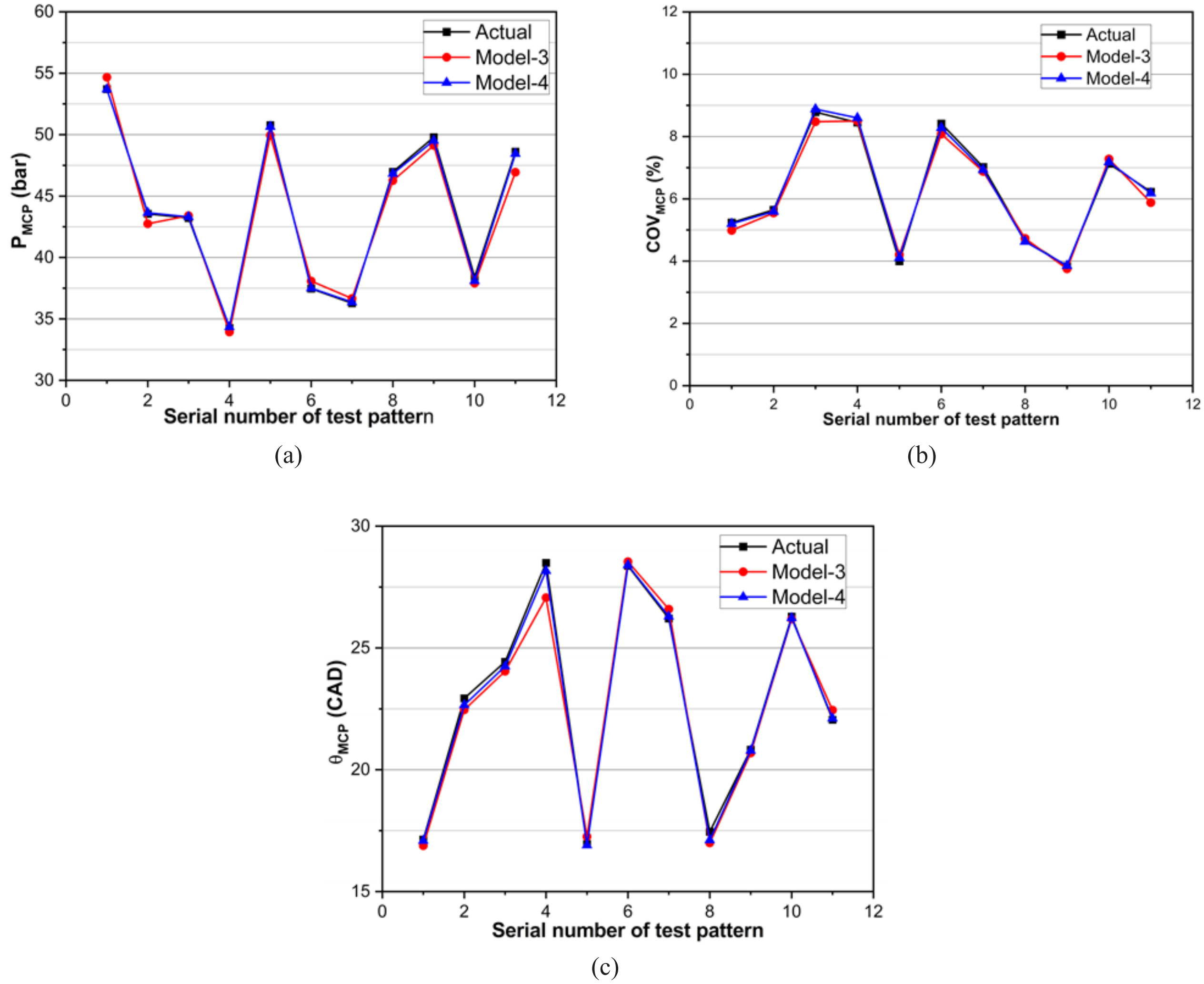


Figure 5. Comparison of prediction performance of Model-3 and Model-4 for a) $P_{MCP,}$ b) COV_{MCP} and c) θ_{MCP}

