OPTIMIZATION ON THE PERFORMANCE AND EMISSION CHARACTERISTICS OF DUAL FUEL COMPRESSION IGNITION (CI) ENGINES USING ARTIFICIAL NEURAL NETWORK (ANN)

A Thesis

Submitted in partial fulfillment of the requirements for the award of the degree of

DOCTOR OF PHILOSOPHY

In

Electronics and Electrical Engineering

By

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LIST OF ABBREVIATIONS

ABDC	After bottom dead centre
ANN	Artificial Neural Network
ANN-HHOWOA	Artificial Neural Network- Harris Hawks and Whale Optimization Algorithm
ASTM	American Society of Testing and Methods
ATDC	After top dead centre
B.P.	Brake Power (kW)
BBDC	Before bottom dead centre
BSFC	Brake specific fuel consumption (kg/kWh)
BTE	Brake thermal efficiency
BTDC	Before top dead centre
CI	Compression Ignition
CO	Carbon Monoxide
CO_2	Carbon Dioxide
DI	Direct Ignition
D80/B20	80% diesel + 20% biodiesel
D60/B40	60% diesel + 40% biodiesel
D40/B60	20% diesel + 60% biodiesel
GA	Genetic algorithm
HC	Unburned Hydrocarbon
IC	Internal Combustion
kVA	Kilo-VoltAmpere
LCV	Lower calorific value (MJ/kg)
MAAE	Mean absolute average error
MLP	Multi-layer perception
m_f	mass of fuel (kg/hr)
NN	Neural Network
O_2	Oxygen

R^2	Regression coefficient
WOA	Whale optimization algorithm

DECLARATION

I, Someet Singh, student of PhD hereby declare that the thesis titled **“**Optimization on the performance and emission characteristics of Dual Fuel Compression Ignition (CI) engines using Artificial Neural Network (ANN)**”** which is submitted by me is my own work and that, to the best of my knowledge and belief, it contains no material previously published or written by another person, nor material which has been accepted for the award of any other degree or diploma of the University or other Institute of higher learning, except where due acknowledgment has been made in the text.

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CERTIFICATE

The thesis entitled **"**Optimization on the performance and emission characteristics of Dual Fuel Compression Ignition (CI) engines using Artificial Neural Network (ANN)**"**, being submitted by **Someet Singh** to the Lovely Professional University, Phagwara for the award of the degree of Doctor of Philosophy is a bonafide research work carried out by him. He has worked under our supervision and has fulfilled the requirements for the submission of this thesis, which has attained the standard required for a PhD degree from the University. The content of the thesis, in full or parts has not been submitted to any other Institute or University for the award of any other degree or diploma.

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Someet Singh

This work is dedicated to my

Wife

Mrs. Navjot Kaur

and kids

Japgun Kaur

&

Sehajveer Singh

LIST OF PUBLICATIONS

[1] S. Singh, A. Jain, and S. K. Mahla, "Sampled-data model validation : An algorithm and experimental setup of dual fuel IC engine," Fuel, vol. 279, no. April, pp. 118517, 2020.

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[4] S. Singh, A. Jain, "A Systematic Approach To Monitor Dual Fuel Engine Emissions," Think India Journal, vol. 22, no. 17, pp. 2797–2806, 2019.

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ABSTRACT

The vehicles that are run on fuel and the industries are contributing in polluting the environment by releasing toxic gasses. This is leading to the air contamination on huge level. In India, the effect of air infectivity and pollution has escalated to worst level.

The gases like nitrogen oxide (NOx), carbon monoxide (CO), carbon dioxide (CO_2) and sulphur dioxide (SO_2) contaminate the atmosphere, due to which human's health is deteriorating. Furthermore, fossil fuels used to run these vehicles are depleting at an alarming rate. Consequently, it is needed to find alternative fuel or alternate technology for running these commercial vehicles and industrial motors. A better and economical alternative can be the use of renewable resources, for instance, bio-fuel genersted from bio-waste. India is having plenty of bio-waste that can generate more than 10 MW of power.

Fossil fuels are rapidly depleting due to increased energy consumption due to people's equipment and facilities needed for civilization. To this end, conventional fuels, especially internal combustion engines, are being depleted at an alarming rate of gasoline and diesel. Alternative fuels planning is necessary for the preservation of fossil fuels or for the future of technology. In view of these and many other related issues, this fuel should be replaced in whole or in part, with a renewable, alternative and harmless, environmentally friendly renewable fuel internal combustion engine. Therefore, a lot of research is being done around the world on the suitability and feasibility of alternative fuels.

In the present work, alternative technique and ways to utilize rice bran oil to produce other practically functional alternative fuel are used to replace conventional diesel and petrol. The current work also includes modeling, optimization of the performance of internal combustion engine and operating parameters of bio-diesel using Artificial Neural Network. To validate the data collected from the experimental setup, Artificial Neural Networks based hybrid Harris Hawks Optimization Whale Optimization Algorithm is used. A four-stroke, single-cylinder conventional diesel engine, has been used for experimentation

which runs on diesel that is used as primary fuel and biofuels along with constant supply of biogas is used as a secondary fuels.

The designed duel fuel engine will operate on biofuel with the combination of B20, B40, B60 and biogas that flows on a constant rate. The experiments have been conducted on IC engine by collecting data by varying injection timings, for example, 23° BTDC, 26° BTDC and 29° BTDC. We can make use of this alternative fuel to run mechanical vehicles by mixing this biofuel with diesel in the ratio of 20%, 40% and 60%.

In the dual-fuel engine, the main purpose is to achieve high BTE and minimum emissions. From the observations taken it is concluded that the highest BTE is achieved with 26^o BTDC using normal diesel + biogas. In addition to this, the minimum CO level is achieved at 29^o BTDC using normal diesel + biogas. Furthermore, Minimum CO_2 level is achieved at 26^o BTDC using B60 bio-diesel combination with biogas inlet. Every-time the target of the proposed research is to attain maximum BTE and minimum emissions. This is possible at a different type of fuels and different BTDC. To solve this problem, optimization is the better solution to achieve the desired targets. The algorithm Artificial Neural Network hybrid Harris Hawks and whale optimization algorithm is created and tested to achieve the same. This ANN hybrid approach helps in getting the optimal solution to the unknown inputs.

To obtain the optimal solution the results are verified using meta-heuristic algorithm by performing trial runs on prescribed functions. The applied methods resulted in better classification rate than other meta-heuristic algorithms.

CHAPTER-1

INTRODUCTION

Air is contaminating day-by-day due to the huge accumulation of toxic gases in abundance. The gases like nitrogen oxide (NOx), carbon monoxide (CO), carbon dioxide (CO_2) and sulphur dioxide (SO_2) contaminate the atmosphere. These gases are mostly generated by vehicles and industries, which put an adverse impact on human health. Furthermore, fossil fuels that are also used to run vehicles are depleting at an alarming rate. Consequently, it is needed to find alternative fuel or alternate technology for running these vehicles and industrial motors. A better and economical alternative can be the use of renewable resources, for instance, bio-waste [1]. India is having plenty of bio-waste that can generate more than 10 MW of power [2].

Bio-waste is a better alternative to make bio-diesel fuel as it meets the 1990's Clean Air Act amendments. Viscosity, the heat of combustion and cetane number of bio-waste makes it different from other fuels. Moreover, the viscosity of these fuels is much closer to diesel fuel which burns clean and has much better lubrication property than today's lower sulphur diesel fuels [3-4]. However, it cannot be used directly in the CI diesel engine as biodiesel holds no petroleum. To make biodiesel blend, bio-waste is mixed with some amount of petroleum [5]. With manual [6] or electronic [7-10] modification, these blends can be utilized in the IC engine. This leads to the motivation to develop innovative engine called Dual fuel engine [11]. In the dual-fuel engine, two types of fuels are used, one called as a secondary fuel and other as the primary fuel [12-13]. This method reduces emission pollutants and also fuel consumption. Merely improving mechanical system will not give appropriate results, so the support of electronic systems is needed to achieve better efficiency of the engine with reduced emissions [14-15]. Developing the new hardware model is complex, costly, time-consuming and the output of the combustion model is not sure as per our requirements. The better alternative approach is neural network modelling [16]. Neural systems are exceptionally advanced displaying procedures fit for demonstrating to great degree complex capacities. The vast range of engine parameters can be considered as complex functions. Based on these parameters the output is predicted as per our design requirements [17-18]. In this whole process, the results from the experimental setup will help to train the neural network and then the result will be optimized.

In this era of revolution, human life is highly influenced by the use of mechanical equipment and motor vehicles. Due to maximum dependency on and utilization of vehicles, noxious gasses such as nitrogen oxides (NOx), carbon dioxide (CO_2), sulphur dioxide (SO_2) and carbon monoxide (CO) are released by them. These gasses are contaminating the air to a huge level. Generation of these gasses by industries and vehicles has put an adverse impact on the health of human beings. Moreover, the (fossil fuels) fossilized remains of prehistoric plants and animals on which vehicles run are also depleting at an alarming rate. Consequently, it of utmost importance to discover the substitute fuel for operating these vehicles and industrial motors. Improved and cost-effective substitutes can be used and invented from renewable resources like bio-waste. India as a country produces a huge amount of bio-waste which is capable of generating power for self-reliance and sustainability.

