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Review of artificial neural networks for gasoline, diesel and homogeneous charge compression ignition engine

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KEYWORDS

Artificial neural network;
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Abstract In automotive applications, artificial neural network (ANN) is now considered as a favorable prediction tool. Since it does not need an understanding of the system or its underlying physics, an ANN model can be beneficial especially when the system is too complicated, and it is too

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Nomenclature

CO	carbon monoxide
CO_2	carbon dioxide
D_{out}	outer mean diameter of injected droplet
NOx	nitrogen oxides
P_{max}	maximum in-cylinder pressure
R	coefficient of correlation
R^2	coefficient of determination
CeO_2	cerium oxide

Acronyms

AAPE	average absolute percent relative
ANFIS	adaptive neuro fuzzy inference system
ANL	artificial neural network noise level
ANP	analytical network process
BBO	biogeography-based optimization approach
BFG	Broyden, Fletcher, Goldfarb & Shanno
BMEP	break mean effective pressure
BPA	back-propagation algorithm
BSEC	brake specific energy consumption
BSFC	brake Specific fuel consumption
BTE	brake thermal efficiency
CFD	computational fluid dynamics
CGF	conjugate gradient with Fletcher-Reeves
CNG	compressed natural gas
CNL	combustion noise level
CR	compression ratio
CPP	cylinder peak pressure
CPT	cylinder peak temperature
Diesosenol	diesel-kerosene-ethanol
DOE	design of experiment
DOI	duration of injection
EGT	exhaust gas temperature
ELM	extreme learning machine
ERM	empirical risk minimization
FAHP	fuzzy analytical hierarchy process
FIP	fuel injection pressure
GA	genetic algorithm
GDA	gradient descent with adaptive learning rate
GDX	gradient descent with momentum and adaptive learning rate
GRNN	general regression neural network
HC	hydrocarbon
HCCI	homogeneous charge compression ignition
HCNG	hydrogen enriched compressed natural gas
HHO	oxy-hydrogen gas
HnOME	Honne oil methyl ester
HSU	Hartridge smoke unit
HORD	hyper-parameter optimization-radial basis function and dynamic coordinate search
ICE	internal combustion engine
ID	ignition delay
IE	indicated efficiency
IMEP	indicated mean effective pressure
KGE	Kling-Gupta efficiency
LM	Levenberg – Marquardt
LP-EGR	low pressure cooled exhaust gas recirculation
LSTM	long short-term memory
MAAE	mean absolute average error
MAPE	mean absolute percentage error
MCDM	multi-criteria decision-making
MFB	mass fraction burned
MIMO	multi-input multi-output
MLP	multi-layer perceptron
MORSM	multi-objective response surface methodology
MPCI	multi-performance characteristics index
MRE	mean relative estimation error
MRPR	maximum rate pressure rise
MSE	mean square error
NaN	not a number
NARXNET	nonlinear autoregressive network with exogenous inputs
NRMSE	normalized root mean square error
NSE	Nash-Sutcliffe coefficient of efficiency
ON	octane number
PME	peanut methyl ester
PSO	particle swarm optimization
RBF	radial basis function
RI	ringing intensity
RMS	root mean square
RNN	recurrent neural network
RON	research octane number
RP	resilient back-propagation
RS	random search
RSM	response surface methodology
SFC	specific fuel consumption
SCG	scale conjugate gradient
SE	scavenging efficiency
SIT	static injection timing
SOC	start of combustion
SoE	summary of emission
SPL	sound pressure level
SPM	suspended particulate matter
SRM	structural risk minimization
SVM	support vector machine
TBC	thermal barrier coating
TBHQ	*tert*-butyl hydroxyl quinone antioxidant
TOPSIS	technique for order preference by similarity to ideal solution
TPE	tree structured Parzen estimator
VE	volumetric efficiency
Vikor	Vise Kriterijumska Optimizacija Kompromisno Resenje
WCO	waste cooking oil

Diesel engine;
Homogeneous charge compression ignition engine;

costly to model it using a simulation program. Therefore, using ANN to model an internal combustion engine has been a growing research area in the last decade. Despite its promising capabilities, the use of ANN for engine applications needs deeper examination and further improvement.

Internal combustion engine; Optimization

Research in ANN may reach its maturity and be saturated if the same approach is applied repeatedly with the same network type, training algorithm and input–output parameters. This review article critically discusses recent application of ANN in ICE. The discussion does not only include its use in the conventional engine (gasoline and diesel engine), but it also covers the ANN application in advanced combustion technology i.e., homogeneous charge compression ignition (HCCI) engine. Overall, ANN has been successfully applied and it now becomes an indispensable tool to rapidly predict engine performance, combustion and emission characteristics. Practical implications and recommendations for future studies are presented at the end of this review.

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1. Introduction

Despite being invented more than a century ago, the internal combustion engine (ICE) remains the most dominant power supply for vehicles [1]. Stricter safety, stringent emissions regulations and increasing demand for fuel economy have triggered both the industry and university to improve ICE [2]. In order to meet the emission target, a number of methods are being investigated to decrease engine emissions. One of the solutions is using diesel/biodiesel additive [3]. Another promising technique is by using nanoadditives [4,5] such as cerium oxide (CeO_2) nanoparticles [6] to decrease harmful emissions whilst enhancing engine performance. In another study by Atarod et al. [7], nanoparticle added to diesel was found to diminish the formation of NOx at moderate load. Therefore, the next ICE should possess both maximum efficiency and minimum emissions [8]. In this regard, strong theoretical and applied understanding of the engine play important roles to enhance the existing technology. The complexity of internal combustion engines can be improved using both innovative experiments and computer simulation.

Various modeling and simulation methods have been examined for a more affordable solution in supplementing the experimental works [9]. To develop and optimize the combustion process, engine modeling plays an increasingly significant role, especially with the increasing computer power and the availability of various engine models. Precise engine simulations will assist the introduction of new technologies and provide an accurate assessment of the preliminary design. The use of computer simulation will shorten research and development time and reduce the cost to manufacture the prototypes of physical products. With conventional engine research process, it is difficult and expensive to meet the growing demand for better performance vehicles and reduced emissions due to strict regulations implemented worldwide.

Although a computational study often has more quantitative uncertainties than that of an experiment, they offer several benefits that make its application a necessity. Instead of constructing each prototype which can be expensive and time-consuming, numerical simulation can provide fast preliminary results for a wide range of parametric studies in which each variable can be determined, and several boundary conditions can be analyzed. More recently, artificial neural network (ANN) has received increasing popularity to solve complex nonlinear real-life scientific and engineering problems due to its great generalization capability [10].

Model accuracy and computer resources have always been a trade-off in the modeling process. Methods such as computational fluid dynamics (CFD) and chemical kinetic modeling can accurately represent the processes inside the cylinder, enabling thorough analysis of the physics and processes of the engines. However, they need high computing power. For a practical application such as in the real-time simulation or the engine control development, low computing resources with fast processing time is preferred. Therefore, an alternative modeling method that requires lower computing resources but with acceptable model accuracy is desirable. This is where the ANN method could solve the trade-off between model accuracy and computer resources [11,12].

ANN is completely different from traditional modeling strategy. It can overcome nonlinear and complicated applications that are difficult to be modeled mathematically [13]. Unlike the classical method, ANN collects and analyze the information using input data [14,15]. Through data training and validation, an ANN model can improve its prediction performance. Therefore, rather than using an empirical equation, an ANN model merely requires adequate input and output data to be trained. Some research groups have compared ANNs with the conventional linear model. Although ANNs gave more accurate prediction than the traditional linear model, they have sometimes conflicting outcomes. In several conditions where the data is already linear without much disturbance, ANN shows relatively poor performance. Overall, ANNs have shown varying degrees of success; thus, they should be applied carefully. Table 1 lists the advantages and disadvantages of using ANN.

Table 1 Advantages and disadvantages of ANN.

Advantages	Disadvantages
• Less statistical learning is required. • Responsive measurement of non-repeatability problems. • Re-learn capability to strengthen its accuracy where new data are obtained. • Availability of various training algorithms. • Flexibility to add or remove input and output. • Possibility to run in online mode owing to ANN's fast convergence. • Accommodation of multiple inputs to estimate multiple outputs. • Ease of optimization, leading to affordable and adaptable non-linear large data analysis. • Robust non-linear mapping capabilities that can estimate any discrete quantitative feature. • Having numerous interconnected variables to address big and complicated structures. • No need for long iterative calculations to solve differential equations. • Possibility to be combined with other optimization approaches such as response surface methodology (RSM).	• Susceptible to overfit. • Uncertain convergency. • Large data are required. • Not well-described validation criteria. • The optimal network structure is generally not known (trial-and-error). • Difficult to identify possible cause and effect correlations (black box). • Regulations regarding the amount and type of data training are limited. • The selection criteria for the best training algorithm with - the rapid convergence of new patterns is not well-understood. • No established standard for determining the neuron numbers in the hidden layer. • Instability with insufficient neurons, particularly hidden layer networks with one or two neurons. • Despite offering more stability and accuracy, more training and data validation are needed for optimization using genetic algorithm.

2. Artificial neural networks for engine applications

The use of ANN for modeling the operation of internal combustion engines is more recent progress where most of the applications are only limited to engine performance and emissions. ANN has been used in numerous fields. In engineering systems, neural networks have been successfully applied to predict several renewable energy problems [16–18]. In the field of automotive, the ANN can be utilized as an alternative approach to model non-linear and complicated engine applications [19,20]. Currently, ANN is considered as a more promising tool to predict engine responses because of its fast delivery. Also, it requires relatively low computing resources compared to conventional computer simulations.

2.1. Artificial neural networks for diesel engine

Due to its comparable properties to diesel fuel, biodiesel is often added in diesel engine [21–25]. It can be produced from a variety of sources that are grown regionally as depicted in Fig. 1 [26]. One of promising biodiesel sources is produced from waste cooking oil (WCO) owing to its affordability and accessibility worldwide [27–29]. Babu et al. [30] developed an ANN model to predict diesel engine performance, combustion and emissions fueled with waste frying oil using multi injection strategy. It was found that for engine performance with four inputs and two outputs, the optimum architecture was achieved with eight hidden neurons (4–8-2). For combustion and emissions, the optimum architectures were 4–14-3 and 4–13-5, respectively. The ANN model developed in this study gave a lower mean square error and correlation coefficient values between 0.01 and 0.02 & 0.980 and 0.998, respectively. In another study, Kshirsagar and Anand [31] used Calophyllum inophyllum methyl ester biodiesel. They suggested using a Nash-Sutcliffe coefficient of efficiency (NSE) to improve the representation of R^2 owing to NSE's sensitivity to differences in the means and variances. Also, the Theil uncertainty or known as the THEIL U2 was introduced as an evaluation criterion. It is a standardized measure to evaluate and validate the prediction quality of a model. It was found that the results of NSE and THEIL U2 indicated robustness and credibility of the proposed model. Salam and Verma [32] used microalgae biodiesel and developed an ANN model trained using operating conditions simulated in Diesel-RK software. The ANN model could predict the performance, combustion and emissions with an average R of 0.9801 ± 0.0146. Other interesting ANN applications for biodiesel were reported by Ramalingam et al. [33] and Fangfang et al. [34].

Tosun et al. [35] used ANN modeling to predict diesel engine performance using peanut methyl ester biodiesel (PME) and its blend with alcohol. The results from ANN were compared with linear regression. The model has a three-layer structure; input, hidden and output layer. One layer for input and output layer, while the hidden layer had 7 neurons for torque prediction, 9 neurons for CO and 13 neurons for NOx predictions. As an activation function, logistic sigmoid (logsig) was used in the hidden layer, while the linear transfer function (purelin) was used in the output layer. Levenberg-

Fig. 1 Potential of biodiesel feedstocks worldwide [26].

Marquardt was used to learn the algorithm. Compared to linear regression, the ANN model was found to be more accurate in which the MAPE values from ANN model were less than that of the linear regression.

Soot, NOx and CO_2 emissions of n-heptane from direct injection diesel engines are often understudied. Taghavifar et al. [36] used a CFD approach with detailed kinetic and thermodynamic database along with ANN to predict emissions of a diesel engine fueled with n-heptane. It was found that satisfying R^2 were achieved for CO_2, soot and NOx emissions at 0.9976, 0.9995 and 0.9951, respectively. Also, Fig. 2. shows that the lowest MSE (0.0001086) was obtained using 18 neurons in the hidden layer.

Nano-catalysts addition is known for its ability to enhance thermo-physical properties of diesel fuel. One of the promising nano-catalysts is alumina [37–39]. Yet, no previous studies investigated the use of alumina addition into biodiesel-diesel blends until Hosseini et al. [40] developed an ANN model to predict alumina effect on diesel engine using numerous input parameters. What is interesting from this study is that it used many parameters as the input and output as shown in Fig. 3. While most studies usually only use two parameters as the input (engine speed or fuel blend ratio) and ignore many important parameters such as fuel properties, this work used 12 inputs involving numerous parameters that could potentially affect engine's behaviors, making the prediction more accurate. These include fuel density, kinematic viscosity, lower heating value, manifold pressure, fuel consumption, exhaust temperature, oxygen in the exhaust gas, oil temperature, relative humidity, ambient pressure, fuel blend and engine speed. The results were exceptionally satisfying where the corresponding R for training, validation and testing had values close to one. Another study utilizing nanoparticles was conducted by Saraee et al. [41]. CeO_2 in 10, 20 and 40 ppm were added to pure diesel. An ANN model with 12 neurons in the hidden layer trained with the Levenberg-Marquardt algorithm was found to give the best network performance with the lowest MSE value of 0.000172. Also, the most stable error convergence giving the least error was provided with the learning rate of 0.4 and momentum coefficients of 0.8.