and increased thereafter. It is seen from Table 8 that Model-4 achieved best performance at 18 neurons in the hidden layer optimally searched by PSO algorithm with least MAPE of 3.06% on test data. Based on the time needed for training the model, Model-3 takes a CPU time of 0.008585 seconds compared a CPU time of 0.998471 seconds of Model-4. This proves Model-3 to be fast out of Model-4 since it is an ELM model which performs in single epoch. Nevertheless, Model-4 is also ELM based model but it needs more time to train because this model incorporated PSO which involves an iterative searching procedure.

Table 8. Model-4 Performance

Neurons in the hidden layer	**18**
MSE Training data	0.00010
MSE Test data	0.00019
MAPE % Training data	1.23
MAPE % Test data	3.06
Executed time (s)	0.998471

The prediction values of Model-3 and Model-4 were compared with the actual values in Figure 5 (a), Figure 5 (b) and Figure 5 (c) for P_{MCP}, COV_{MCP} and θ_{MCP} respectively. It is seen that in all the cases, the values predicted by Model-4 are nearest to the actual values in comparison to Model-3. Hence Model-4 proves to be the best in ANN model development for predicting P_{MCP}, COV_{MCP} and θ_{MCP} parameters.

4.3 MRPR Prediction Model

Two models, Model-5 based on ELM and Model-6 based on PSO-ELM were developed to predict three parameters i.e. P_{MRPR}, COV_{MRPR} and θ_{MRPR}. The Table 9 and Table 10 presents the performance of Model-5 and Model-6 respectively.

In Model-5, neurons in the hidden layer was manually set, so the performance results of this model were presented for varying neurons in the hidden layer. In Model-6, neurons in the hidden layer were optimised using PSO. It is seen from Table 9 that for Model-5, the lowest MAPE of 1.17 % on training data is obtained for 25 neurons in the hidden layers by taking a CPU time of only 0.005494 seconds. It is seen from Table 10 that the Model-6 obtained a best result at 22 neurons selected optimally in the hidden layer using PSO algorithm with a lowest MAPE of 1.03% on training data with a CPU