1.1 Energy Usage and Environment

As discussed previously, renewable resources put a negligible impact on the surroundings and the environment. As if electric power generated by utilizing solar energy produces fewer emissions than using coal to generate power in thermal plants. Electricity power generated through coal also leads to emission of Carbon monoxide, Sulphuroxide and Nitrogenoxide along with fly ashes and other pollutants. Such pollutants result in degradation of the environment. Apparently, at national and global level, our current pattern of consumption of energy depends upon non –renewable resources and fossil fuels. In an attempt to save the environment, one must take preventive measures to reduce energy consumption, switch from non-renewable resources to renewable resource because renewable sources produce less pollution.

As the majority of the total populace, today is without fundamental comforts of life, consequently, for comprehensive, economical development and dynamic social change, the last alternative is required to be put into operation.

1.2 Diesel Engines and Requirement of Substitute Fuel

Now a day, due to the high utilization of vehicles and gasses released by them is contaminating the air to the huge level. This undesirable effect of air pollution has been experienced to the worst level in India this year. Release of poisonous gasses by the vehicles is at an alarming level and burning of silage is leading to an increase in parts per million levels to the risky level. This paper proposes a few alternative techniques and ways to utilize hay to produce other practically functional alternative fuel. We can make use of this alternative fuel to run mechanical vehicles by mixing this biofuel with diesel in the ratio of 20%, 40% and 60%. This research paper also proposes the use of biogas to run vehicles which are produced from biowaste. To understand how an engine works with dual fuels, data for various before the top dead centre is calculated and recorded.

In this era of revolution, human life is highly influenced by the use of mechanical equipment and motor vehicles. Due to maximum dependency on and utilization of vehicles, noxious gasses such as CO, CO_2, SO_2 and NOx are released by them. These gasses are contaminating the air to a huge level. Generation of these gasses by industries and vehicles has put an adverse impact on the health of human beings.

Moreover, the (fossil fuels) fossilized remains of prehistoric plants and animals on which vehicles run are also depleting at an alarming rate. Consequently, it of utmost importance to discover the substitute fuel or technical equipment for operating these vehicles and industrial motors. Improved and cost-effective substitutes can be used and invented from renewable resources like bio-waste. India as a country produces a huge amount of bio-waste which is capable of generating power more than 10 MW. Bio-waste has emerged as a substitute to generate bio-diesel as a fuel. It also follows Clean Air Act amendments. Its cetane number, the heat of ignition and consistency makes it unique to different fuels. In addition to this, the consistency of these fuels is a lot nearer to diesel fuel which consumes clean and has much preferable oil property over the present lower sulfur diesel fuels. However, this produced Bio-diesel cannot operate the CI diesel motor because biodiesel does not hold petroleum base. These blends can be utilized in CI motor with amendment either mechanically or electronically. This process leads to invention and growth of a novel type of engine called Dual fuel engine. Dual fuel engine operates upon two different kinds of fuels. One fuel act as primary fuel and the other as secondary fuel. Use of two fuels decreases the consumption of fuel as well as emission pollutants. Many ideas have been proposed to improve the mechanical system to achieve less consumption of fuel but only by advancing the mechanical system will not generate the required outcomes. An efficient electronics system support and utilization are required to attain improved efficiency of the engine with reduced emissions.

As shown by projection results, the consumption of petroleum derivatives in the form of basic amenities has increased tremendously from 1990 to 2020. Engine emissions produced over the years create a severe impact on the environment. The significant reason for high contamination levels, regardless of the stringent discharge measures that have been authorized, is the expanding vitality interest for all parts and most broadly the expansion in the utilization of IC motors for portability and power. The gas and diesel are commonly used fuels and re highly in demand. These fuels are used to operate IC engines and spark-ignition engines. As for use, diesel motors are to a great extent preferred over a wide range of daily and industrial activities.

In the year 2005, the proportion of utilization of diesel to gas was 4.80. In the year 2012, this proportion further reduced to 4.31. This decline in the use of diesel shows that use of gas is increasing at a high rate over the years. In comparison to the utilization of gas as fuel, utilization of diesel as fuel is higher by 4.5 times in India. In this manner, still, a fractional replacement of mineral diesel by any other sustainable and carbon impartial elective fuel can have a critical beneficial outcome on the financial market system and environmental condition as far as a decrease in carbon impressions and reliance on imported unrefined petroleum. The broad utilization of diesel in the developing economy of India has required the quest for an inexhaustible substitute of diesel.

The name “dual fuel” does not imply to double fuel application of petrol engines in which the fuel in liquid form does not combust with gas fuel. The dual-fuel engine is a diesel engine that works on the principle of the internal combustion engine. In such engines, a fraction of the energy discharges by ignition that occurs by burning the gas fuel. The burning of liquid diesel fuel yields throughput which is achieved through chamber infusion. The combustion internal engine is filled with gas which is the secondary fuel for the engine. Then it is compressed with air in the engine cylinder. The little amount of primary fuel, diesel is added through the conventional diesel fuel system to ignite the fuel. Dual fuel engine works in periodic cycles. The gas fuel is mixed with the air at a pressure which is more than atmospheric pressure. Certain factors lead to the need of invention of a dual-fuel engine which includes, the lack of fluid fuel and the acknowledgement that vaporous powers are far less expensive than fluid powers have prompted consideration on double fuel engine. In addition to this, Gaseous petrol accessible to the majority of part of the world at rates less expensive than fluid energizes.

1.3 Working of Dual Fuel Engine

1.3.1 Dual Fuel Operation

Dual operation is achieved in the internal combustion engine by burning of both biofuel and diesel at the same time. Injection of little quantity of diesel can be used as a source of ignition.

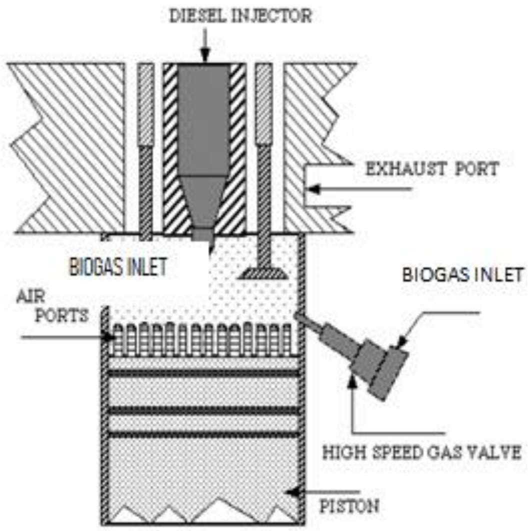


Figure 1.1: Dual-Fuel Operation [19]

It works on the diesel cycle. Fuel is supplied by the supercharger. The pilot fuel is injected and it acts as an ignition source.

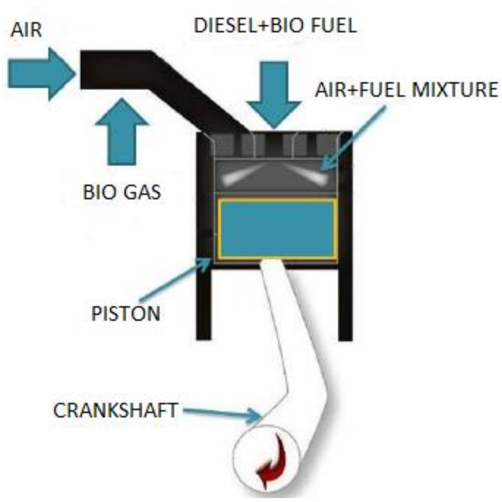


Figure 1.2: Working of Dual Fuel Engine

1.3.2 Biogas Diesel Engine

Biogas is produced by the anaerobic breakdown of natural organic material. It is a renewable energy source and acts as an alternative fuel. Biogas as fuel is capable to power the planet for years to come. Biogas can reduce CO_2 emission as compared to fossil fuels.

In the current era of the utilization of technology, over the years the implementation, performance and utilization of artificial intelligence and machine learning have become well-linked and useful for implementing solutions for constrained/unconstrained, real-world, discrete, linear/nor linear engineering problems. Research done over the decade and results obtained from the continuous research has resulted that optimal solution for non-continuous and multi problems can not the effects provided by the existing methods so, for effective behaviour and result, meta-heuristic algorithms are considered. Various methods used to find an optimal solution for computational problem frame is termed as heuristics.

1.4 Artificial Neural Networks

In Artificial Intelligence, Machine Learning is a suitable technology to find better possible solutions for engineering problems. Neural networks have the capability of finding solutions for complex problems. ANN is suitable for performing tasks like making clusters, classification. ANN helps in object and pattern recognition, modelling data and performing statistical analysis.