One of the important engine parameters is cycle-by-cycle variations. They represent extensive pressure, thus potentially deteriorating engine performance, lowering efficiency and increasing exhaust emissions. Cyclic variability in a gasoline engine has been extensively investigated [42–46], but it is often neglected in the diesel engine. This is because the diesel engine is relatively stable than the gasoline engine. Yet, the addition of alternative fuels into diesel fuel may affect its cycle-by-cycle variations due to their different fuel properties [47]. Therefore, control strategy plays an important role to reduce cyclic issues in the diesel engine. An ANN model could be a promising tool to control combustion variation. Gürgen et al. [48] developed an ANN model using Levenberg – Marquardt (LM) and scaled conjugate gradient (SCG) to predict diesel engine's cyclic variability fueled with butanol-diesel fuel. The results showed that the coefficient of determination values varied between 0.737 and 0.9677 with MAPE and MSE were lower than 8.7 and 0.042, respectively.

One of the promising methods to improve engine performance and reduce its emissions is the use of oxy-hydrogen gas (HHO) enrichment dual-fuel in a diesel engine. Kenanoğlu et al. [49] used soybean biodiesel (B25) enriched with oxy-hydroxy gas with 3, 5 and 7 L/min. Unlike previous studies who exhaustively used back-propagation network, this study used cascade forward network trained with the Levenberg-Marquardt algorithm. Cascade forward network is comparable to the feed-forward network, but it differs by including a connection from the input with each previous layer being connected to the subsequent layer. It was found that the ANN model could predict the target response with 95,82%,

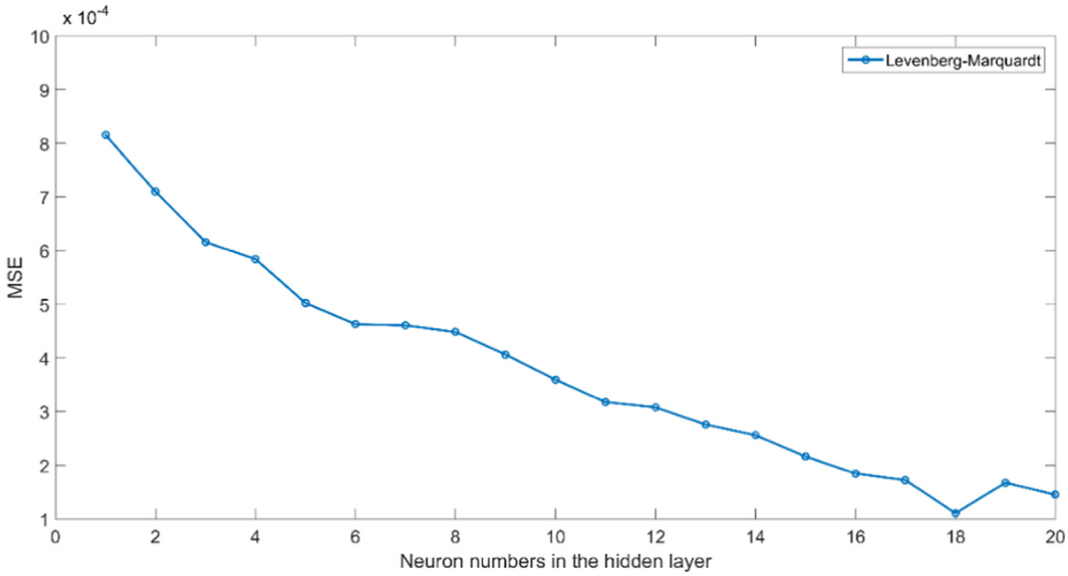

Fig. 2 MSE vs. Neuron numbers in the hidden layer; re-plotted from [36].

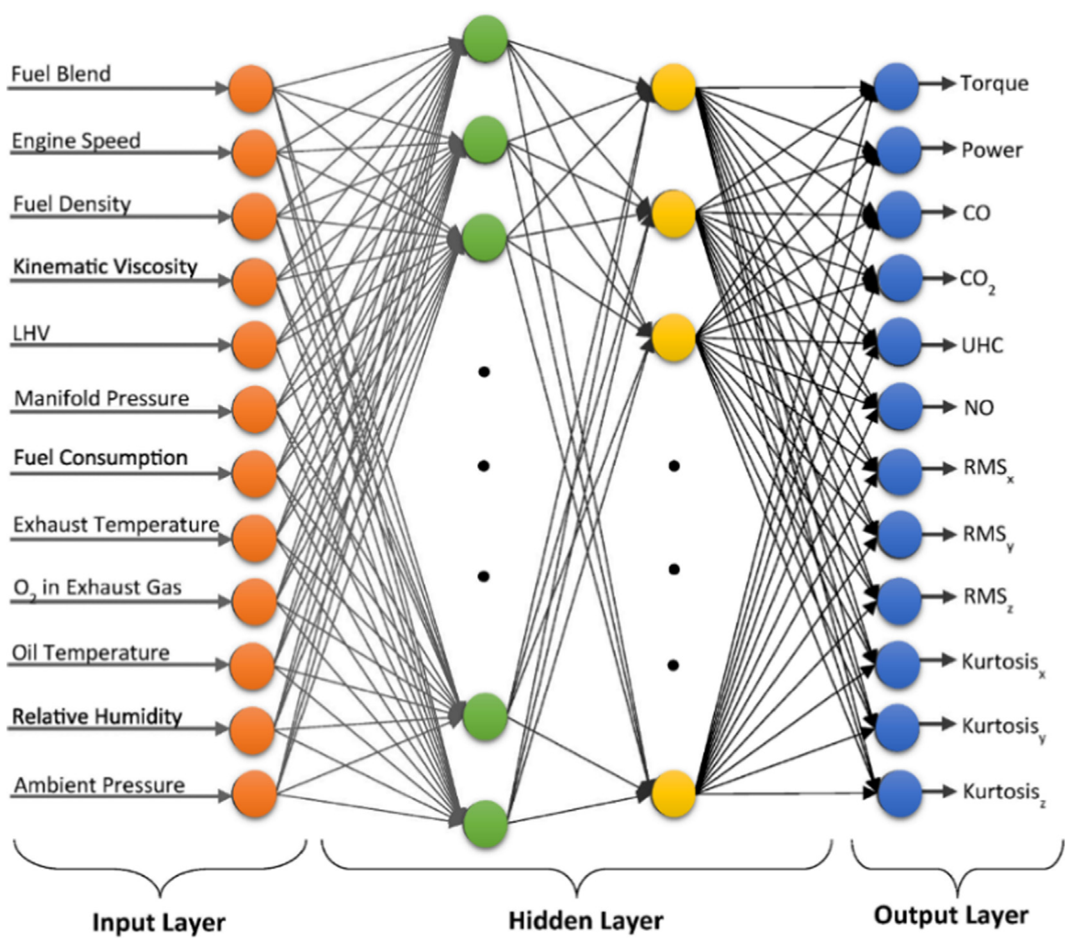

Fig. 3 An ANN model with multi-input and multi-output parameters developed by Hosseini et al.; . reproduced from [40]

96,07% and 92,35% accuracies for torque, power and NOx emission, respectively.

In some cases, ANN models need to be optimized with other methods. Baranitharan et al. [50] combined an ANN model with RSM to predict and optimize the performance and emission of a diesel engine fueled with Aegle marmelos pyrolysis oil/diesel/Tert-butyl hydroxyl quinone antioxidant (TBHQ) blend. The ANN and RSM gave R and R^2 of 0.998 and 0.991, respectively with A20D80T blend presenting the optimum blend. Studies using RSM alone to optimize the output of the diesel engine can be found in Refs. [51–54]. Furthermore, Bhowmik et al. [55] used multi-objective response surface methodology (MORSM) to improve prediction of the operating parameters in an indirect injection diesel engine fueled with diesel-kerosene-ethanol (diesosenol) blends that were previously modeled using ANN. The optimal operating condition was found at 74.14% engine load using 2.42% kerosene and 10% ethanol. In another study utilizing both ANN and RSM, Samuel and Okwu [56] used waste cooking oil in a diesel engine with the ANN model being developed to predict the engine response. The RSM was used to optimize the exergy and energy efficiencies. It was found that the optimum engine performance was achieved at 80% engine load with B10 and B20 according to energy analysis. As for the exergy analysis, the optimal point was obtained at the same engine load but with B90 and B100. Other studies investigating the combined application of ANN and RSM in a diesel engine can be found in Refs. [57–59].

Another optimization method known as a genetic algorithm was used by Channapattana et al. [60] to obtain the optimal engine's performance and emission characteristics using various second-generation biofuels. It was found that that the optimum values of static injection timing were 18 and 22° bTDC, while the fuel injection pressure and Honne oil methyl ester (HnOME) blend were 227 bar and 60%, respectively. Fuzzy logic was another promising optimization method. It is employed by Deb et al. [61] to optimize the ANN model to predict the performance and emissions behavior of hydrogen in dual-fuel mode. They aimed to find MPCI (multi-performance characteristics index) for optimum value. It was found that the highest MPCI was 0.742 using a combination of both logsig and tansig with the minimum error of 2.14×10^{-6}. Furthermore, little is known about the application of the analytical network process technique for order preference by similarity to ideal solution (ANP-TOPSIS) in an internal combustion engine. It is a multi-objective optimization multi-criteria decision-making (MCDM) technique. Sakthivel et al. [62] employed such a technique to look for the optimum blend under various loads while trying to maximize engine efficiency and minimize emissions. Prior to the application of ANP-TOPSIS, an ANN model was developed and optimized using a genetic algorithm as shown in Fig. 4. Given the success of the ANN-GA-TOPSIS model, it would be interesting to see the implementation of other integrated models to obtain more satisfying outcomes such as fuzzy logic-GA-FAHP (fuzzy analytical hierarchy process) TOPSIS or fuzzy-GA-FAHP Vikor (Vise Kriterijumska Optimizacija Kompromisno Resenje).

Selection of training algorithm, transfer functions and neuron numbers in the hidden layer plays a substantial role in determining the efficiency of an ANN model. Thus far, most studies seem to use one learning algorithm i.e., Levenberg – Marquardt (LM) with small number combinations of transfer functions. Other training algorithms and combinations of transfer functions are worth investigating. Syed et al. [63] developed an ANN model for a hydrogen dual fueled diesel engine using seven different training algorithms; (1) Levenberg – Marquardt (trainlm), (2) Gradient descent with adaptive learning rate (traingda), (3) Gradient descent with momentum and adaptive learning rate (traingdx), (4) Resilient back-propagation (trainrp), (5) Conjugate gradient with Fletcher-Reeves updates (traincgf), (6) Scale conjugate gradient (trainscg) and (7) Broyden, Fletcher, Goldfarb & Shanno (trainbfg). This study also combined eight transfer functions of tansig, logsig and purelin for each algorithm (tansig-tansig, logsig-tansig, tansig-logsig, logisg-logsig, logisg-purelin, tansig-purelin, purelin-logisg, purelin-tansig). It was found that the ANN model built with trainbfg gave the best result with regression coefficients varied between 0.9869 and 0.9996.

Almost similar to Syed et al. [63], Javed et al. [64] also used seven different training algorithms with five combination transfer functions of tansig, logsig and purelin for each algorithm. The engine was operated using Jatropha Methyl Ester. The data were normalized into numeric values between 0.1 and 0.9 before being randomized for network training. Later, these data were reverted by denormalizing them. The ANN model was performed for different learning algorithm and training functions mentioned above for 100 iterations. Results indicated that the best model was achieved by Levenberg – Marquardt training algorithm using logsig and tansig transfer functions with R, MSE and MAPE being 0.9936, 0.0011 and 4.863% respectively.

Air mass flow is an important variable in an internal combustion engine [65]. To determine its performance, volumetric efficiency is normally quantified. The use of a physical model using thermo-fluid dynamic model is the most popular method. Such a model, however, involves a non-linear and complex process. Luján et al. [66] proposed a novel adaptive learning algorithm to predict volumetric efficiency in a diesel engine. The algorithm was developed based on the rise of hidden layer weight update speed with training epochs number being 200–15,000. It was found that the proposed model gave satisfying results with the maximum generalization error about 13% with an average relative error of 5.5%.

To objectively present its prediction accuracy, ANN should be compared with other soft computing approaches such as support vector machine (SVM). Both ANN and SVM have analogous architectures in which ANN used weights and activation functions to estimate nonlinear problems, whereas SVM uses nonlinear mapping to generate linear function. Niu et al. [67] used both ANN and SVM to predict performance and emissions of a marine diesel engine. As the marine engine experiment involves a considerable amount of time and resources, the Taguchi orthogonal array was used to reduce the experiment time. Results showed that SVM presented more stable predictive accuracy compared to ANN. SVM could look for the global solution, while ANN was prone to local minima and overfitting. To enhance the stability and accuracy of ANN, its initial weights and threshold values should be enhanced. The detailed summary of ANN application in diesel engine discussed in this section is listed in Table 2.