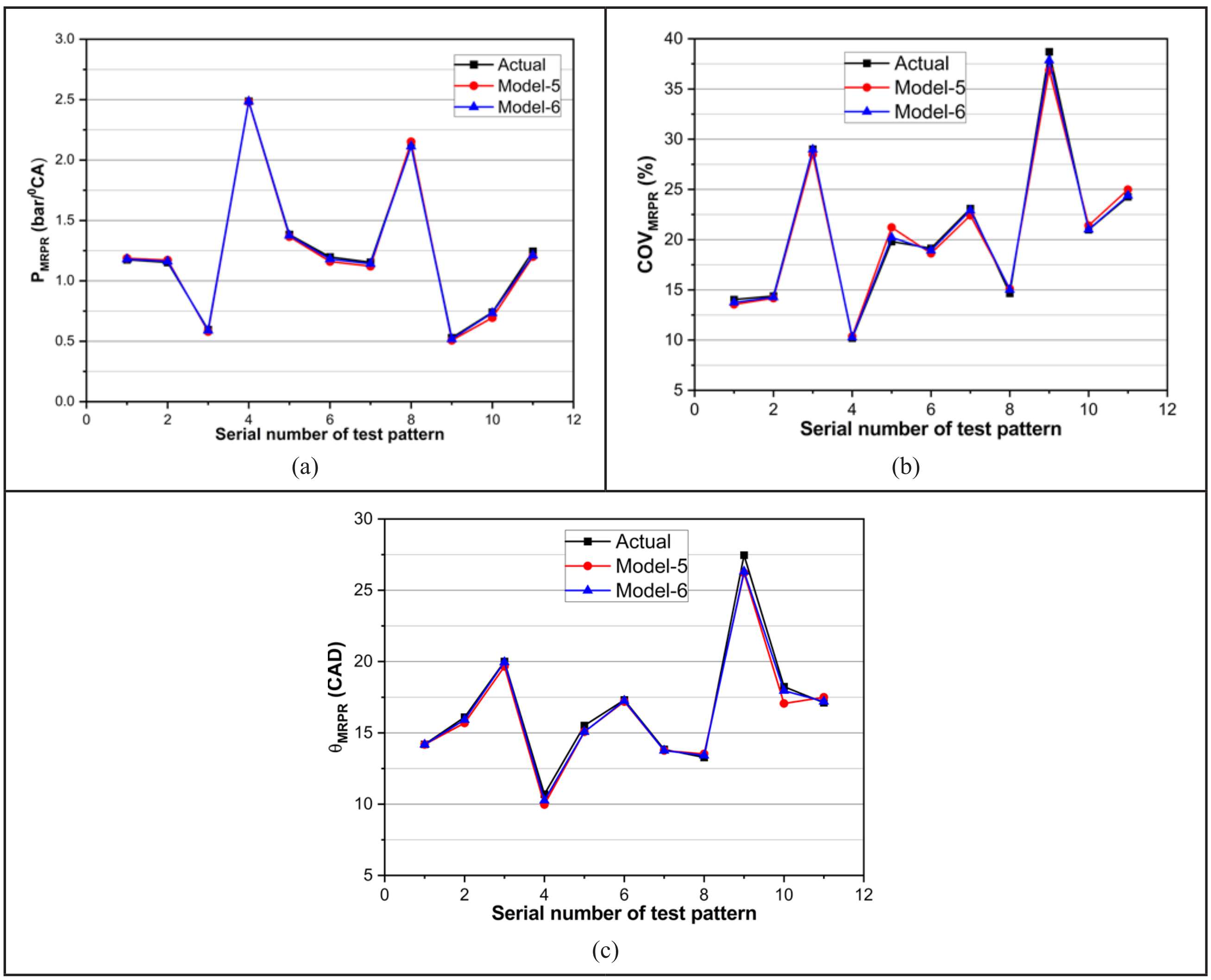


Figure 6. Comparison of Prediction performance of Model-5 and Model-6 for a) P_{MRPR}, b) COV_{MRPR} and c) θ_{MRPR}

Table 9. Model-5 Performance

Neurons in the hidden layer	**5**	**10**	**15**	**20**	**25**	**30**
MSE Training data	0.00065	0.00042	0.00039	0.00034	**0.00022**	0.00025
MSE Test Data	0.00082	0.00075	0.00061	0.00048	**0.00036**	0.00041
MAPE % Training data	5.03	4.27	3.32	2.99	**1.17**	3.05
MAPE % Test data	8.73	7.23	6.50	4.05	**2.80**	5.46
Executed time (s)	0.004385	0.004601	0.004925	0.004703	**0.005494**	0.005826

Table 10. Model-6 Performance

Neurons in the hidden layer	22
MSE Training data	0.00019
MSE Test data	0.00030
MAPE. % Training data	1.03
MAPE % Test data	2.64
Executed Time (s)	0.978515

time of 0.978515 seconds. Based on the comparison, the Model-6 performs best since it has resulted in lowest MSE and MAPE (%) for both training and test data. With respect to the time, Model-6 consumes more time because it involves the PSO algorithm that obtained the optimal solution by searching iteratively.

Figure 6(a), Figure 6(b) and Figure (c) presents the comparison between the results of Model-5 and Model-6 respectively for $P_{MRPR,}$ COV_{MRPR} and θ_{MRPR}. From the figure, it is viewed that, the values predicted by Model-6 are nearer to the actual values compared to Model-5. This shows that Model-6 performs better by taking the advantage of PSO in ELM model.

4.4 Comparison of ELM and PSO-ELM models

The performance comparison has been done between ELM and PSO-ELM models IMEP, MCP and MRPR parameters. The comparison presented in Table 11.