Neural Network is an interlinked connection of nodes or hubs. Working of neural network resembles working and processing of the human brain. Neural Networks takes various inputs and different weights which results in one output. Characterized inputs play a vital role in the generation of output. Neural Network is best suitable to solve problems where output is known. It learns itself and does not have any need to program it again and again. During the training, process neurons are trained to differentiate various designs [20].

Neural Networks put forward an effective approach to figure out and comprehend the working of the human brain. NN takes different inputs with various weight values and results in one output [21]. A neural network is widely used because of its ability to generalize and to respond to unexpected inputs/patterns. NN learns itself so one need not train it. During the process of training, neurons are trained to yield effective output to find the optimal solution of defined engineering problems. For example during the implementation phase to achieve optimal output, the neurons select the input values that have a unique relation with the set of outputs [22].

1.4.1 Working of Artificial Neural Network

The Artificial Neural Network as shown in Figure 1.3 obtains input in the form of pattern and image. Each input (H_1,H2,……,H_n) is multiplied by its corresponding weights (P_1,P_2,…...,P_n). Weight speaks to the potency of the intercontinental the middle of neurons inside those neural systems. The weighted inputs would be summed up. In the event those weighted aggregate will be zero, the inclination will be included should aggravate the yield 1 alternately to scale up that framework reaction. Furthermore, bias has weight and information constantly equivalent to '1'. The whole corresponds will whatever numerical worth extending starting with 0 to boundlessness [23].

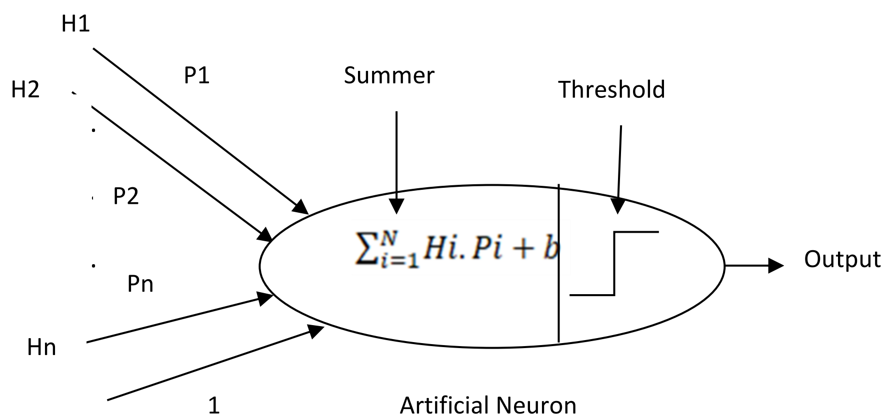


Figure 1.3: Working of Artificial Neural Network

Layers of Neural Network are independent. These layers can have any number of nodes. The number of hidden layers should be more than all the input nodes. There has to be minimum one hidden layer connected to the bias and value of bias is 1.

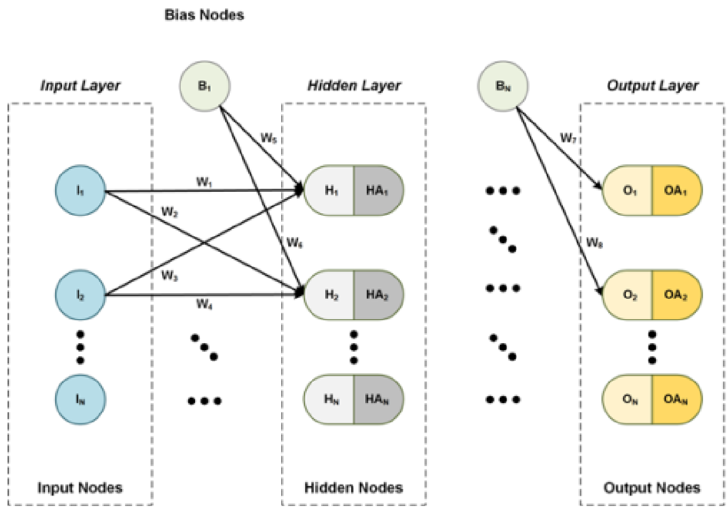


Figure 1.4: General Architecture of Neural Network [24]

1.4.2 Feedforward Neural Network

In this type of network, nodes do not create a cycle. A succession of data is unidirectional in the feed-forward network. To generate an optimal solution, data flows to the nodes through hidden layers.

1.4.3 Back-propagation

In back-propagation, to achieve the best possible optimal value from the collected data the loads are balanced progressively. Meta-heuristic algorithms are a group of receptive methods to improve the effectiveness of heuristic techniques. In this, to find optimal solutions the population-based methods are used. The first step to start optimization is to define population-based sets. In every iteration made, the values of the population set will be changed. The newly generated values are replaced with existing population set and population sets are updated with currently generated values. Process of iteratively updating the values of population set continues until an optimal result is achieved. An artificial neural system (ANN) has multilayer feed-forward neural system collection and utilizes the back-propagation method to adjust and improve the weight over the network. To speed up the utilization and execution of GD methodology with HHO and WOA, the meta-heuristic algorithms are implemented efficiently and effectively.

The proposed research aims to improve and upgrade the performance of a dual-fuel engine. This is done to achieve high BTE is achieved and fewer emissions are produced. An efficient artificial neural network-based hybrid meta-heuristic algorithm hybrid-ANNHHOWOA, this is stimulated by the natural phenomenon of Harris Hawks and Whales to get the best possible solution to locate the position of prey is used for optimization. The basic idea to develop and use ANN based hybrid HHOWOA algorithm for optimization is to encourage the utilization of meta-heuristic algorithms which resemble and are based on the natural attacking way of Harris Hawks and Whales i.e. to encourage the use of natural efficient way to find best possible optimal values to reduce emissions and achieve high BTE.

1.4.4 Artificial Neural Networks Learning

Learning in the neural network is done by changing its weights and threshold i.e bias iteratively to yield the desired output. the neural network is trained for initiating learning process with the help of suitable learning algorithms [25].

1.4.5 Structural Design of Artificial Neural Networks

The basic structure of ANN includes three layers named input, hidden and output. The structure is shown in Figure 1.5.

- **Input layer**- Holds the individuals' units which accept information from those outside globes concerning which system will learn, perceive transform.
- **Output layer**- Holds units that react to the data something like how it's gained at whatever assignment.
- **Hidden layer**- these units are in sandwiched between input and output layers. Hidden layer converts the input into the output unit.

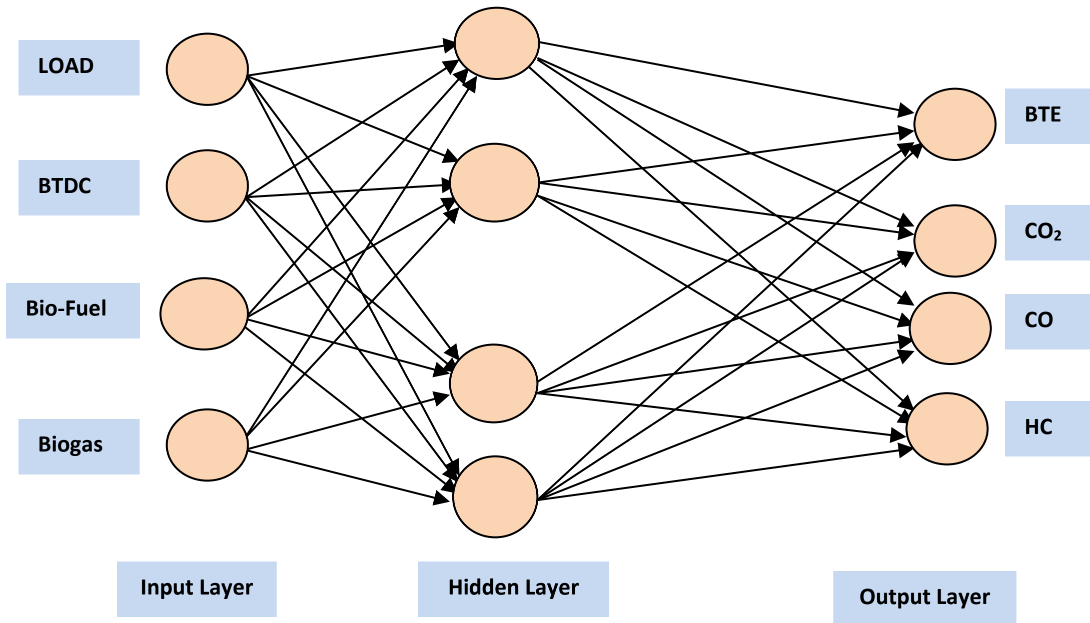


Figure 1.5: Basic ANN Model

In Figure 1.5, the input layer consists of input parameters Load, BTDC, B where ‘A’, ‘B’, ‘C’ and ‘D’ stands for percentage load, biogas inlet quantity, injection timing and type of biodiesel blend used respectively. These inputs are individually connected to the neurons of the hidden layer and are not visible as a network output. Hidden layer neuron's yield is associated with the inputs of other neurons for the output layer. The network output layer consists of BTE, CO, CO_2, and HC.