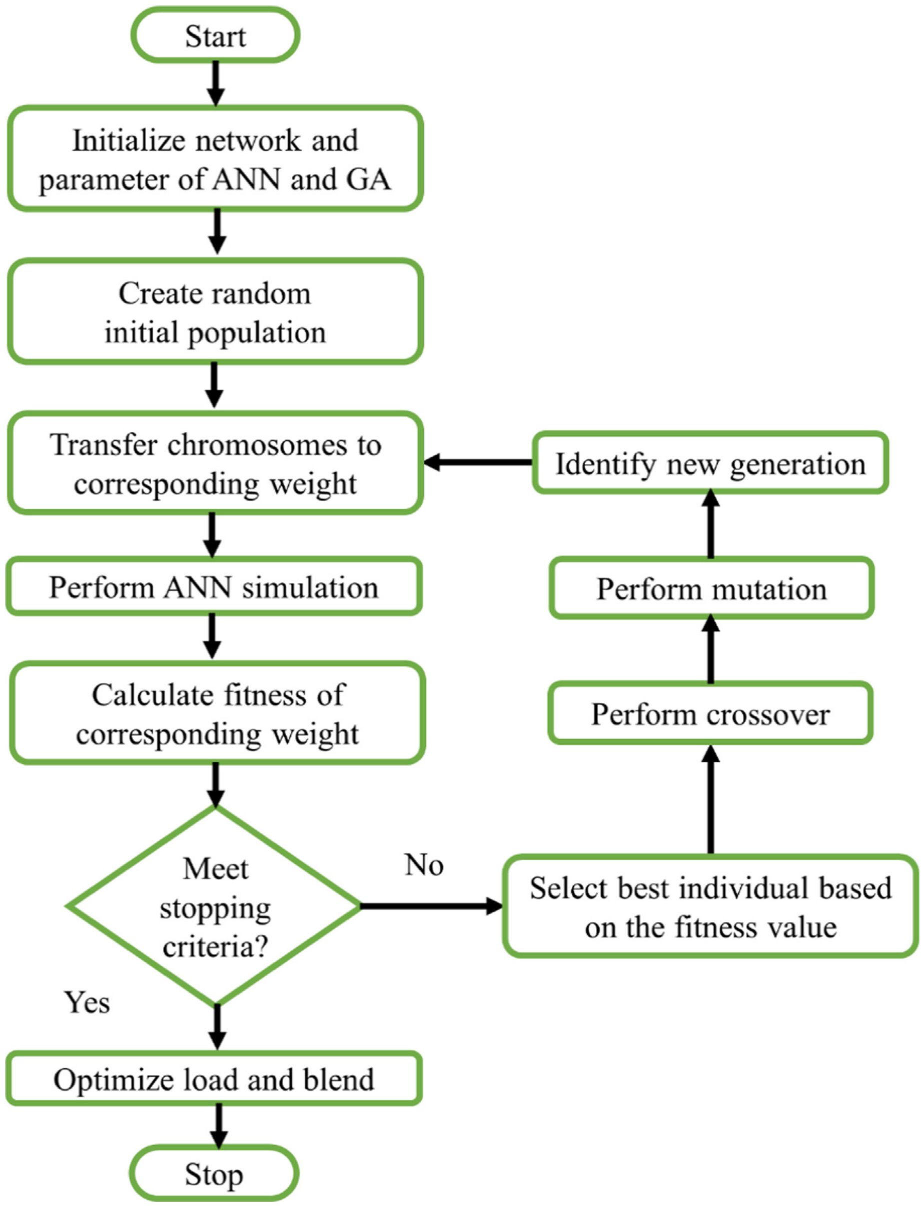

Fig. 4 An ANN model optimized with GA coupled with ANP-TOPSIS; . reproduced from [62]

2.2. Artificial neural networks for gasoline engine

Despite its promising capabilities, the ANN has not been applied in gasoline engine as much as in diesel engine. However, several studies have tried to utilize it. Table 3 lists the detailed summary of the ANN application in gasoline engines discussed in this section. Liu et al. [73] established an ANN to predict the performance and emissions of a port fuel injection gasoline engine under different equivalence ratio. They used butanol-gasoline blends as the fuel with ratio from B0 (pure gasoline) to B60. Results showed that a correlation coefficient and a mean relative error were at 0.9929 to 0.9996 and 0.1943% to 9.953%, respectively. Also, Tosun et al. [74] used ANN as an estimation tool to predict operational parameters of direct injection turbocharged gasoline engine and compared the results with regression analysis. The authors used a three-layer feed-forward and back-propagation ANN algorithm to train the experimental data. It was found that, compared to linear and non-linear regression techniques, the ANN model gave better accuracy.

Researches in the ethanol-gasoline blends for gasoline engine has long been established [75], but the application of ANN in this area is still relatively new [76–78]. Tekin and Saridemir [79] predicted engine performance using ethanol-gasoline blends with the assistance of ANN. This study found satisfying prediction results where the correlation coefficient for the power, torque, CO, CO_2, HC, exhaust temperature and BSFC were 0.9992, 0.9991, 0.9987, 0.9989, 0.9977, 0.9993, and 0.9979, respectively. Similarly, Thakur et al. [80] also used ethanol-gasoline blends in SI engine. The ratio was varied ranging from E0 to E100 with 20% interval. Seventy per cent of the data was used randomly to be trained, while 15% was used for validation. The remaining 15% was used to enhance the results for network generalization. For all

Table 2 ANN for diesel engine.

Research groups	Engine specification	Fuel	ANN model				
			Input	Hidden layer	Output	Network (Training)	Evaluation criteria
Babu et al. [30]	1-cylinder, 553 cc, 16:5 compression ratio, direct injection diesel engine	Waste frying oil biodiesel	4 inputs (pre injection timing, main injection timing, post-injection timing, test fuels)	Single layer with 8 neurons (performance), 4 neurons (combustion) and 13 neurons (emission)	2 outputs for engine performance (BSEC, BTE) 3 outputs for combustion (ignition delay, combustion duration, cylinder peak pressure) 5 outputs for emission (CO, CO_2, HC, NO, smoke)	Back-propagation multilayer perceptron feed-forward (Levenberg-Marquardt)	R^2, RMSE, MAPE, MSRE, NSE
Kshirsagar and Anand [31]	1-cylinder, 553 cc, 16:7 compression ratio, direct injection diesel engine	Calophyllum inophyllum methyl ester biodiesel	4 inputs (load %, blend %, injection pressure, injection timing)	Single layer with 16 neurons for engine performance and double layers for emission with 14 neurons for each hidden layer	3 outputs for engine performance (BTE, BSEC, EGT) 6 outputs for emissions (CO, CO_2, UHC, NO, dry soot, O_2)	Feed-forward (Levenberg-Marquardt)	MSE, RMSE, R, R^2, MAPE, MSRE, NSE, THEIL U2
Salam and Verma [32]	1-cylinder, direct injection diesel engine	Microalgae biodiesel	3 inputs (load, blending, FIP)	Single layer with 10 neurons	17 outputs (SFC, BTE, IE, SE, EGT, CPP, CPT, MRPR, Dout, ID, HSU, smoke, SPM, CO_2, NOx, SoE, NO2)	Feed-forward back-propagation (Levenberg-Marquardt)	R, MAPE
Tosun et al. [35]	In-line 4-cylinder, 3907 cc, direct injection diesel engine with glow	Diesel, peanut methyl ester (PME), ethanol + PME, methanol + PME, butanol + PME	5 inputs (engine speed, fuel properties, cetane number, lower heating value, density)	Single layer with 7,9 and 13 neurons for torque, CO and NOx	3 outputs (torque, CO and NOx)	Back-propagation feed-forward (Levenberg-Marquardt)	R^2, MAPE

(*continued on next page*)

Table 2 (*continued*)

Research groups	Engine specification	Fuel	ANN model				
			Input	Hidden layer	Output	Network (Training)	Evaluation criteria
	plug						
Taghavifar et al. [36]	4-cylinder, 1800 cc direct injection diesel engine	N-heptane	6 inputs (crank angle, equivalence ratio, temperature, pressure, O_2, liquid mass evaporated)	Single layer with 18 neurons	3 outputs (NOx, soot, CO_2)	Back-propagation multilayer perceptron feed-forward (Levenberg-Marquardt)	R^2, MSE
Hosseini et al. [40]	1-cylinder, 510 cc, 17.5:1 compression ratio, common rail diesel engine	Diesel-biodiesel blends added with alumina nano-catalyst	12 inputs (fuel blend, engine speed, fuel density, kinematic viscosity, LHV, manifold pressure, fuel consumption, exhaust temperature, O_2 in the exhaust gas, oil temperature, relative humidity, ambient pressure	Double layer with each layer has 25 neurons	12 outputs (torque, power, CO, CO_2, UHC, NO, RMS_x, RMS_y, RMS_z, $Kurtosis_x$, $Kurtosis_y$, $Kurtosis_z$)	Back-propagation multilayer perceptron feed-forward (Levenberg-Marquardt)	R, MSE
Saraee et al. [41]	6-cylinder, 5800 cc direct injection diesel engine	Diesel fuel added with CeO_2 nanoparticles	3 inputs (engine speed, nano addition, ISFC)	Single layer with 12 neurons	4 outputs (power, NOx, HC, CO)	Back-propagation multilayer perceptron (LM, SCG, RP, DX)	R, MSE
Gürgen et al. [48]	1-cylinder direct injection diesel engine	n-butanol-diesel blend	2 inputs (engine speed, fuel blend ratio)	Single layer with 11 neurons	1 output (COV_{IMEP})	Back-propagation (LM, SCG)	R^2, MSE, MAPE
Kenanoğlu et al. [49]	4-cylinder, 3567 cc, in-line diesel engine	Diesel and soybean methyl ester enriched with HHO (oxy-hydrogen gas)	3 inputs (motor speed, fuel type, fuel consumption)	Double layers, 10 neurons in the first layer and 15 neurons in the second layer	3 outputs (torque, power, NOx emission)	Cascade forward (Levenberg-Marquardt)	AAPE, R^2, MSE
Baranitharan et al. [50]	1-cylinder multi-fuel, variable compression ratio (12:1 to 18:1) diesel engine	Aegle marmelos pyrolysis oil-diesel-Tert-butyl hydroxyl quinone antioxidant (TBHQ) blend	2 inputs (compression ratio and engine load)	–	2 outputs for engine performance (BSFC, BTE) 4 outputs for emissions (CO, HC, CO_2 and NOx)	Feed-forward back-propagation (Levenberg-Marquardt) + RSM	R, R^2, MSE, RMSE, MAAE
Bhowmik et al. [55]	1-cylinder, 318 cc indirect injection diesel engine	Diesel-kerosene-ethanol (Dieseosenol)	3 inputs (engine load, kerosene share, ethanol share)	Single layer with 9 neurons	5 outputs (BTE, BSEC, NOx, UHC,	Feed-forward back-propagation (Levenberg-Marquardt) + MORSM	R, R^2, MSE, MAPE, MSRE, NSE,

Table 2 (*continued*)

Research groups	Engine specification	Fuel	ANN model				
			Input	Hidden layer	Output	Network (Training)	Evaluation criteria
					CO)		KGE, THEIL U2
Channapattana et al. [60]	1-cylinder, direct injection diesel engine with a variable compression ratio	Diesel, HnOME, diesel-HnOME	5 inputs (CR, SIT, FIP, load, blend)	Single layer with 28 neurons	8 outputs (BTE, BSEC, EGT, CO_2, CO, HC, NOx, smoke)	Multilayer perceptron back-propagation (LM, RP, SCG, GDX) + GA	MAPE, MSE, Prediction accuracy
Aydin et al. [57]	1-cylinder diesel engine with 200 bar injection pressure	Biodiesel-diesel blends	3 inputs (injection pressure, biodiesel ratio, load)	Single layer with 10 neurons	7 outputs (BSFC, EGT, BTE, NOx, HC, CO, smoke)	Feed-forward back-propagation (Levenberg-Marquardt)	R^2, MRE, RMSE
Uslu [58]	1-cylinder, 296 cc, 18:1 compression ratio diesel engine	Palm oil-diesel blend	3 inputs (engine load, palm oil percentage, and injection advance)	Single layer with 10 neurons	6 outputs (EGT, BTE, CO, HC, smoke and NOx)	Feed-forward back-propagation (Levenberg-Marquardt)	R^2, MRE, RMSE
Syed et al. [63]	1-cylinder, 553 cc, direct injection diesel engine	Diesel and hydrogen	2 inputs (load and H_2)	Single layer with 8 neurons	6 outputs (BTE, BSFC, CO, NOx, HC, EGT)	Multilayer perceptron back-propagation (LM, GDA, GDX, RP, CGF, SCG, BFG)	R, RMSE, MAPE, NSE, KGE
Javed et al. [64]	1-cylinder, 553 cc, direct injection diesel engine	Diesel and Jatropha Methyl Ester (JME) enriched with hydrogen	3 inputs (load, biodiesel blend, H_2)	Single layer with 16 neurons	8 outputs (BTE, BSFC, CO, O_2, CO_2, NOx, HC, EGT)	Feed-forward back-propagation (LM, GDA, GDX, RP, CGF, SCG, BFG)	R, MAPE, MSE
Niu et al. [67]	Common rail direct injection-assisted marine diesel engine	Diesel	4 inputs (rail pressure, injection timing, charge pressure, charge temperature)	Single layer with 4 neurons for BSFC, max pressure, NOx, and 3 neurons for soot and efficiency	5 outputs (BSFC, max pressure, NOx, soot, efficiency)	Feed-forward back-propagation (Levenberg-Marquardt) + SVM	R^2, MSE, MAPE
Rao et al. [68]	1-cylinder, 447.3 cc, indirect diesel injection engine	Rice bran methyl ester (RBME)-Isopropanol blend	2 inputs (engine load and fuel)	Single layer with neurons being varied from 14 to 23	9 outputs (EGT, BSFC, BSFC, HC, CO, CO_2, O_2, NOx and smoke)	Feed-forward back-propagation (Levenberg-Marquardt)	R, MSE
Uslu and Celik [69]	1-cylinder, 296 cc, 18:1 compression ratio, direct injection diesel engine	Diesel and diesel-DEE	3 inputs (engine load, blend, engine speed)	–	7 outputs (BSFC, BTE, EGT, NOx, CO, HC and smoke).	Feed-forward back-propagation (Levenberg-Marquardt)	R^2, MRE, RMSE
Yang et al. [70]	In-line 6-cylinder, 9726 cc, high-pressure common-rail, turbocharged and intercooled diesel engine	Diesel	7 inputs (V, Tor_{exp}, $p_{exp,in}$, $p_{exp,out}$, $T_{exp,in}$, $T_{con,out}$, $p_{p,out}$)	Single layer (no information about the neuron numbers)	1 output W_{exp}	Feed-forward back-propagation (LM, GD, DM, GDA) + GA	R, MSE

(*continued on next page*)

Table 2 (*continued*)

Research groups	Engine specification	Fuel	ANN model				
			Input	Hidden layer	Output	Network (Training)	Evaluation criteria
Çelebi et al. [71]	In-line 4-cylinder, 3907 cc, direct injection diesel engine with glow plug	Diesel, sunflower and canola biodiesel, natural gas,	5 inputs (engine speed, CNG flow rate, cetane number, density)	Single layer with 4 neurons for vibration and 5 neurons for SPL	2 outputs (Vibration and SPL) with different ANN architecture	Feed-forward back-propagation (Levenberg-Marquardt)	R^2, MAPE
Dharma et al. [72]	1-cylinder, 638 cc direct injection diesel engine	Jatropa curcas-Ceiba pentandra biodiesel-diesel	2 inputs (engine speed and biodiesel blends)	Single layer with 9 neurons	5 outputs for engine performance (BSFC, torque, brake power, EGT, BTE) 4 outputs for exhaust emissions (CO, CO_2, NOx, smoke opacity)	–	R, MAPE, MSE, RMSE

engine performance and emissions, the ANN model gave correlation coefficients from 0.9999 to 0.9999. Mean relative errors were found between 0.12% and 5.56% with root mean square errors being exceptionally low. Also, by increasing the number of neurons in the hidden layer above 20 (i.e., 21, 22, 23 and 24), the R values were not found to raise. Thus, the authors concluded that the optimal ANN model for this study was achieved with a single hidden layer of 20 neurons.