Table 11. Comparison of model's performance

Models	**Output parameters**	**Learning algorithm**	**Hidden layer size**	**MSE Training data**	**MSE Test data**	**MAPE % Training data**	**MAPE % Test data**	**Executed Time (s)**
Model-1	P_{IMEP} and COV_{IMEP}	ELM	25	0.0002	0.00033	1.77	2.33	0.004095
Model-2	P_{IMEP} and COV_{IMEP}	PSO-ELM	19	0.00016	0.00024	1.002	2.24	0.986012
Model-3	$P_{MCP,}$ COV_{MCP} and θ_{MCP}	ELM	20	0.00013	0.00022	1.93	3.24	0.008585
Model-4	$P_{MCP,}$ COV_{MCP} and θ_{MCP}	PSO-ELM	18	0.0001	0.00019	1.23	3.06	0.998471
Model-5	$P_{MRPR,}$ COV_{MRPR} and θ_{MRPR}	ELM	25	0.00022	0.00036	1.17	2.8	0.005494
Model-6	$P_{MRPR,}$ COV_{MRPR} and θ_{MRPR}	PSO-ELM	22	0.00019	0.0003	1.03	2.64	0.978515

Model-1, Model-3 and Model-5 are models using BP learning whereas Model-2, Model-4 and Model-6 are ELM based models.

It is clear from the Table 11 that in all the three parameters *i.e* IMPEP, MCP and MRPR, PSO-ELM model performs better than ELM model with respect to minimum neurons in the hidden layer, MSE and MAPE%. But PSO-ELM takes more execution time than ELM in all the parameters as it takes in only single epoch. Further, PSO-ELM model is found to be more compact and excellent generalization performance with high predictive accuracy on training and test data through least effort of human being.

5.0 Conclusions

The purpose of present study is to develop an efficient ELM model by employing PSO for optimizing the neurons in the hidden layer. The prediction accuracy of this combined PSO-ELM model has been compared with base ELM model. Accordingly, the following conclusions can be obtained under this modelling study.

- PSO-ELM based models have compact network structure compared to ELM based models since it takes a fewer number of neurons in the hidden layers. The optimum model architectures for Model-3 and Model-4 are 4:20:3 and 4:16:3 respectively.
- PSO-ELM based model provides the best possible performance with the least error with respect to MSE and MAPE % compared to ELM model. The MSE and MAPE % on test data for Model-6 (PSO-ELM) are 0.0003 and 2.64 respectively in contrast to 0.00036 and 2.8 for Model-5 (ELM).
- PSO-ELM based Models takes more time as compared to ELM as it works on iterative procedure to find the optimal solution. The Model-2 (PSO-ELM) takes 0.986012s as ccompared to 0.004095s taken by Model-1 (ELM), since ELM operates with single epoch.

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Nomenclature and Abbreviations

ABC	Artificial Bee Colony	LSTM	Long Short-Term Memory
ANN	Artificial Neural Network	LT	Logarithmic Transportation
BBO	Biogeography-Based Optimization	MAPE	Mean Absolute Percentage Error
CAD	Crank Angle Degrees	MLP	Multilayer Perceptron
COV	Coefficient of Variation	MSE	Mean Square Error
EGB05	Ethanol gasoline blend with 5% ethanol	P_{IMEP}	Indicated Mean Effective Pressure
EGB10	Ethanol gasoline blend with 10% ethanol	P_{MCP}	Maximum cylinder pressure
EGB15	Ethanol gasoline blend with 15% ethanol	P_{MRPR}	Maximum rate of pressure rise
EGB20	Ethanol gasoline blend with 20% ethanol	PSO	Particle Swarm Optimization
ELM	Extreme Learning Machine	RBF	Radial Basis Function
GA	Genetic Algorithm	RMSE	Root Mean Square Error
GP	Genetic Algorithm	SA	Simulated Annealing
IGN	Ignition timing	SI	Spark Ignition
K-ELM	Kernel ELM	SVM	Support Vector Machine
LM	Levenberg-Marquardt	TSI	Twin spark ignition
LS	Least Square	WOA-BP	Whale Optimization Algorithm