1.5 Harris Hawks Optimization Algorithm

The Harris Hawks Optimization Algorithm (HHO) is based on the phenomena of a surprise attack. In this algorithm, the hunting style of Harris Hawks is discussed. Harris Hawks uses a surprise attack strategy to hunt the rabbit. The working of the HHO algorithm is categorized into the Exploration stage and Exploitation stage. HHO is inspired by a natural phenomenon and is a population based algorithm.

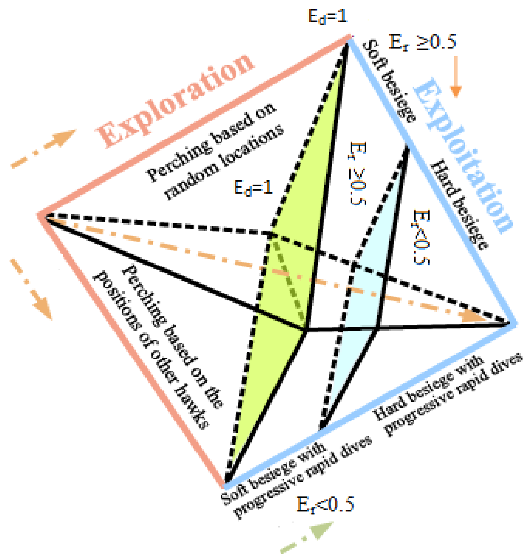


Figure 1.6: Various stages of HHO

For detecting the location to attack prey, the Harris Hawks scrutinize and supervise for many hours. Suppose C1 is the possibility that Harris Hawks hunt the prey. This behaviour is depicted in equation (1.1). When the value of C1 reaches less than 0.5, it depicts that Harris Hawks are near the prey and are trying to attack it. Also, Harris Hawks try to unwavering on some random positions. This behaviour is depicted by equation (1.2).

To find the location of Harris Hawks, equation (1.3) is used.

$$\mathrm{A(t1+1) = \; Arand(t1) - zr1 \mid Arand(t1) - 2zr2A(t1)j \quad C1 \geq 0{:}5} \tag{1.1}$$

$$\mathrm{A(t1+1) \; = \; Arabbit(t1) - Am(t1)) - zr3(LB1 + zr4(UB1 - LB1))\; C1 > 0{:}5} \tag{1.2}$$

Here A(t1 + 1) location of hawks in the succeeding iteration t1, A rabbit(t1) refers to the position of rabbit, A(t1) is the current position of all hawks, zr1, zr2, zr3, zr4, and C1 referred as random numbers that lie in [0,1]. These values are updated in every rotation, Arand(t1) refers to the location of hawk that is currently going to attack the prey. LB1 and UB1 is the lower limit and upper limit of variables. Am() represents the current location of all existing hawks.

The average position of hawks is calculated by

$$\mathrm{Am(t1) = 1/N} \sum_{i=1}^{N} \mathrm{Ai(t1)} \tag{1.3}$$

Where Ai(t1) is the location of each Harris hawk in every rotation t1 and N refer to the total count of hawks.

1.5.1 Translation of Exploration to the Exploitation

1.5.1.1 Exploration Phase

A process of searching and locating an unknown area is referred to as Exploration. In this phase, to search for target the Harris hawks move to random positions. The main idea of this phase is to exhaust the rabbit so that its energy is decreased and it becomes convenient for Harris Hawks to attack the prey.

The energy released/utilized by the rabbit to escape from harris hawks is termed as escape energy. It is determined by equation (1.4).

$$\mathrm{EP1} = 2\mathrm{EP10}\left(1 - \frac{\mathrm{t1}}{\mathrm{T1}}\right) \tag{1.4}$$

Where *EP1* is the escape energy of the rabbit, *T1* is the maximum number of iterations, *t1* refers to present rotation and *EP10* is the initial range of energy of the rabbit.

The value of EP10 changes between -1 to 1 for each rotation. When the value of EP10 reduces to -1, it refers that the prey is running short of energy and is losing stamina. EP10 <0 refers that rabbit is tired. In contrast to it when EP10>0 refers that rabbit is full of energy and is strengthening. On the other hand, when the value of EP1≥1 refers Harris hawks locate the location of prey. In contrast to it if EP1<1 it means Harris Hawks find the best possible way to hunt the prey.

1.5.1.2 Mathematical description of soft and hard encircles utilized by Harris Hawks to hunt the prey

In addition to escaping energy of rabbit and the strategy followed by Harris Hawks to hunt the prey, chances of rabbit to escape also draws attention. Let E_{r1} defines the chances of prey to escape from the attack of Harris Hawks. The rabbit escapes successfully when the value of E_{r1} becomes less than 0.5. If $E_{r1} \geq 0.5$ it means prey cannot successfully escape from the hunter. To confuse the prey Harris Hawks can attack suddenly. Depending upon the energy and activities of the prey, Harris Hawks surround the prey softly or hardly. The retained energy of prey let the Harris hawks decide about the attack. To decide whether the Harris Hawks should attack the prey or not an extra parameter E_{d1} is taken. Soft encircle is indicated when the value of E_{d1} is greater than 0.5 and when $|E_{d1}|<0.5$ it means hard encircling of the prey by Harris Hawks.

1.5.1.3 Soft Encircle

The values of $E_{r1} > 0.5$ and $|E_{d1}| \geq 0.5$ means the rabbit has enough power to run away from the Harris Hawks, Harris Hawks first encircle the prey and try to drain its energy, later Harris Hawks make a surprise pounce. The effort done by Harris Hawks to catch the prey is depicted by the following equations:

$$XE1(t1 + 1) = \Delta XE1 - EX\,|Rj1Arabbit(t1) - XE1(t1)| \qquad (1.5)$$

$$\Delta XE1(t1) = Arabbit(t1) - XE1(t1) \qquad (1.6)$$

Where ΔXE1 refers to the location of a rabbit.

Arbitrary hops made by the rabbit to escape from Harris Hawks are calculated by Rj1=2(1-r_5). Value of r_5 is lies between (0,1).

1.5.1.4 Hard Encircle

When the value of E_r is greater than 0.5 and $|E_d|$ less than 0.5, it reflects that the rabbit is tired and is left with little energy to run and escape from Harris Hawks. This behaviour of the rabbit is calculated by using equation (1.7).

$$XE1(t1 + 1) = Arabbit - EX|\Delta XE1(t1)| \qquad (1.7)$$

By keeping the potential of fast dives in soft encircle, the final position of prey is mathematically represented as:

$$A(t1 + 1) = \{Mn1, \text{if } F(Mn1) < F(A(t1))\} \qquad (1.8)$$

$$A(t1 + 1) = \{P1, \text{if } F(P1) < F(A(t1)\} \qquad (1.9)$$

By keeping probability to locate the actual position in hard encircling where the rabbit does not have sufficient energy to escape from Harris Hawks, equations (1.8) and (1.9) can be updated as follows to find the next location:

$$\mathrm{Mn1} = \mathrm{Arabbit(t1)} - \mathrm{EP1}\,|\,\mathrm{K\,Arabbit(t1)} - \mathrm{Am(t1)}\,| \quad (1.10)$$

$$\mathrm{P1} = \mathrm{Mn1} + \mathrm{RS1} \times \mathrm{LFT1\,(DIM1)} \quad (1.11)$$

Value of A_m(t1) can be obtained from equation (1.3).

1.6 Whale Optimization Algorithm

Whales are considered to be superlative and large creatures on earth. There exist various types of whales, among them, the one type of whales is Humpback whales. This whale uses an intelligent strategy to hunt the prey. By observing and studying this hunting behaviour of humpback whales the researchers have implemented Whale Optimization Algorithm [26] which is also a meta-heuristic algorithm and is inspired by the natural behaviour of whales. The hunting strategy of humpback whales is expressed in 3 major steps which include encircling the prey, efficiently going towards the prey and locating the prey respectively.

1.6.1 Encircling the prey

As soon as whales identify the position of prey, it encircles prey. This method is considered to be an efficient and effective method to find prey for hunting. Whale updates and informs other whales when the location of prey is identified; in turn, other whales update their location. Equations (1.12) and (1.13) model the same.

$$\mathrm{A(t1+1)} = \{\mathrm{P1, if\;F(P1)} < \mathrm{F(A(t1)}\} \quad (1.12)$$

$$\mathrm{S(n1+1)} = \mathrm{S1} * \mathrm{(n1)} - \mathrm{A1.W1} \quad (1.13)$$

Here, *n1* is recent iteration, *A1* and *P1* are coefficient vectors, *S* refers location where the optimal result is obtained and S1 refers position vector, | | refers the absolute value, and '·' refers to Cartesian product [26].