One of the promising renewable energy sources is biogas. It can be used not only for thermal and electricity application but also for internal combustion application [81–85]. Kurtgoz et al. [86] developed an ANN model to predict thermal and volumetric efficiency as well as the brake specific fuel consumption of gasoline engine fueled with biogas using various methane ratios. The ANN model was found to provide satisfying results with high correlation value and low error rates. Another promising gaseous fuel for the gasoline engine is compressed natural gas (CNG) enriched with hydrogen. The addition of hydrogen is believed to improve the efficiency of existing CNG engines without penalty in the exhaust emissions. Despite its straightforward and promising accuracy, the use of ANN for hydrogen-enriched compressed natural gas (HCNG) is difficult to find in the literature. Mehra et al. [87] investigated the performance and emission behaviors of HCNG under different ignition timings and excess ratio. Various neuron numbers were tested as shown in Fig. 5. and Fig. 6. They trained the model 100 times for every neuron, generating different weights that determine MSE and R. Fig. 5 shows that at the beginning (few neuron numbers), the MSE values are quite high for BSFC and torque. With increasing neuron numbers, the MSE value fluctuates with a decreasing trend, indicating a good simulation accuracy. The trend in coefficient correlation (Fig. 6) also shows that the ANN model presents satisfying results, giving coefficient correlation close to 1.00 with the increase of neuron numbers.

Compared to port fuel injection, gasoline direct injection (GDI) engines are known for their higher thermal efficiency and power output [88]. However, little is known about the effect of in-combustion pressure on the low pressure cooled exhaust gas recirculation (LP-EGR) in a turbocharged gasoline direct injection. Jo et al. [89] developed an ANN model to predict the LP-EGR utilizing in-cylinder pressure data, and combined it with three optimization algorithms; random search (RS), tree-structured Parzen estimator (TPE) and hyper-parameter optimization using radial basis function and dynamic coordinate search (HORD). The three algorithms were found to be able to enhance the efficiency to find the multidimensional hyper-parameters with HORD showing the best performance with stable convergence. Its R^2 was above 0.9896 with total RMSE of less than 0.63%.

It is known that internal combustion engines suffer from heat loss as a result of cooling system elements. One of the effective approaches to minimize such loss is by applying thermal barrier coating (TBC) [90,91]. Hazar and Gul [92] used chrome carbide (Cr_3C_2) to coat piston, exhaust and inlet valves. Yet, to measure the performance and emission of a gasoline engine coated with chrome carbide would be a time-consuming process. Therefore, an ANN with multi-layered, feedforward, back-propagation algorithm was developed to decrease the experiments repetitions and costs.

In most cases, a feed-forward neural network for engine application is trained using back-propagation neural network. This type of ANN is widely used to solve various engine application to predict performance and emissions characteristics. However, the back-propagation neural network has significant problems such as high reliance on the initial weights, the

Table 3 ANN for gasoline engine.

Research groups	Engine specification	Fuel	ANN model				
			Input	Output	Network	Training	Performance
Liu et al. [73]	1-cylinder, 575 cc PFI gasoline engine	Gasoline, gasoline-n-butanol	2 inputs (equivalence ratio, butanol ratio)	6 outputs (power, BTE, BSFC, CO, HC, NOx)	Back-propagation feed-forward	Levenberg – Marquardt, Scale Conjugate Gradient	R, MRE, RMSE
Tosun et al. [74]	4-cylinder, 1368 cc, 10:1 compression ratio, turbocharger DI gasoline engine	Gasoline	2 inputs (engine speed and BMEP)	4 outputs (DOI, SFC, exhaust gas at turbine inlet and within the catalytic converter brick)	Back-propagation feed-forward	Levenberg – Marquardt	MAPE, RMSE, NRMSE
Thakur et al. [80]	1-cylinder, 4.5:1 compression ratio, PFI gasoline engine	Gasoline, gasoline-ethanol	2 inputs (engine load, ethanol-gasoline blend)	9 outputs (brake power, torque, BSFC, BTE, volumetric efficiency, CO, CO_2, HC, NOx)	Back-propagation feed-forward	Levenberg – Marquardt	R, MSE, RMSE
Kurtgoz et al [86]	4-cylinder, 3610 cc, 11:1 compression ratio gasoline engine	Biogas	5 inputs (methane content, load, Tin, air fuel ratio, Pmax)	3 outputs (BTE, VE, BSFC)	Back-propagation feed-forward	Levenberg – Marquardt	R, RMSE, MAPE
Mehra et al. [87]	In-line 6-cylinder, 11.5:1 compression ratio, turbocharged gasoline engine	Hydrogen-CNG	4 inputs (Excess air ratio, engine load, ignition timing, HCNG blends)	6 outputs (BSFC, torque, NOx, CO, THC, CH_4)	Back-propagation feed-forward	Levenberg – Marquardt	R, MRE, RMSE
Jo et al. [89]	4-cylinder, 1998 cc, 10:1 compression ratio, DOHC, GDI	Gasoline	12 inputs ($pMAX_p$, $IMEP_p$, $MFB5_p$, $MFB10_p$, $MFB20_p$, $MFB30_p$, $MFB40_p$, $MFB50_p$, $MFB60_p$, $MFB70_p$, $MFB80_p$, $MFB90_p$)	1 output (LP-EGR)	Back-propagation feed-forward	Levenberg – Marquardt	R^2, RMSE
Uslu and Celik [96]	1-cylinder, 196 cc gasoline engine	Gasoline and gasoline-isoamyl alcohol (isopentanol)	3 inputs (CR, blending ratio, speed)	6 outputs (BMEP, BTE, BSFC, NOx, CO, HC)	Back-propagation feed-forward + RSM	Levenberg – Marquardt	R^2, MRE, RMSE

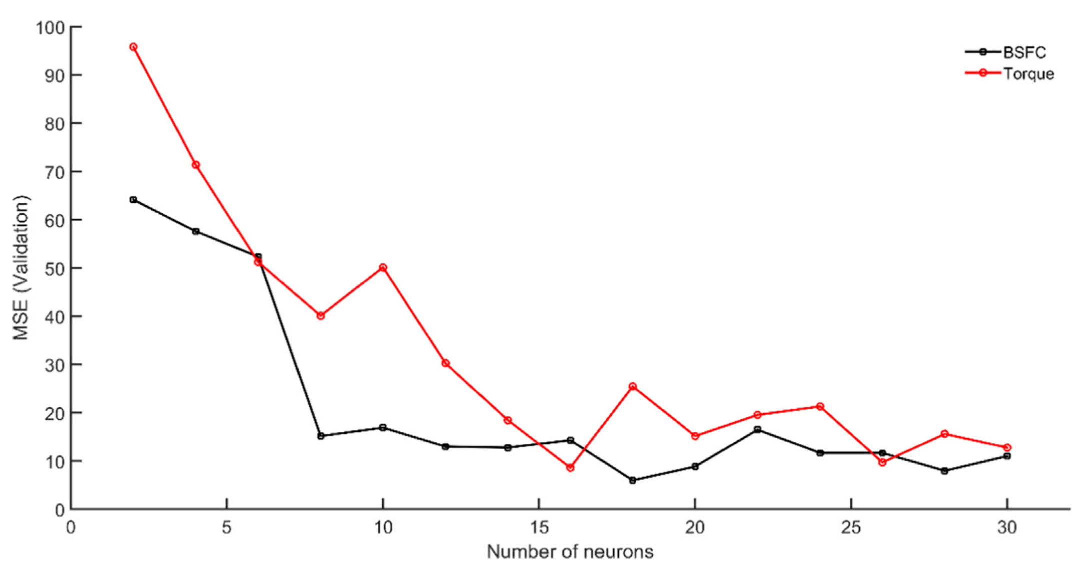

Fig. 5 MSE vs. Neuron numbers for BSFC and torque; re-plotted from [87].

possibility of being trapped in local minima and slow convergence. In this regards, extreme learning machine (ELM) has several promising features to solve such problems. Mariani et al. [93] developed an ELM design based on a modified biogeography-based optimization approach (BBO) to predict the in-cylinder pressure of a gasoline engine. The proposed design comprises of three steps; (1) dataset reading, (2) ELM model linked with BBO approach and (3) 5-fold cross-validation as shown in Fig. 7. Results showed that the ELM-BBO optimized model had satisfying accuracy with reasonable consistency with experimental results.

ANN can be useful to predict the octane number. Octane number (ON) is a measure of the quality of gasoline which determines its resistance to detonation. The effects of ON have been studied on engine performance and exhaust emissions. The requirement of octane number is influenced by engine design and compression ratio. Other factors that influence the ON include weather, driving conditions and mechanical conditions of the engine [94]. Moreover, decreased cooling efficiency, problems in fuel and ignition systems as well as failure in emission control also alter the ON requirements. Therefore, to model the prediction of ON using a traditional computa-

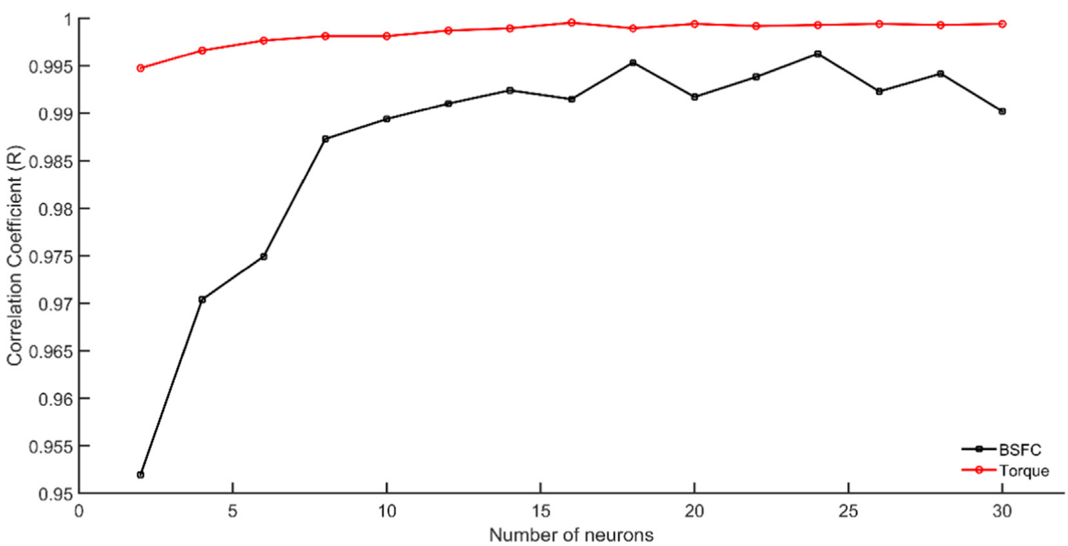

Fig. 6 R vs. neuron numbers for BSFC and torque; re-plotted from [87].

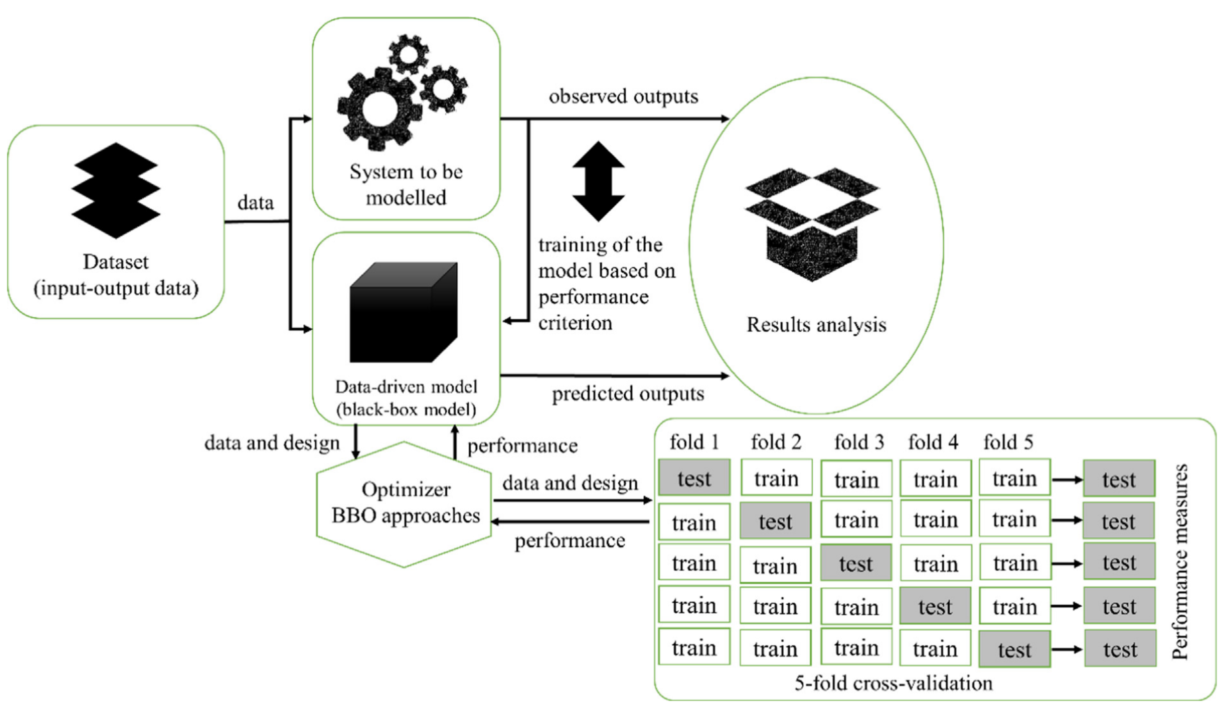

Fig. 7 Design of ELM; reproduced from [93]

tional model requires numerous mathematical equations. This is where the ANN can be used to model the physical phenomena of complex systems without mathematical representations. More recently, most studies have combined ANN with other optimization approaches such as RSM.

RSM has been applied successfully as an optimization tool in many chemical and biochemical studies. Now, its application has gained more attention in internal combustion engines. Elfghi [95] combined the ANN with RSM to model and optimize research octane number. This study found that ANN showed better performance than the RSM in terms of data fitting and prediction accuracy. However, RSM offered a more efficient approach as it only required relatively fewer experiments to provide a large of dataset information, resulting from its design of experiment (DOE) characteristic. Another study combining the application of ANN with RSM in gasoline engine was conducted by Uslu and Celik [96]. In their study, the ANN model was developed to predict the effects of I-amyl alcohol/gasoline fuel blends on gasoline engine performance and emissions, while the RSM was used to find appropriate optimal operating conditions. The correlation coefficients were found to be between 0.94 and 0.99 and the MRE is less than 7%. The optimal engine parameters based on the RSM method is at the i-AA ratio of 15% using a compression ratio of 8.31 under 2958 rpm. This study implied that the ANN along with RSM could be used as a promising prediction tool to optimize engine response with minimal experiment data.

Thus far, we have seen that most ANN applications for internal combustion engine are mostly developed to solve fitting problems where a neural network was designed to map between a dataset of numeric inputs and a set of numeric targets. Other ANN applications are worth investigating such as pattern recognition [97], classification [98], clustering or dynamic time series. Ghanaati et al. [99] developed an ANN model based on neural pattern recognition for on-board fuel octane number classification. It was found that the ANN model could classify the research octane number (RON) at various spark advances as shown in the confusion matrix in Fig. 8. Here, the rows represent the predicted (output) class, while the columns correspond to the true (target) class. The last column in the right displays the accuracy for each output class, and the last row at the bottom shows the accuracy for each target class. The overall accuracy is shown in the blue cell at the bottom right of the matrix. Another study using an ANN model for classification was conducted by Zheng et al.

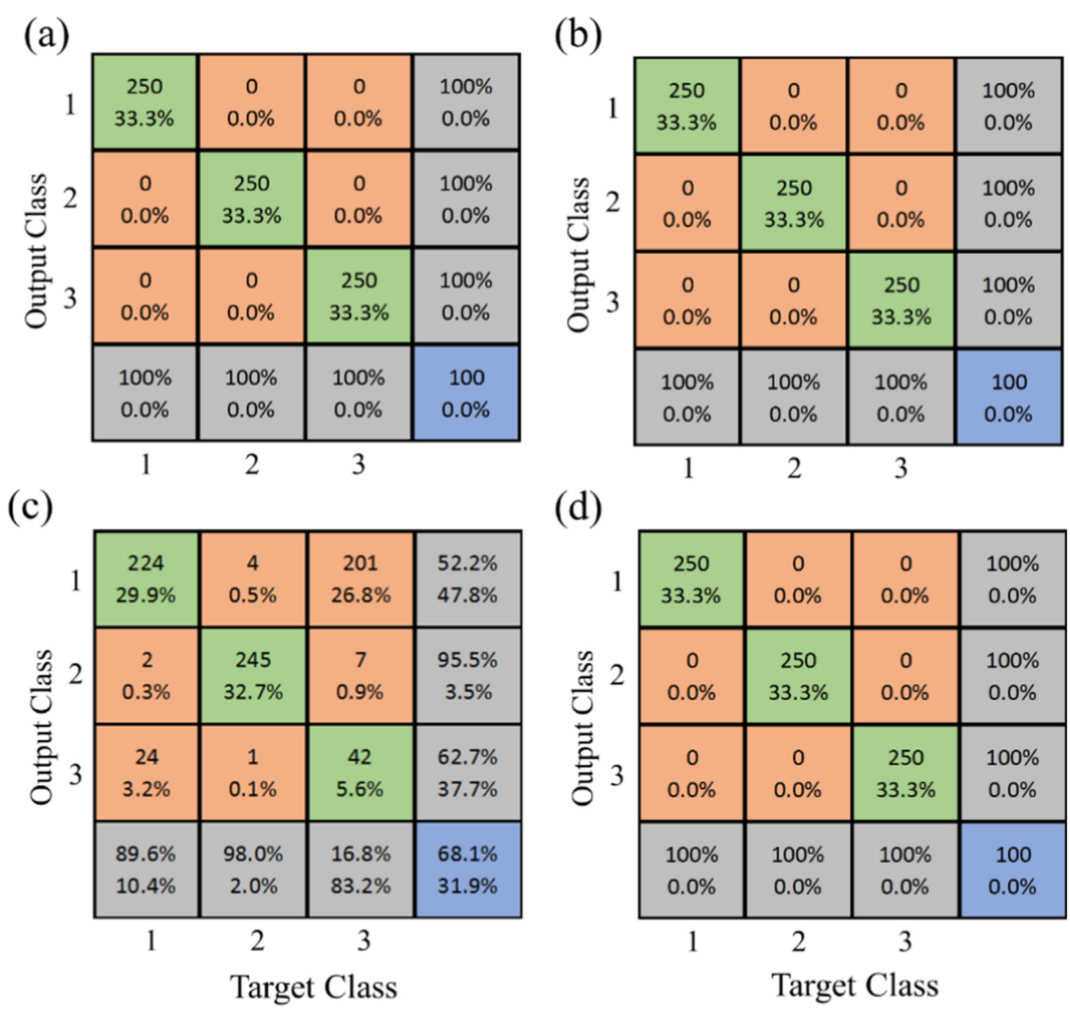

Fig. 8 Confusion matrix plot for three RON classes at different spark advance (a) – 10° bTDC, (b) – 30° bTDC, (c) – 10° bTDC, and (d) – 30° bTDC; . reproduced from [99]

[100] for dynamic misfire fault diagnosis. Back-propagation neural network, Elman neural network and SVM were examined and compared. Results showed that the three methods were able to detect misfire efficiently under transient conditions, but the Elman neural network was found to be more effective.

Although most studies have successfully developed an ANN model based on the feed-forward network due to its accuracy, another network is worth investigating. Recurrent neural network (RNN) for instance. Compared to feed-forward ANN, RNN can process sequential inputs, enabling it to present dynamic temporal behavior in a time sequence manner. Zhao et al. [101] developed a bidirectional RNN model coupled with long short-term memory (LSTM) to estimate the in-cylinder flow fields in an optical gasoline engine as schematically presented in Fig. 9. Here, both RNN and bi-RNN process the inputs sequentially in a similar way except that the bi-RNN model processes the inputs in opposite directions, allowing it to use information from before and after the target time. Also, the LSTM with three multiplicative gates to store and attain information over a longer period was introduced since both RNN and bi-RNN models could experience the gradient exploding and vanishing issues during the training process.

2.3. Artificial neural networks for homogeneous charge compression ignition engines

In addition to premixed charge compression ignition strategy (PCCI) [102–104], another innovative combustion mode known as the homogeneous charge compression ignition (HCCI) engine is a promising advanced combustion technology [105]. It offers high-efficiency and low-emission engine characteristics due to its low-temperature combustion modes [106]. However, its operation is limited at high load conditions caused by rapid pressure rise rate, short combustion duration and ringing operation. Fig. 10 shows the development of heat release, combustion and the formation of emissions in a typical HCCI engine. Moreover, controlling HCCI engines remains a major challenge. While experimental testing is not a feasible option, an efficient and accurate model to control HCCI combustion needs to be developed. Using an ANN model instead of CFD simulation or kinetic modeling is relatively less time-consuming and more affordable. This is because the thermo-kinetic HCCI model needs a considerable amount of time. Also, despite its high HC and CO emissions, no model can be found in the literature to predict its emissions. To simulate emissions for just one HCCI engine cycle, which is only 40–120 ms long, it takes several hours to a couple of days to finish [107].

In general, HCCI models can be categorized into three main groups as shown in Fig. 11. The first group, the empirical model, needs a large amount of experimental data, whereas the second group, the thermo-kinetic model, requires computational resources which are not available for real-time engine control. The third group, the ANN model, offers the competitive advantage of the first and second model, providing a compromise between accuracy, computational resources and experimental data. Of all the three groups, the ANN model is mainly used to predict the performance and to detect a fault. Many studies have used ANN model on internal combustion engines. However, its application on HCCI engines is still limited. Table 4 lists the detailed summary of the ANN application in HCCI engines discussed in this section.

Rezaei [107] developed a model for the HCCI engine that is able to run real-time and can predict its performance and emis-

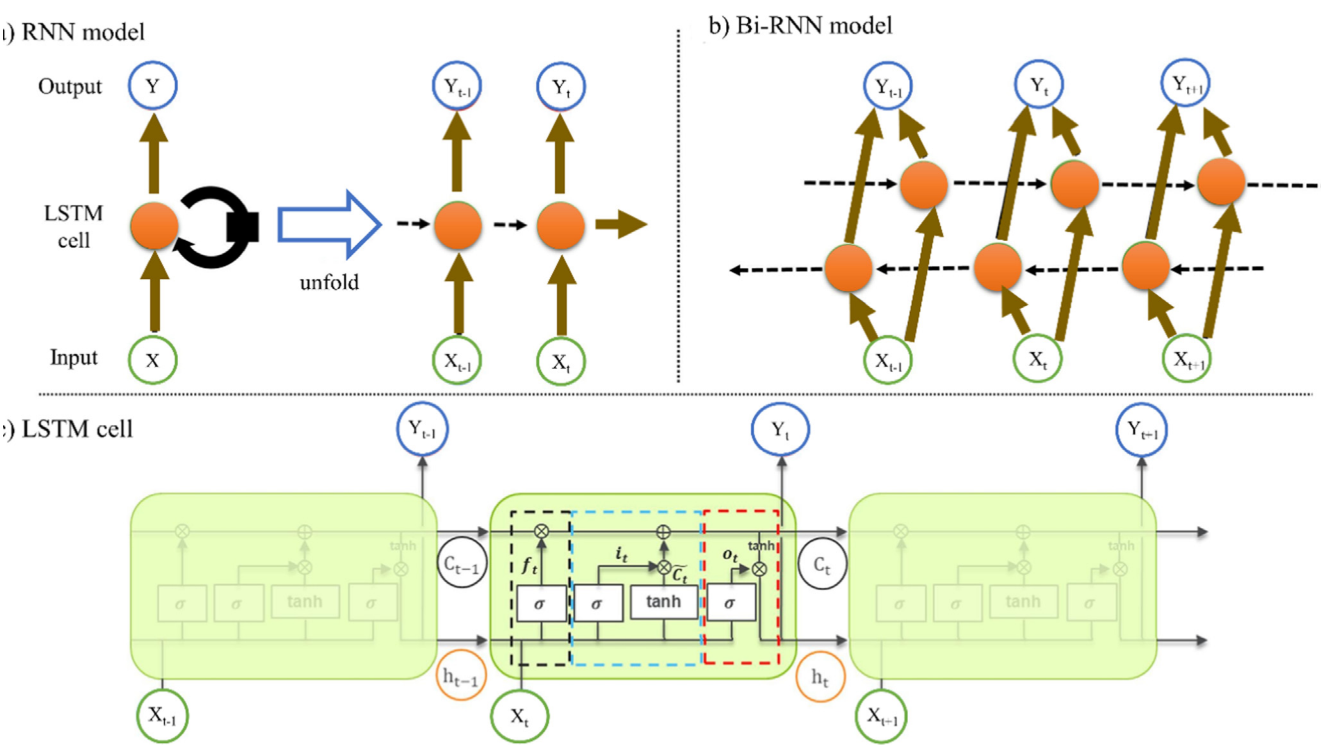

Fig. 9 Different schematic representation between an RNN and bi-RNN models with LSTM cell; reproduced from [101]