To calculate values of *A1* and *P1* following equations are used:

$$\mathrm{A1} = 2\mathrm{a1}.\mathrm{r} - \mathrm{a1} \quad (1.14)$$

$$\mathrm{P1} = 2.\mathrm{r} \quad (1.15)$$

Where the value of *a1* declines 2 to 0 in each rotation and *r* is a random vector that lies in [0,1].

Figure 1.7: Encircling the prey [127]

1.6.2 Going towards the prey

Humpback whales use the bubble-net feeding strategy to move toward the prey. Whales block and blur the view of prey by forming bubbles around the target prey. To approach towards the prey humpback whales uses 2 methods named Spiral Movement and Narrow down the circle method.

Whales narrow down the circle and cover the prey. This can be achieved by decreasing the value of ‘a1’ in equation (1.14).

By using equation (1.12), total distance difference in the prey and whale is computed. This calculated value is utilized in equation (1.13) to depict spiral movement.

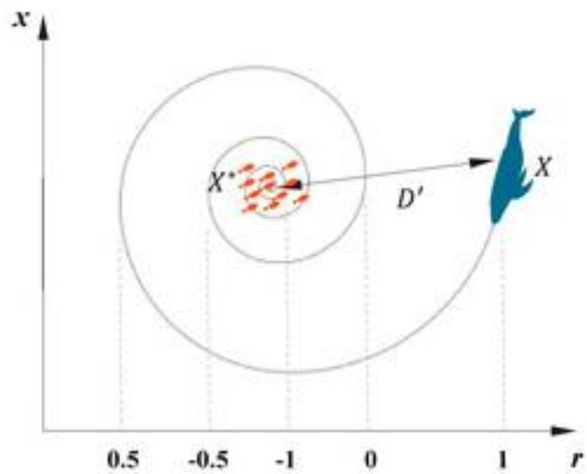


Figure 1.8: Spiral Movement [127]

$$S(n1+1) = S1*(n1) - A1.W1 \tag{1.16}$$

$$S(n1+1) = S1*(n1) - A1.W1 \tag{1.17}$$

log spiral constant is referred to as b and value of ‘l’ lies from [-1,1].

The probability of whether spiral or else linear movement method will be applied is 50% and is calculated by using equation (1.18):

$$X(t1+1) = X^{x}(t1) - A1.D1, p1 < 0.5 \tag{1.18}$$

$$X(t1+1) = D1'.e^{bl}.\cos(2\Pi l) + X1*(t1), p1 \geq 0.5 \tag{1.19}$$

p1 is arbitrary number lies in [0,1].

1.6.3 Searching of the prey

Whales locate the prey by altering their locations randomly. This is modelled as:

$$D1^{'} = C1.Xrand - X1 \tag{1.20}$$

$$X(t1+1) = Xrand - A1.D1 \tag{1.21}$$

Xrand is a solution vector and is selected arbitrarily.

1.6.4 Basic Steps of Whale Optimization Algorithm Steps

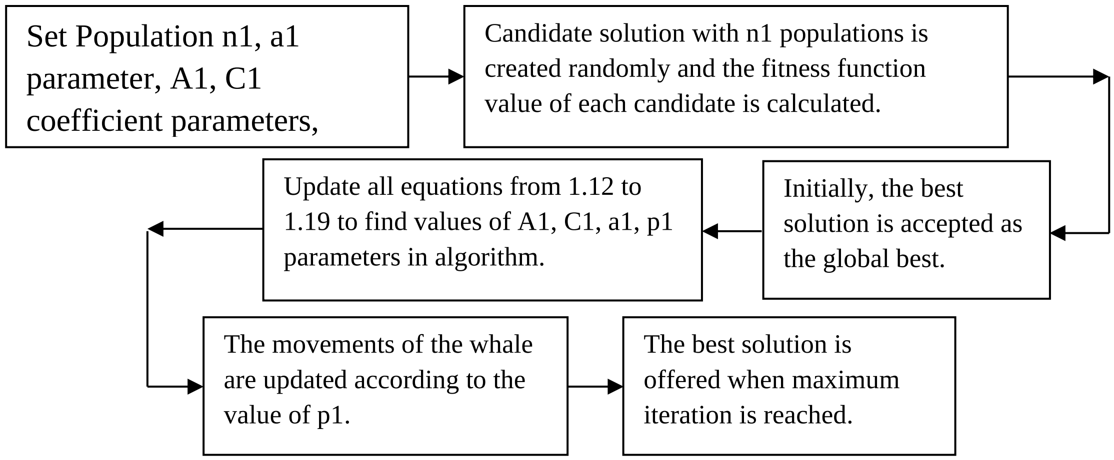


Figure 1.9: Basic Steps of Whale Optimization Algorithm Steps

1.7 Research Objectives

The current work includes modelling, optimization of the performance of internal combustion engine and operating parameters of bio-diesel using Artificial Neural Network. The following objectives are envisaged for the present research work based upon the observation.

1. To investigate the compatibility of various algorithms suitable for dual fuel engine.
2. To implement modern optimization algorithms for estimation of performance and emission characteristics.
3. To evaluate the system performance and validate with the experimental results.

1.8 Organization of Thesis

The current work aims to describe the modeling and optimization of compressed ignition engine performance and emission characteristics for bio-fuels using ANN networks.

The thesis report consists of five chapters. The organization of the report has been done as mentioned below.

1.8.1 Chapter 1 Introduction

The thesis begins with an introduction giving a concise close importance of Dual fuel Engine run on various bio-blends as a secondary fuel for diesel engine. Along with it the need of ANN in automation field is described and the same is implemented using MATLAB 2008a.

1.8.2 Chapter 2 Literature Survey

This chapter presents a logical and complete review of the literature on the use of various types of Dual Fuel Engines and their biodiesel as alternate fuels for diesel engines. The literature review also includes few available studies related to artificial neural network for the optimization of the engine.

1.8.3 Chapter 3 Methodology

Various study related to the experimental setup of engine and the development of ANN model along with validation of ANNHHOWOA hybrid model is explained in Chapter 3.

1.8.4 Chapter 4 Results

In this chapter the data of experimentation is analyzed. The results would then be discussed in detail and compared with the findings of previous researchers. The results of modelling through ANNHHOWOA for engine exhaust gas emissions and performance will also be discussed in this chapter. At the end of this chapter optimization process was carried out.

1.8.5 Chapter 5 Conclusion and Future Scope

The findings, outcomes and future scope of the study is discussed in this chapter.

CHAPTER-2

LITERATURE SURVEY

The basic idea of a dual fuel responding engine maybe not new. In the 1890s, Rudolf Diesel explored different avenues regarding this approach throughout as much innovative work of the diesel engine. He presented that may be usually alluded with concerning illustration pipeline natural gas under those air admission complex and observed upgrades engine execution. Since then, dual-fuel engines bring been accessible clinched alongside huge numbers markets, including stationery requisitions in the gas compression business. These types of engines were used as early as the 1930s. The literature review includes theoretical, simulation models as well as the experimental work undertaken from time to time along with the development of the DUAL FUEL ENGINES for enhancing efficiency, engine life and less Nox.

In this research Saadi et. al. [27], focuses on the emission control parameters in the CNG-Diesel engines. The scientist also emphasized that exploration of alternative fuels to be used for less emissions and high performance vehicles. While research the scientist emphasized that emission by existing CNG-Diesel vehicle result in significant decrease as compared to conventional pure diesel vehicles engines. In addition to this, Banapurmath et. al. [28], emphasized on the alarming annihilation of fossil fuels and their risky natural effect created eventually automotive car systems, which need prompted the utilization about substitute ignition loop methodologies Furthermore renewable fills to CI engines. Customary CI engines radiate expansive sum for particulate matter because of their different incineration. The alarming situation is high NOx emission by the diesel engines which also pollute the environment and result in health hazards. For resolving the problem the researcher focused on use of an advanced combustion innovation named as Homogeneous Charge Compression Ignition (HCCI) which needs possibility to decrease particulates and NO comparable to CI combustion. The idea from claiming double fuel approach is with settle on utilization of distinctive sorts of fuels for diesel engines also clinched alongside effect have bring down smoke also HC outflows. The researcher recommended test investigations once a solitary piston chamber from claiming four stroke layering ignition loop (CI) motor fuelled with diesel for solitary fuel mode and CNG also home infusion to a changed double fuel mode utilizing HCCI operation mode. CNG fuel injected under those consumption valve utilizing a suitableness injector and electronic control unit (ECU). The HCCI engines yielded superior effects over double fuel engines to accepted mode. Furthermore, Tayarani et. al. [29], focuses on Meta-heuristic algorithms which are stimulated by natural phenomena, including the development about species in darwinian characteristic determination theory, burrowing little creature practices to biology, group practices from claiming a portion birds, Also strengthening over metallurgy. Because of their incredible possibility for fathoming was troublesome streamlining problems, meta- heulandite calculations have discovered their approach under car engine plan. There would diverse streamlining issues that happen in distinctive regions from claiming overseeing those auto engines including calibration, control system, shortcoming diagnosis, and displaying. In this research the specialist accentuated looking into machine of meta-heuristic calculations to motor calibration, upgrading motor control systems, motor deficiency diagnosis, and optimizing and modeling parts of engines. Moreover, Gnanam et. al. [30], proposed a framework which is based on Neural Networks. The proposed framework was used to find control of the intake of complex air and fuel proportion in CNG-Gasoline dual fuel motor. This module controls the complete system using electronic control units (ECUs). Commonly the ECU is adjusted for gas What's more gives a great control of the admission complex air/fuel proportion for fuel. Those neural system built control framework is formed on permit the transformation of a gas ECU with A bi-fuel type with compacted characteristic gas in negligible expense. The adequacy of the neural control framework may be showed toward utilizing a reenactment of a avoid four-stroke bi-fuel motor..Furthermore, Al-himyari et. al. [31], focused on air contamination caused specially caused due to vehicle discharges. These discharges of vehicle motor exhausts need aid answerable for 50 percent of air contamination. Different sorts from claiming discharges radiate starting with vehicles including carbon monoxide, hydrocarbons and

NOx. There is an inclination on creating methodologies about motor control which rapidly accomplish this task. The researcher is pointing at review of investigations on the prediction and control of the AFR, concerning the illustration to examine the expectations with distinctive approaches.