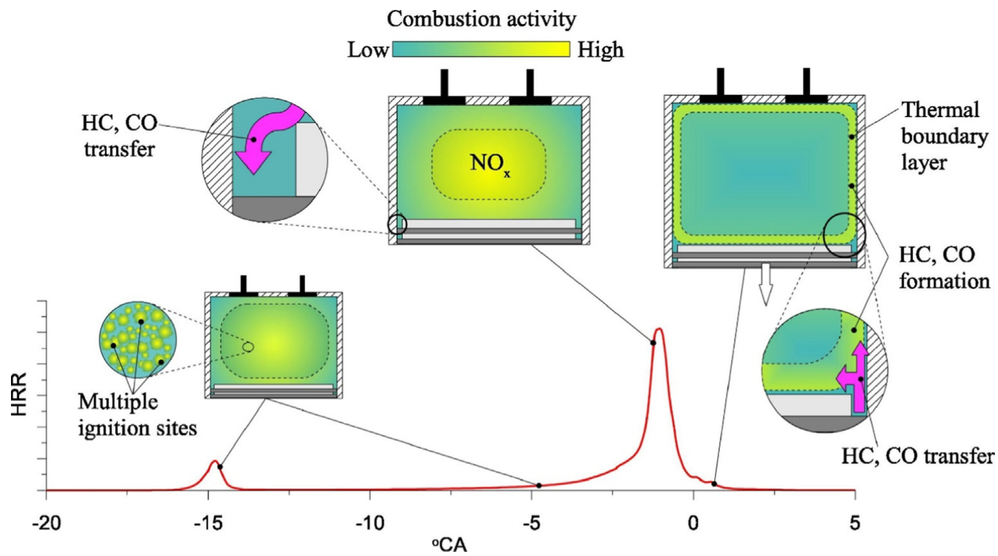

Fig. 10 Heat release, combustion and emissions formation in an HCCI engine; reused with permission from Elsevier [108]

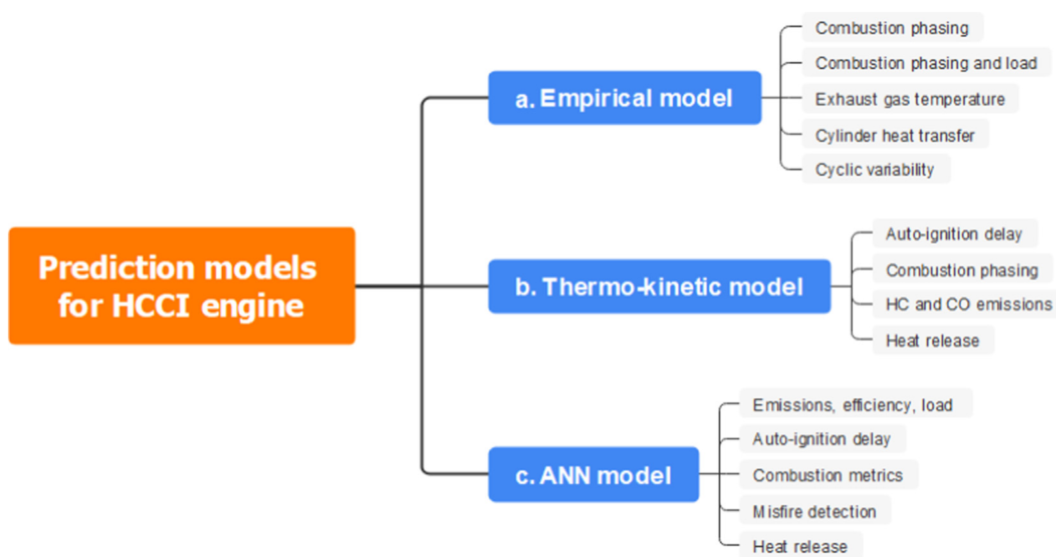

Fig. 11 The position of ANN for HCCI engine; . adapted from [107]

sions characteristics. They used oxygenated fuels i.e. butanol and ethanol, whereas the model itself was a multi-input multi-output (MIMO) that predicted HCCI emissions, heat release, maximum in-cylinder pressure, indicated mean effective pressure (IMEP) and thermal efficiency. The proposed ANN model used two functions: feed-forward and radial basis function. The model was then validated with the experimental data gathered from 123 HCCI operating conditions. The results showed that the proposed ANN model could predict the engine performance characteristics for both engines with less than 4% error. It was also found that the feed-forward neural network model required only fewer neurons and less complicated, but it needed two-fold training time than radial basis function model.

It is known that the HCCI engine is limited by intense noise during ringing operation. Ringing intensity is one of the biggest problems in HCCI engine. The maximum acceptable ringing intensity of an HCCI engine is normally set to 5 MW/m^2. To evaluate the ringing operation, Maurya and Kumar [109] developed a real-time model to identify the ringing intensity of an HCCI engine fueled with hydrogen. An ANN model was developed, and it was found that the CA50 was strongly affecting the ringing operation with a coefficient correlation of 0.99. Also, the ringing intensity was reported to increase with the early combustion phasing, higher intake air temperature and equivalence ratio. Furthermore, Bahri et al. [110] developed an ANN model to detect ringing operation in real-time for HCCI engines. They proposed an ANN model which could predict the ringing intensity (RI) of the HCCI engine and identify its operating points region. The main HCCI combustion parameters and exhaust emissions were also investigated. The results showed that the RI increased in two

Table 4 ANN for HCCI engine.

Research groups	Objective	The novelty of the method
Rezaei et al. [107]	To predict HCCI performance metrics fueled with oxygenated fuels using a comprehensive ANN model.	Used a novel multi-input multi-output to predict HCCI performance, combustion and emission characteristics.
Maurya and Kumar [109]	To characterize the ringing operation of hydrogen-fueled HCCI engine.	Developed a model for real-time identification of ringing intensity for HCCI engine fueled with hydrogen.
Bahri et al. [110]	To examine the ringing operation of an HCCI engine.	Proposed an ANN model to detect ringing operation in real-time for HCCI application.
Bahri et al. [111]	To investigate the combustion characteristic noise level of an HCCI engine fueled with ethanol above 100 dB.	Developed a real-time ANN modeling using minimum data of in-cylinder pressure.
Bendu et al. [112]	To predict ethanol-fueled HCCI engine's performance and emission characteristics.	Used GRNN model for the first time to predict HCCI engine performance and emission behaviors.
Bendu et al. [113]	To optimize the performance and emission behaviors of the HCCI engine fueled with ethanol.	Proposed a hybrid GRNN-PSO model for HCCI application
Anarghya et al. [114]	To study the HCCI engine's behaviors using various fuels and trapped residual gases method.	Used a radial basis function neural network (RBFNN) and genetic algorithm utilizing CFD results.
Nazoktabar et al. [115]	To develop a multi-zone HCCI model optimized with a genetic algorithm.	Combined a control model with ANN that was optimized using a genetic algorithm.
Nazoktabar et al. [116]	To develop an HCCI controller to find the optimum combustion phasing with minimized emissions as a function of engine load.	Developed a multi-input multi-output controller capable to remove emissions in power demand phase.
Leo et al. [117]	To examine the use of gasoline premixing in HCCI-DI engine fueled with waste cooking oil.	Used ANN with response surface methodology for optimization.
Taghavi et al. [118]	To predict HCCI's SOC on the basis of the mixture properties which takes into account the input delays and network targets.	Used an ANN-GA method to predict the start of combustion in HCCI engine.
Wick et al. [119]	To develop ignition measurement algorithm of HCCI engine using a wider database to predict misfires.	Developed a novel algorithm to obtain dynamic measurement data to be trained with ANN.

ways. First was by advancing crank angle of 50% fuel burnt (CA50) and the second was by decreasing burn duration. Since all the extreme noise data points had CA50 smaller than 9 CAD aTDC, adjusting CA50 could provide a control knob for the RI. In-cylinder pressure at 5, 10, 15 CAD aTDC (P_5, P_{10} and P_{15}) and its maximum pressure (P_{max}) had a strong relationship with RI. Therefore, to develop an ANN model that could predict RI, the in-cylinder pressure value of P_5, P_{10}, P_{15} and P_{max} were used. In addition to that, experimental data from 155 steady-state points were also collected to evaluate the model for two conditions: low and high-octane fuels. The results showed that the proposed ANN model could predict RI with a reasonable agreement between experimental and simulation results as shown in Fig. 12 where the error was less

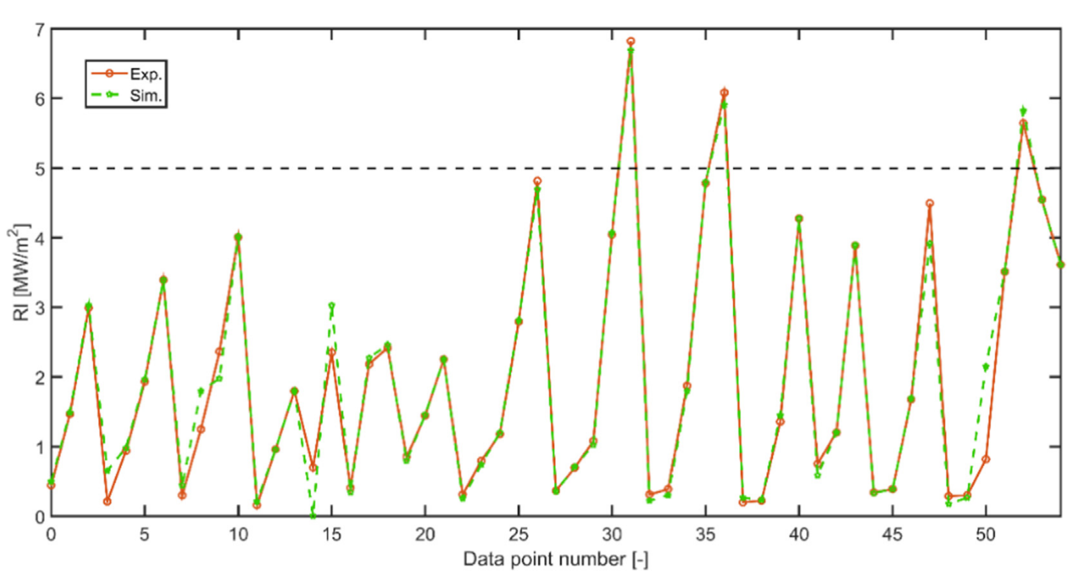

Fig 12 Steady state test cases comparison between experimental and predicted RI, re-plotted from [110].

than 4.2%. This model could be employed to detect HCCI ringing operation for combustion control appliances.

In their subsequent study, Bahri et al. [111] investigated the combustion noise level (CNL) in an HCCI engine fueled with ethanol. CNL can be used to estimate an engine's noise level. Despite its significant indicator, it is difficult to find a published work investigating CNL for HCCI application. Bahri et al. [111] examined extreme combustion level with CNL over 100 dB and developed an ANN noise level (ANL) model. It was found that the CNL was strongly correlated with in-cylinder pressure at 10, 15, 20 CAD aTDC and its Pmax. The ANL only gave less than 0.5% error. Fig. 13 reveals the prediction of ANL for 50 steady-state test cases. The dashed line in Fig. 13 indicates the boundary between misfire, normal and ringing areas.

Back-propagation neural networks have been extensively investigated for ANN application in the internal combustion engine. However, such a model needs lengthy training time and may experience local minima problem. If the predicted values are not satisfying, the ANN will be restarted using different settings until the model give comparable results with the actual values. To solve this problem, Bendu et al. [112] devel-

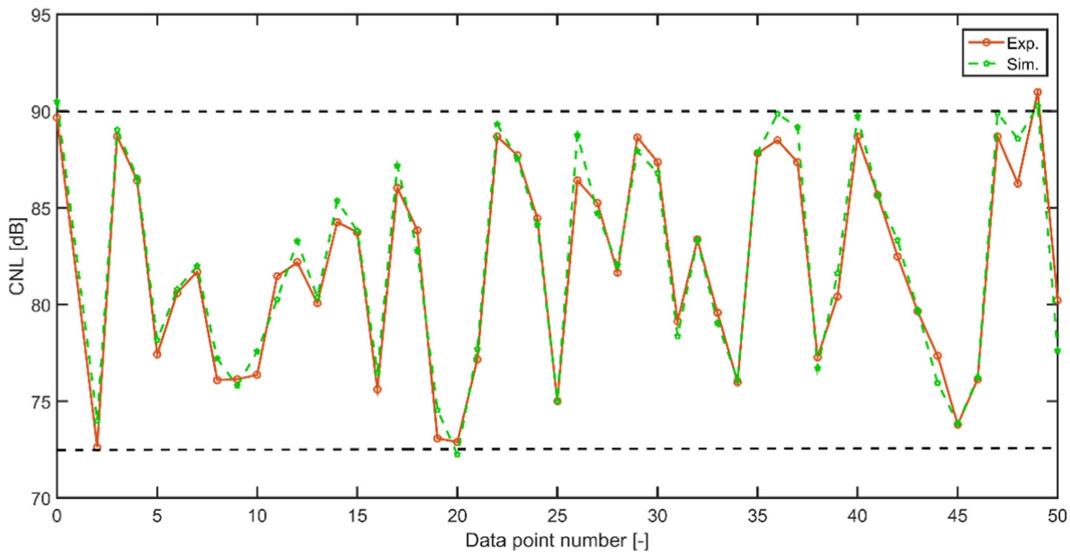

Fig 13 Test cases comparison between experimental and predicted CNL, re-plotted from [111].

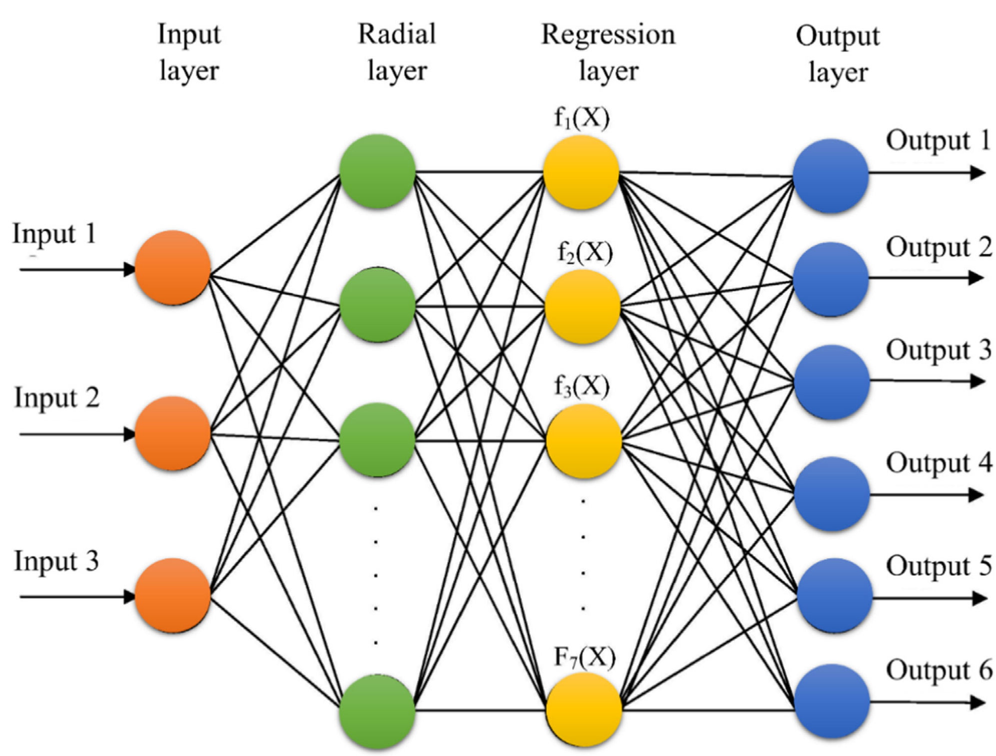

Fig. 14 Typical GRNN architecture; . reproduced from [113]

oped a general regression neural network (GRNN) model to predict the HCCI engine's performance and emission behaviors. GRNN works using a probabilistic functional network with typical architecture is shown in Fig. 14. It has four layers i.e., the input, radial, regression and output layer. The result showed that the maximum error was merely 2%. Compared to other ANN models, this study also revealed that the GRNN needed less training data. In their subsequent study, Bendu et al. [113] proposed a novel method by combining GRNN with particle swarm optimization (PSO) to optimize the operating condition of an HCCI engine. The methodology is illustrated in Fig. 15. It was found that at 170 °C intake air temperature, 72% engine load and 4% EGR, the HCCI engine reached its optimum operating condition within a merely short amount of time, 60–75 ms.

Using both ANSYS FLUENT simulations and neural network models, Anarghya et al. [114] investigated the efficiency and combustion qualities of the HCCI engine. Experimental results using various fuel properties and decreased valve lifts to trap the exhaust gases were applied to confirm the numerical and neural network performance. Experiments with different reference fuels (PRF30, PRF50, PRF70) and methanol to verify the CFD and ANN-GA measurements were conducted on the 800-cc engine at various speeds and inlet air temperatures. It was found the ANN-GA model provided satisfactory prediction for HCCI's combustion characteristics and emissions. Reducing valve lifts have been found to delay the phasing of combustion at the knock boundary.

Relying on the physical model to predict HCCI emissions involves a complex process owing to its non-linear characteristic. Its dependency on mixture charge properties makes the process even more complicated. Nazoktabar et al. [115] developed a gray-box HCCI model by combining physical and ANN model to minimize the data for the physics of the combustion (Fig. 16). Here, the main inputs of the CA50 gray-box model were the outputs from the physical model. The outputs of the gray-box model were then used as the main inputs of the gray-box emissions model. Furthermore, the IMEP demand was introduced as the third parameter to determine the optimum CA50 and minimum emissions trajectory as shown in Fig. 17. To obtain optimal engine operating conditions, a large excessive amount of experimental data is needed. However, this study showed that by using a thermo-kinetic model coupled with the genetic algorithm, the optimum engine operating conditions could be obtained without the need of experiment results. In their subsequent study, Nazoktabar et al. [116] developed a multi-input multi-output controller for HCCI engine that was capable to remove emissions in power demand phase to find the optimum combustion phasing with minimized emissions as a function of engine load. It was found that

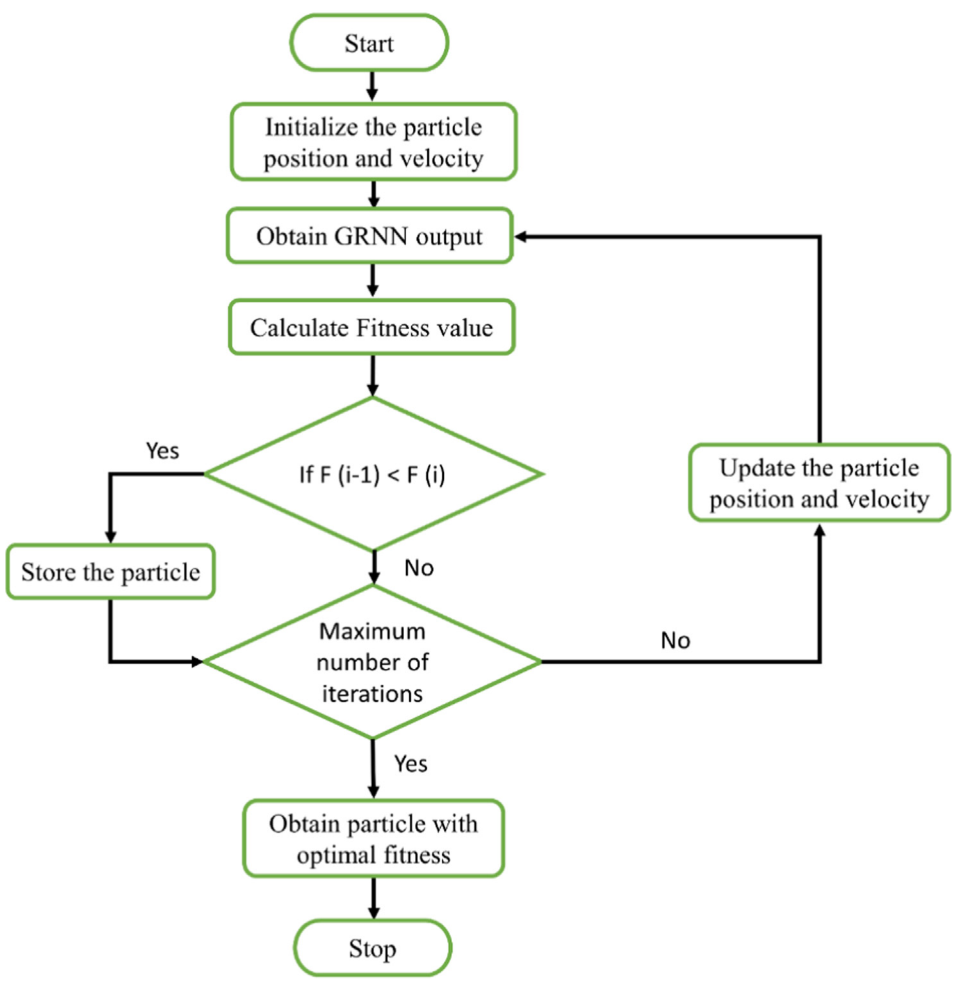

Fig. 15 Flowchart of the hybrid model GRNN-PSO developed by Bendu et al. [113].

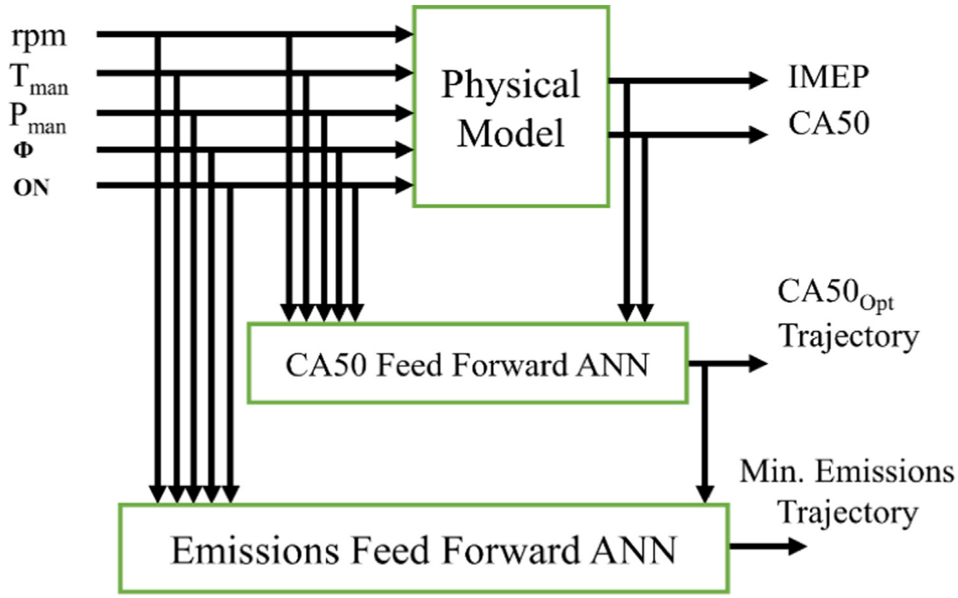

Fig. 16 Physical + ANN model for HCCI engine application; . reproduced from [115]

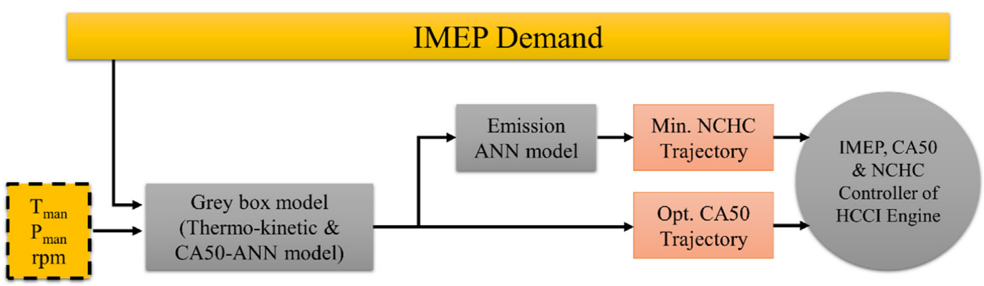

Fig. 17 Gray-box model and controller layout; . reproduced from [115]

the controller was able to quickly reject the disturbances in merely fewer than five cycles with deviations being within 0.04 bar, 0.5 CAD and 0.03 for IMEP, CA50 and emissions, respectively.

ANN does not require a detailed definition and comprehensive system relationship. Through analyzing previous data, an ANN model can discover the relationship between input and output parameters. Leo et al. [117] developed ANN model to predict HCC-DI engine fueled with waste cooking oil. This study used WCO-diesel as the DI fuel and gasoline as the premixed fuel. It was found that the WCO in DI mode caused an early start of combustion. The R values from the ANN model were in the range between 0.9946 and 0.9996, while the R^2 values were between 0.9952 and 0.9991. For the optimization purpose, RSM was used, and it was reported at WCO-biodiesel blend at part load gave the best optimal operating conditions.

While ANN was used successfully to analyze HCCI engines, the ANN-GA method that can predict HCCI's start of combustion (SOC) had not been examined on the basis of the mixture properties which takes into account the input delays and network targets. Taghavi et al. [118] used three widely known optimization techniques; (1) the nonlinear autoregressive network with exogenous inputs (NARXNET), (2) multi-layer perceptron (MLP) and (3) radial basis function (RBF). Experimental data were firstly obtained from Ricardo's one-cylinder engine. The networks were then trained and optimized employing a genetic algorithm. It was found that the suggested networks had optimum architectures and enhanced predictive characteristics. Also, the regression ratio between the MLP outputs and the accompanying experimental data was improved from 0.8965 to 0.96166. This value was increased from 0.7623 to 0.8399 using RBF after the optimization. The results also showed that GA could significantly reduce the time required to train the NARX from 3.12 s to merely 0.46 s. This study implied that the neural network architectures could be used as a promising strategy to predict the non-linearity of the HCCI engine's SOC.

One significant problem with the existing HCCI combustion models is the prediction of outliers due to their stationary measurement conditions. This is because a cycle-dependent individual from the previous process could affect the subsequent depending on the feedback variables. Wick et al. [119] developed a new transient measurement technique by setting manipulated variables on a cyclic basis that relied on the previous cycle. Fig. 18 illustrates their first-order autoregressive model combustion as a function of feedback and manipulated variables. The new algorithm was then trained using ANN to obtain dynamic measurement data. It was found that the models were able to predict misfires under certain circumstances by considering the interaction between feedback and cycle individual manipulated variables. Compared to conventional stationary measurement technique, the model developed with

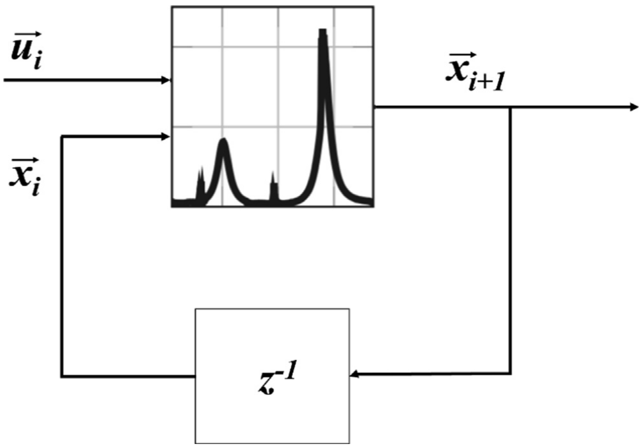

Fig. 18 HCCI first order autoregressive model, . reproduced from [119]

dynamic training data could overcome one of the major problems in HCCI combustion models i.e., prediction of outliers.