Furthermore, Kurniawan et. al. [32], proposed a mathematical learning to simulate and examine the ignition methodology which motivated the researcher to use compacted natural gas direct infusion (CNG-DI) motor towards using an multi-dimensional computational fluid dynamics (CFD) code. The scientist performed the experiment around a solitary barrel of the 1.6 ltr motor operating at open throttle towards a modified speed of 2000 rotations per minute. The network was protected by doing calculations to achieve an nearly exact transient condition of the operating engine. Eddy-break-up model was used to describe ignition methodology and 100% methane gas was used. Time difference of when a valve was open and before an exhaust valve was open resulted in CFD simulation. Results of CFD reenactment were later compared with the result taken from single-cylinder engine. Moreover, Su et. al. [33], established a control system which was the mixture of biogas-gasoline. The proposed framework uses electronic control unit (ECU) also utilize MC9S12XS128 micro control unit (MCU) as core. As a result, to manage the amount of biogas used engine is operated efficiently. So researchers tried to achieve best possible air-fuel ratio to match the claimed tests those were performed using different parameters on different conditions.

In addition to this, Kumaraswamy et. al. [34], proposed a electronically controlled dual fuel engine operated by using LPG and diesel as fuels. In this research, the researchers put forward the comparison of load and external characteristic of traditional diesel engine and dual fuel engine operated using LPG and diesel. From the analysis of results, it was demonstrated that smoke emission of dual fuel is less than traditional diesel engine. It was also concluded that diesel engine had moderate change in emission of NOx but emission of HC and CO was increased. Whereas, dual fuel engine showed better efficiency and consumed less fuel.

Furthermore, Yadav et. al. [35], explained the possibility of hybrid technology considering LPG-Diesel as base fuels. In this research the scientist proposed investigation utilizing Artificial Neural Network (ANN). ANN is connected on a retrofitted experimental setup utilizing diesel as essential and LPG as auxiliary fuel advancing the thermodynamic parameters to acquire most extreme work yielded at higher thermal effectiveness. The ANN is trained with the experimental data to stimulate the results for the network which gives least Mean Square Error (MSE) and lowest Mean Absolute Percentage Error (MAPE) being a function to optimize the results. The optimization is done with the assistance of genetic algorithm to limit the cynicism of capacity to get expanded outcomes. Similarly, Rai et. al. [36], explained the need of Dual fuel engines nowadays to conquer deficiency of non-renewable energy sources and satisfy stringent exhaust gas outflow controls. They have a few favorable circumstances over conventional diesel motors. Scientist proposes to make utilization of outcomes from dual fuel engines for creating models to anticipate execution and outflow parameters. The researchers proposed the use of Adaptive Neuro-fuzzy Inference System (ANFIS) to develop the models to predict emission and performance parameters of dual fuel engine. Researcher Anticipated execution and outflow parameters for which they utilizes neural fuzzy method with Genetic calculation approach to yield parameters such as Brake Thermal Efficiency (BTE), Exhaust Gas Temperature (EGT), Brake Specific Energy Consumption (BSEC) and smoke.

Furthermore, Bora et. al. [37], explained that to manage the stop and control the contamination of diesel engines process of emulsification plays a vital role. In this research, the scientist efficiently propose a method that finds the impact of compression ratio and injection timing of primary fuel on dual fuel engine which is controlled by rice bran biodiesel (RBB) biogas. Researchers also did the dual layer water emulsification of rice bran methyl ester. It was optimized by using five and ten % of water, three % of surfactants HLB with values 4.3, five and six. The researchers have used DFM (Dual Fuel Mode) with carburetor. Mechanically bio diesel and biogas are emulsified.

In this research Sumit et. al. [38], studied the performance and emission parameters. He focused on the development of neural net model to predict the BSFC, BTE, Nox etc. parameters using single cylinder CRDI four stroke engines. In the model CNG-Diesel was used in the dual fuel engine model. From the research the scientist concluded that ANN modelling was a robust and better reliable identification tool in IC engine as compared with other prevalent artificial Intelligent (AI) techniques'. In addition to this, Sumit et. al. [39], studied the performance emission trade off in CRDI single cylinder engine. The fuel used in this engine was CNG as secondary fuel. In this research scientist used Particle Swarm Optimization (PSO) technique. The researcher used ANN metamodel for correlating the objective function with some selected variables. Furthermore, author used CNG-diesel operated dual fuel engine to foresee the emission and performance parameters of CRDI engine. Data was gathered from experimental setup to check GEP. To predict BTE, NOx, BSFC, HC and PM GEP model was developed. Researchers considered CNG, load and pressure on which fuel is injected as parameters to check the performance of engine. Prediction results calculated using GEP gave better results than prediction done by using ANN.

In addition to this, Sumit et. al. [40], researched on emission and performance prediction of dual fuel engine using Adaptive-neuro fuzzy inference system (ANFIS). The results reflected the overall high accuracy with correlation coefficient ranging 0.998875 to 0.999989 with mean percentage error ranging between 0.08% - 1.84%. The results of this research showed that its result is better than the ANN alone. In context to this, Syed Javed et. al. [41], researched on dual fuel engine in which hydrogen and diesel fuels were used. For the prediction of emission characteristics and performance the researchers utilized and applied ANN modeling. The scientist used blend of Jatropha methyl ester biodiesel as a secondary fuel and noted that neural networks were the good tools for predicting the dual fuel engine behavior. Furthermore, Madhujit Deb et. al. [42], did research on CI engine in dual mode. Hydrogen was used to operate the dual fuel engine. He used ANN approach with fuzzy logic to optimize the performance of CI engine. The results showed the overall accuracy with correlation coefficient ranging from 0.995 to 0.999.

In this experimental work, Charudatta et. al. [43], response of diesel engine with ANN was studied. The data was collected at different injection timings 21o, 23o and 25o BTDC with different pressures. The neural network was utilized to forecast the performance and emission of engine. It showed the better results in mean absolute error and correlation coefficient. The result depicts the BTE to be highest at 20 percent blend of biodiesel and BSEC was greater to some extent. In addition to this, Channapattana et. al. [44], worked on optimization of DI-CI operating parameters with artificial neural network. The scientist proposed neural network and Bio fuel based model. The standard parameters of engine like BSEC, BTE and EGT were evaluated using regression model using Minitab. Multilayer perception was created to optimize the parameters using experimental data. In context to this, Sumit et. al. [45], researched on multi-objective parameters of CRDI engine with CNG as secondary fuel. The scientist optimizes the parameters using Gene Expression Programming model. The data was collected using the experimental setup of dual fuel engine.

Goga et al. [46], used a dual fuel engine to examine its emission properties and performance when biogas at varying mass flow rates was inducted in it together with bio diesel and diesel. Performance characteristics of the engine demonstrated that BSFC augmented whereas BTE diminished by using biogas as a primary fuel in assessment with pure diesel. Concerning emission contents, it was reported that exhalations of HC and CO increased owing to lower amount of oxygen content in biogas. In contrast, there was a simultaneous reduction in NOx and smoke emanations. Thus, regardless of having all the optimistic properties biogas is culprit of producing more HC and CO emissions vis-à-vis natural diesel. The reason for the same has been reconnoitered to be deficiency of oxygen in biogas. To overcome this problem a fuel having abundant amount of oxygen in its molecular structure needs to be used in consort with biogas. Biodiesel has nearly eleven%

amount of oxygen, can be unified with diesel effortlessly, and assistances in dropping hazardous CO, HC, and smoke exhalations.

Dual fuel engine operate upon two different kinds of fuels. One fuel acts as pilot fuel and the other as secondary fuel. Use of two fuels decreases the consumption of fuel as well as emission pollutants. Many ideas have been proposed to improve mechanical system to achieve less consumption of fuel but only by advancing the mechanical system will not generate required outcomes. An efficient electronics system support and utilization is required to attain improved efficiency of engine with reduced emissions. The dual fuel engine is based on the concept of compression ignition. In such engines, a fraction of the energy discharges by ignition that occurs from the burning of a gas fuel while the diesel fluid fuel keeps on giving all throughout, through timely planned chamber infusion, the rest of the piece of the energy discharge. The combustion internal engine is filled with the secondary fuel ‘gas’. Then it is compressed with air in the engine cylinder. Little amount of primary fuel, diesel is added through the conventional diesel fuel system to ignite the fuel. Dual fuel engine works in periodic cycles. The gas fuel is mixed with the air at a pressure which is more than atmosphere pressure. Certain factors lead to need of invention of dual fuel engine which include, the lack of fluid fuel and the acknowledgment that vaporous powers are far less expensive than fluid powers have prompted consideration on double fuel engine. Dual operation is achieved in internal combustion engine by burning of both a bio-fuel and diesel at the same time. Injection of little quantity of diesel fuel can be used as an ignition source.

Aljarah et al. [47], proposed the use of Whale Optimization Algorithm in preparing MLPs. The quick convergence speed and the high optimal avoidance were the main key motivations to implement the WOA to prepare MLPs. The issue of preparing MLPs was first defined as a minimization issue. The goal was to limit the MSE, and the factors were association loads and predispositions. The WOA was utilized to locate the optimal qualities for loads and inclinations to limit the MSE.

Alameer et al. [48], put forward whale optimization algorithm, which is used to train MLP neural network. The proposed research also compares the results of this model with basic neural network and other meta-heuristic algorithms. Furthermore, for accessing the efficiency and usefulness of the proposed technique, ARIMA models were applied. The results concluded that in comparison to other existing models, the WOA-NN model resulted in better outcome.

Harikarthik et al. [49], invented the experimentation methods aim to perform the practical examinations that enhance reach for every situation. After performing this, the observations are put on priority by using a hybrid Artificial Neural Network–Whale optimization technique. The proposed method result in less prioritization time and memory prerequisites as compared to already implemented methods. These methods result in yielding nearly correct results. From the achieved results, the researcher concluded that the proposed hybrid ANN-Whale algorithm achieves optimal results by using various classifiers.

Vaheddoost et al. [50], in this research, the researcher proposed an ANN-WOA technique to assess the FC and PWP. Different performance criterion was assessed to use results generated by the model. The results generated by the proposed algorithm came out to be best than the results of the hybrid of ANN-WOA and the ANN models individually.

Table 2.1: Engine characteristics at different ANN models

Ref. No.	**Fuel combinations used**	**Input Parameters**	**Output Parameters**	**Network used**	**Prediction**
51	WCO biodiesel-diesel blend	percentage load, injection timing, compression ratio, blend percentage,	NOx, UBHC, BTE, Texh, smoke, BSE	Back-propagation method	93.7%

52	Lemon grass oil and hydrogen	load, LGO and hydrogen	HC, NOx, BSEC, CO, BTE and smoke	Levenberg-Marquardt algorithm	R^2 -0.99457
53	Mahua oil and hydrogen	Fuel injection pressure, Engine load, and fuel injection timing, high octane fuel flow rate	CO, EGT, HC, NO, BTE and smoke	Feed forward back propagation algorithm	R- 0.84145–0.99988, MSE- 0.1479–0.00029
54	Hydrogen and diesel	varying engine speed, H2 energy substitution ratio and blends of biodiesel	CO, CO_2, vibration, noise, and NO	Levenberg Marquardt algorithm	R^2- 0.993
55	Biodiesel-diesel blends	engine load, biodiesel ratio and injection pressure	BTE, EGT, NO_x, CO and smoke , BSFC, HC	feed-forward multi-layer perceptron network	R^2-0.8663 to 0.9858, MRE >10%
56	diesel and palm oil blend	palm oil %, engine load, injection advance	CO, BTE, smoke, and HC, NO_x and EGT	Feed-forward back propagation network type	R^2-0.88 to 0.95

57	diesel-biodiesel blends with natural gas addition	Engine speed, CNG flow rate, fuel density, cetane number	Vibrations & speed	Levenberg-Marquardt (LM) algorithm	R^2-0.95
58	Biogas-diesel	Biogas flow rate, engine load	BTE, HC, CO, NOx and smoke	autoregressive integrated moving average (ARIMA)	R^2-0.98
59	Bio-oil/diesel/TBHQ	CR, engine load	BTE, BSFC, HC,CO,CO_2 and NOx	feed forward back propagation algorithm	(MAAE)-0.552%

It is clear from the open survey that limited research studies were performed on the usage of ANN based model for forecast and optimization of combustion emission properties and performance of engine and for dual fuel engines at various engine working conditions. The usage of Artificial Neural Network-hybrid Harris Hawks and whale optimization algorithm (ANN-HHOWOA) for prediction of performance and emission characteristics of dual fuel engine powered by biofuels has not been explored so far. To fill this void, an attempt has been made to develop the hybrid ANN based algorithm as an important step towards accurate predication and optimization of performance and emissions characteristics of biodiesel-biogas fuelled dual fuel diesel engine at various engine characteristics.

2.1. Problem Statement

In the light of the comprehensive and important literature survey and the ensuing investigation, problem statement of the present research was formulated. The current work plans to manage the impact of fuel injection timings on engine performance parameters and exhaust emissions. From the literature survey, it has been observed that ANN modeling with bio diesel-blendsalong with biogas on CI engine were scantly reported. The current work involves modeling and optimization of compressed ignition engine performance and emission characteristics for bio-fuels using ANN networks. On the basis of this valuable information, the following objectives are envisaged for the present research work.

1. To investigate the compatibility of various algorithms suitable for dual fuel engine.
2. To implement modern optimization algorithms for estimation of performance and emission characteristics.
3. To evaluate the system performance and validate with the experimental results.

CHAPTER-3
METHODOLOGY

In this chapter, the methodology has been proposed in order to accomplish enlisted objectives. It has been observed that the designed objectives be achieved after having dual fuel experimental setup and software tool such as MATrix LABoratory (MATLAB). MATrix LABoratory is a technical computing programming language designed for engineering and scientific applications. The experimental setup helps in collecting data which further help in optimizing the output of the software.

The purpose of the research work is to design a duel fuel engine which will operate on bio-fuels with the combination of B20, B40, B60 and biogas that flows on a constant rate. The research data is collected by varying injection timings i.e, 23° BTDC, 26° BTDC and 29° BTDC.

3.1 Materials and Methods

Biogas was produced by anaerobic digestion process utilizing kitchen organic waste and cow dung by means of feedstock in a preset arena biogas plant of $6m^3$ volume. The biogas plant is shown in Figure 3.1. Biogas composition was checked with biogas analyzer which is tabulated in Table 3.1. Gas was produced in biogas digester, which was later given as an input to the diesel engine. The baseline diesel was purchased from the wholesale store of Indian oil Limited near campus. Non-edible rice bran oil was used to generate biodiesel. The significant properties of the diesel, biogas and various biodiesel-diesel blends (B20/D80, B40/D60 and B60/D40) were considered in accordance with ASTM-D6751 stipulations which are shown in Table 3.2. The energy content of the biodiesel (41.53 MJ/kg) was established to be lesser than then that of the diesel (43.40 MJ/kg). The flash point, calorific value, cloud point and fire point of diesel-biodiesel blends were noted to reduce when biodiesel was added.

Figure 3.1: Fixed dome biogas plant of capacity $6m^3$

Table 3.1: Composition of Biogas (% Vol.)

Chemical Formula	Components	%age
H_2O	Water	0.35%
N_2	Nitrogen	1-3%
H_2	Hydrogen	4-10%
CO_2	Carbondioxide	35-45%
CH_4	Methane	55-65%
H_2S	Hydrogensulphide	Traces

Table 3.2: Test fuel properties

Property	**Diesel**	**Biogas**	**B20/D80**	**B40/D60**	**B60/D40**	**ASTM Limits**
Density (kg/m^3)	835	1.07	842	850	857	900
Viscosity (cSt)	2.72		3.64	4.26	4.96	1.9–6
LCV (MJ/kg)	43.40	22.57	42.72	42.04	41.36	>33
Flash Point (^oC)	73		89	105	121	>130
Fire Point (^oC)	78		96	114	130	-
Cloud Point (^oC)	-8		-6	-4	-2	-2 to 12

3.2 Experimental Framework

In the experimental setup as shown in Figure 3.2, the single cylinder, four stroke engine is used to collect the data. The conventional engine is being converted to the dual fuel engine with little modification. This waste can be cow dunk cakes, kitchen waste and man waste. This engine is further connected with the load box to calculate the voltage and current outputs with varying load. The internal combustion engine is fitted with 100 ml pipette through which the diesel is supplied to the engine. After, every 10 ml consumption of diesel, the output parameters are calculated at varing load and injection pressure. The engine is also fitted with air surge box from where engine sucks in the air. This is further connected with the biogas supply unit.