3. Challenges in the application of artificial neural networks

ANN is a promising approach that can challenge conventional simulation programs that are known for their expensive and time-consuming procedures. An ANN model extracts data and learns directly from them to solve non-linear and complex problems, avoiding the use of complicated mathematical equations. However, the implementation of ANN for automotive application tends to be repetitive. The same network type, learning algorithm and training function are used time and time again. This section presents the authors' concluding remarks and final comments.

3.1. Number of neurons and splitting dataset

There has been no established standard to determine the number of neurons in the hidden layer. Different cases have a different number of neurons. To avoid selecting an ANN architecture randomly, the optimum network is usually achieved by examining different neuron numbers, normally between 1 and 25, by trial-and-error until the MSE gives the desired lowest value (e.g. less than 0.001). Too few hidden neurons may lead to a high error as a result of underfitting, while too many hidden neurons, despite its relatively low error, may result in overfitting. Therefore, most studies did a number of trial-and-error testing by altering the neuron numbers. While optimal network configuration may differ from one to another, the approximate neurons number of the hidden layer varies between 10 and 25. It can also be estimated using the following equation [120];

$$N = \frac{I+O}{2}\sqrt{P_i} \tag{1}$$

where N is the number of neurons in the hidden layer, I and O are the number of input and output parameters, respectively. P_i is the number of training data. As for the split of dataset, the size of the data influences the division. Generally, the data are split randomly by 70%, 15%, 15% for training, test and validation. However, with a large number of data, thousands for example, 90% can be trained since even at the remaining 10%, there will be more significant data to test and validate the model.

3.2. Performance and transfer function

To develop an ANN model, the network is subjected to two processes: training and validation. In training, the network is trained to estimate output values relative to the input data. After the training process, another important step in ANN modeling is validation or testing. While in training, the network is conditioned to approximate output values using the input data, in testing, the network is conditioned to stop the training once the desired output values and accepted errors have been obtained. Due to the importance of the validation process, some types of errors have been proposed to evaluate the ANN model performance.

This review article has shown that the two measurements are commonly used as the evaluation criteria; mean square error and correlation coefficient. MSE is a convenient way to calculate average data change. It also has an excellent metric for optimization. MSE assesses the discrepancy between predicted and actual values with a high MSE indicating a low-accuracy prediction. Therefore, MSE should be minimized and when its percentage starts to rise, the training is ceased. The error of MSE can also be represented by the root mean square error. Another evaluation criterion is the correlation coefficient, R. An ANN model expects a higher R-value. In addition to MSE and R, the absolute fraction of variance (R^2) and mean absolute percentage error (MAPE) are often used. Also, other evaluation criteria such as KGE, NSE, THEIL U2, MAAE and AAPE are used in some studies to assess the ANN model's accuracy as shown in Table 2.

Transfer or activation functions are not many. Despite being only a few, selection of transfer function is critical since ANN is susceptible to the input and output being used. Therefore, variations in the use of activation transfer functions will have different results. Normally, hidden layer transfer functions are set to log-sigmoid (logsig) due to its self-limiting behavior that can limit the output and make it easier to be distinguished. As for the functions for the output layer, the linear (purelin) is normally selected.

3.3. Data normalization

The efficiency of an ANN model is influenced by the spread in the dataset. Large differences in the output values will slow the training process and reduce the fitting accuracy. To solve this problem, normalization is often preferred. Some studies were found to normalize their datasets either by fitting a normal distribution to a dataset or by changing a variable to a normal variable. This is done by changing the nominal variable into numeric value such as −1 to 1 or 0 to 1. However, instead of using the range between 0 and 1, range of 0.1–0.9 or 0.05–0.95 should be used to prevent 'not a number' (NaN) as a result of dividing the value by zero and to obtain faster training as it prevents transformations of very small values, thus avoiding the computation of activation functions for extreme values without penalty on the accuracy. It is important to note that normalization is particularly important when there is an assumption of the model, but ANN does not have any predefined prediction. Also, normalization is prone to outliers. Therefore, standardization may be better for ANN as it generates new unbounded data.

3.4. Hybridization of artificial neural networks with the optimization method

To increase its prediction accuracy, the hybridization of ANN is strongly recommended by combining it with optimization methods. Study in ANN may reach its maturity and be saturated if the same approach is implemented recurrently. With the increasing computational power, the hybridization of the ANN model with an optimization method can play an important role in the future of neural networks application. This is because ANN is merely a black box or mystery models learning approach, lacking physical concepts. It cannot explain the relationship between input and output and unable to address uncertainties, thus it cannot optimize the solution. To overcome these limitations, several optimization approaches need to be combined with ANN.

One of the best optimization methods is the genetic algorithm. Conventional modeling using numerical techniques have been widely utilized for optimization purpose in internal combustion engines. Yet, it is difficult to avoid the local minima using numerical techniques, depending on the preliminary chosen value. Also, the numerical technique is only suitable for continuously differentiable functions. This is where GA plays an important role as it can avoid the existence of local minima. GA can be used to optimize the weights of the ANN model. It is a global optimization method based on Darwin's theory of evolution involving selection, crossover and mutation as depicted in Fig. 19. GA algorithm is initialized with a random population. Individuals are then evaluated based on the fitness function to fulfill certain criteria. The use of GA resulting in multi Pareto-optimal solution has been most successfully implemented to find the optimum dataset in an internal combustion engine with multi-objective target [60].

Another optimization approach that is increasing in popularity for engineering application is RSM. Currently, RSM techniques are often used to optimize the desired engine responses and operating conditions. Particle swarm optimization is another promising optimization method. It was invented by Kennedy and Eberhart in 1995, inspired by the social nature of birds flocking [122]. An ANN model can be combined with PSO. The fitness of the particle is examined with ANN, while random particle inside the search space is generated by the PSO. The birds in PSO are known as swarm, while a bird in the swarm is called a particle. In their movement, each bird or particle will change its position. The new position is then updated along with its velocity (Fig. 20). Each particle has its own best position. Since each particle's new position and velocity can be shared among particles in the swarm, the global best position can be determined. When coupled with ANN, the PSO method can help to achieve the optimum dataset [123]. Other optimization algorithms such as ant colony, killer whale and artificial beef colony algorithm are also worth investigating. Another approach to finding the optimum solution is the technique for order preference by similarity to ideal solution (TOPSIS). This approach can be incorporated with the ANN model, for instance, to find the optimum engine input parameters to give high thermal efficiency with low emissions.

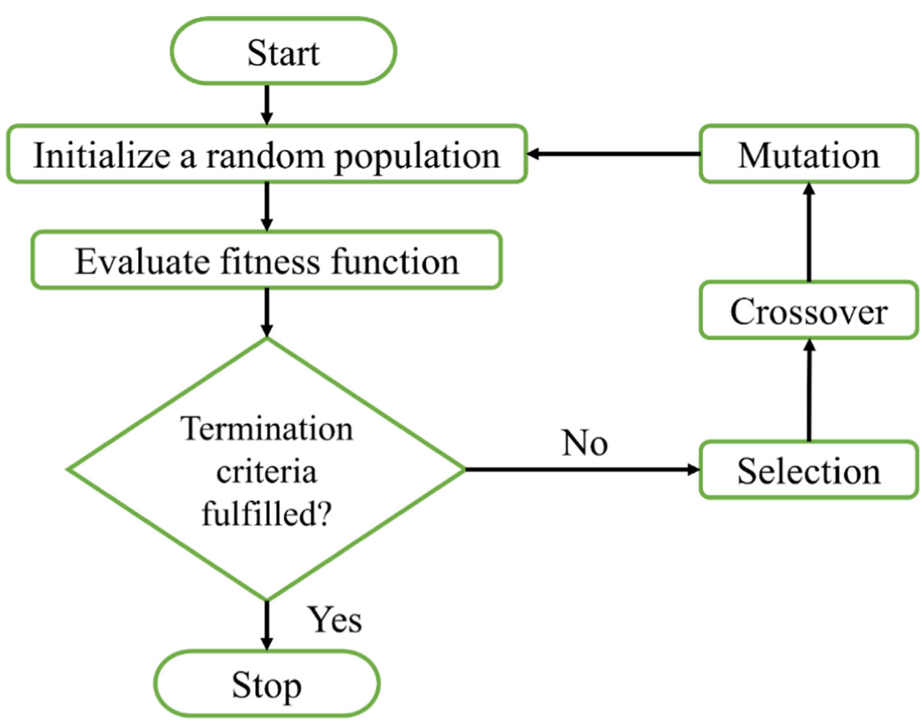

Fig. 19 Flowchart of GA, . reproduced from [121]

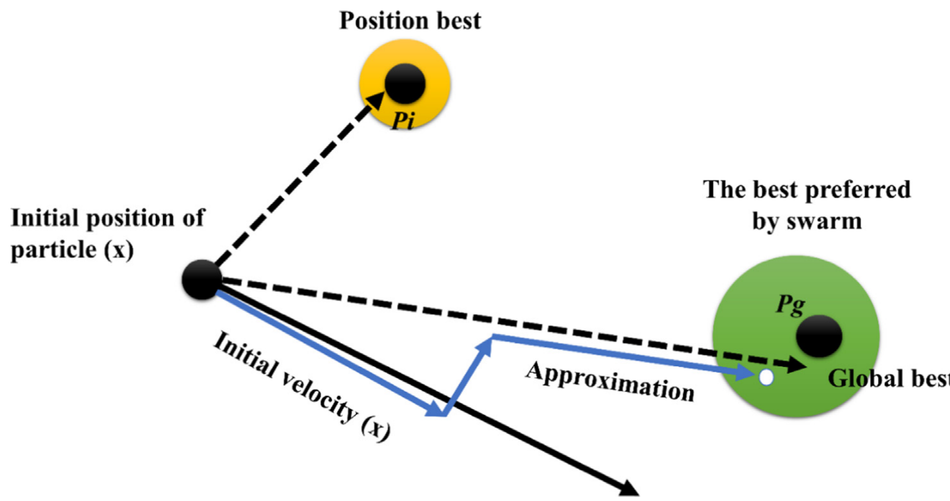

Fig. 20 Structure of particle swarm optimization, . reproduced from [113]

4. Implication of the present study

Having reviewed the papers for artificial neural networks application in internal combustion engines (gasoline, diesel and HCCI), the following implications should be taken into consideration:

- Given the conventional trial-and-error method that is commonly performed in this area, a combination of ANN with optimization methods is strongly recommended.
- The use of ANN in ICE application is case-specific with restricted pertinency to a varied situation, thus developing generic ANN models that can be applied to a wide range condition worth investigating.
- Some published ANN models were built using inadequate number of datasets. The amount of data for training, validation and test should be thoroughly established to achieve significant results.
- Despite being very useful as a prediction tool, the use of ANN for real-time engine monitoring has not yet been extensively explored in spite of its huge potential. This is particularly very beneficial to improve overall engine performance and reduce harmful emissions using real-time engine setting.

5. Future scope

Compared to the gasoline engine, the diesel engine is more widely investigated to perform ANN modeling. This may be attributed to the fact that diesel engine can be operated using a number of alternative biofuels such as biodiesel, a research area that has been increasingly popular due to the increasing oil prices. Also, this review article has shown a growing trend of ANN application in advanced combustion technology such as HCCI engine. This is because of the complexity of HCCI combustion that is difficult to be simulated using conventional computer software. In addition to the HCCI engine, other engines such as Stirling [124–127], flex-fuel and dual-fuel engine [128–130] are also worth examining.

Most studies generally use two or three inputs (engine speed, load, fuel blend) and overlook other important variables such as fuel's physico-chemical properties. Fuel properties normally represented by density, kinematic viscosity and calorific values are known to significantly affect the engine's characteristics. Also, performance, combustion and emission behavior are investigated repetitively with output response such as fuel consumption, thermal efficiency and emissions being investigated frequently. Other engine responses including combustion noise level, cyclic variations, vibration, knocking and misfire characteristics are often disregarded. These are parameters that are costly to experiment and difficult to understand due to their underlying principles and complex relationship with other parameters. These are the areas where ANN can play an indispensable role. Also, the ANN applications for the internal combustion engine are predominantly developed to solve fitting problems. Other ANN functions such as pattern recognition, classification, clustering or dynamic time series need further investigation for automotive application. Pattern recognition for example. This ANN feature may be beneficial in classifying the octane or cetane number of a fuel that is known to significantly affect the performance, combustion and emissions of an internal combustion engine.

6. Conclusion

Different architecture is needed for different data. It is impossible to generally apply one network architecture for all applications. Despite the variety of network type, algorithm and learning function to choose from, it is important to note that the success or failure of the algorithm relies heavily on the parameters defined by the user. Also, ANN should be compared with other soft computing approaches such as support vector machine (SVM) and adaptive neuro-fuzzy inference system (ANFIS). An ANN model aims to minimize error based on the empirical risk minimization (ERM). This, however, can result in convergent to local minima owing to the gradient descent learning algorithm that can lead to overfitting even with the well-trained ANN. In contrast, unlike ANN which follows ERM, SVM aims to minimize the upper bound of the generalization error based on the principle of structural risk minimization (SRM) by considering the empirical risk at the same time, thus facilitating to find the global solution. Therefore, to objectively present its prediction accuracy, the ANN model needs to be compared with other artificial intelligence methods.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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