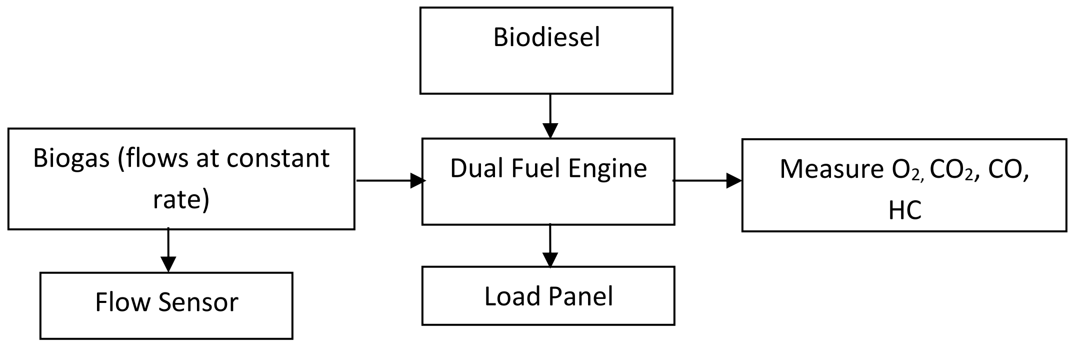


Figure 3.2: Experimental setup

Figure 3.3 and 3.4 show the graphical arrangement and actual investigational test rig, which comprises of single cylinder, four-stroke, and direct injection diesel engine cooled by using air is utilized for the research. The numerous stipulations of the utilized diesel engine are demonstrated in Table 3.3. An invariable speed of 1500 rotations per minute was conserved during the course of the investigation. The engine was fitted out with an alternator type dynamo-meter fixed with electrical load bank and adjustments to regulate loads of engine. To obseve temperatures of inlet air, engine oil and outlet gases, the thermocouples of K type were utilized. Consumption of liquid fuel was checked by calibrated burette (volumetrically) and stopwatch. To work in dual fuel mode, the engine was suitably modified. To avoid backfiring of basic fuel, a fire entrap was made available.

The biogas flow meter (Make: Itron, Model: Gallus 2015) was connected prior to inlet manifold to adjust the flow of biogas. To damp the oscillations in intake stroke of engine, a surge tank was fitted in conduit. The biogas flow rate was varied from 1.5 to 3.5 kg/h, fixed at various levels through engine load spectrum.

Exploration and examination of dual fuel and manual diesel engine, engine load is modified from twenty to hundred percentages at a speed of 1500 rotations per minute. The injection timings were established at various levels i.e. 23^o BTDC, 26^o BTDC (standard) and 29^o BTDC. The injection timings were altered as per given recommendations [28]. Before starting the trials, the IC-engine was controlled according to the references of manufacturer recommendations. Primarily, the engine was energized with traditional diesel and heated up for half an hour uninterruptedly up to the oil and cooling water temperatures becomes almost equal to reach stable state.

The exhaust gas analyzer (Make: AVL Digas 444N) was utilized to observe the emissions of unburned remains of hydrocarbon (HC), carbonmonoxide (CO), carbondioxide (CO_2) and oxygen (O_2) whose technical specifications are depicted in Table 3.4. The concentration of HC is in ppm whereas CO, O_2 and CO_2 are in (% volume). The exhaust tailpipe harmful gasses were calculated as per ASTM D6522 standards. Figure 3.4 depicts the gas analyzer utilized in the investigation.

3.3 Uncertainty Analysis

All type of assessing instruments put up certain quantity of error which could emerge from various working conditions, inspection, standardization, trial planning, and environments. Therefore, all the research was functioned in a way that the values were simulated more than twice and to find an equitable value, the mean of all arithmetic values were projected. The overall uncertainty is calculated by using succeeding relationship.

$$\text{Overall uncertainty} = \sqrt{\begin{matrix}(\mathrm{BTE})^2 + (\mathrm{CO})^2 + (\mathrm{CO2})^2 + (\mathrm{HC})^2 \\ +(\mathrm{O2})^2 + (\text{Engine load})^2\end{matrix}} \tag{3.1}$$

$$= \sqrt{(1.2)^2 + (1.3)^2 + (0.45)^2 + (0.35)^2 + (0.65)^2}$$

= ± 1.96, the values lies in the acceptable range of the experiments

Figure 3.3: Actual experimental test rig

Description of engine set up: (1) Internal Combustion Engine (2) Dynamo,(3) Resistive load bank (4) Electric control panel (5) Air surge tank (6) Biogas flow meter (7) Digital tachometer (8) Exhaust gas temperature thermocouple (9) AVL Digas 444 N exhaust gas analyzer (10) Probe (11) Fuel measuring burette (12) U tube manometer.

Table 3.3: Technical details of IC-engine

Make and Model	KirloskarIndia Ltd. (DAF 8)
Bore/stroke (mm)	95/110
Rated Power (kW)	5.9
Rated Speed (rev/min)	1500
Number of Cylinder	Single

Compression Ratio	17.5:1
Cooling Type	Air Cooled
Lubrication Type	Forced Feed
Displacement Volume (cc)	780
Fuel Injection Pressure (bar)	200
No. of holes (nozzle injector)	4
Static Injection timing (^{o}BTDC)	26 (standard)
Inlet Valve Opening (^{o}BTDC)	4.5°
Inlet Valve Closed ($^{\circ}$ ABDC)	35.5
Exhaust Valve Opening ($^{\circ}$ BBDC)	35.5
Exhaust Valve Closed ($^{\circ}$ ATDC)	4.5
Alternator Specifications	
Dynamometer (Rating)	Electrical Alternator (AC), 230 V/5 kVA Phase 01 (Single)
Speed Rating (rev/min)	1500
Rated Frequency	50Hz
Power Factor	1

Table 3.4. Technological specifzication of AVL Digas 444 N Analyzer

S.No.	Measured Parameter	Range	Accuracy	Resolution
1	Oxygen	0-22% Vol.	±0.1%vol	0.01% vol
2	Carbon Monoxide	0-10 Vol.	±0.03%vol	0.01% vol
3	Carbon Dioxide	0-20 Vol.	±0.5%vol	0.1% vol
4	Hydrocarbon	0-20,000 ppm	±10 ppm	Upto 2000ppm, 1ppm >2000ppm, 10ppm
5	Engine Speed	400-6000 rpm	±1%	1 rpm
6	Lambda (λ)	0-9.999	---	0.001

3.4 Performance Characteristics

The performance parameters were evaluated by considering the following calculations;

$$\text{Brake Power (kW)} = \left[\frac{\text{Voltage}\times\text{Current}}{\eta\times 1000}\right] \quad (3.2)$$

where η is generator efficiency, normally taken as η=0.8

For single fuel mode:

$$\text{Brake thermal efficiency (\%)} = \left[\frac{\text{Brake Power}\times 3600}{\text{mf}\times\text{LCV}}\right]\times 100 \quad (3.3)$$

For dual fuel mode:

$$\text{Brake thermal efficiency (\%)} = \frac{\text{Brake Power}\times 3600\times 100}{(m_{bg}\times LCV_{bg} + m_{bd}\times LCV_{bd})} \quad (3.4)$$

Where m_{bg} & m_{bd} represents the mass flow of biogas (Kg/hr) and pilot liquid flow (Kg/hr)

Whereas LCV_{bg} & LCV_{bd} depicts the heating value of biogas (kJ/kg) and pilot liquid fuel (kJ/kg)

3.4.1 Brake Thermal Efficiency (BTE)

It is also termed as brake power of a thermal engine. It defines the efficiency of thermal engine which can be measured using equation (3.4). BTE is utilized to estimate and evaluate that how an engine by burning fuel generates mechanical energy efficiently.

Figure 3.4: Experiment setup

3.5 Training and Optimization

In the training phase, those exact class for every record is well-known accordingly the yield nodes can be assigned adequate qualities - 1 for those nodes relating of the right class, and 0 for those others.

3.5.1 Learning Process

In this procedure information cases such that rate load, biogas bay quantity, infusion timing and so forth throughout this way, observing the weights connected with those enter qualities are balanced each time. All considered cases are presented; the procedure begins once more. A throughout this taking in phase, the characterized system takes in toward changing the weights with the goal so as to be able to predict the ideal output. With this process, those introductory weights would decide haphazardly. Weights are used in hidden layers. After this complete procedure, the obtained outputs are compared with the desired results. Errors would afterward propagated once again through those system, bringing on the framework to conform those weights to the next record will be transformed. The same data set is processed many times during the training of network as the connection weights are refined continually.

Proposed system has 3 layes, hidden, input and output. All these layers are connected with each other. Every layer will be completely associated with succeeding layer. The training process begins for those computed contrast between the genuine outputs and the fancied outputs.

3.5.2 Process Flow

The collected data from the experimental setup will be used to train the neural network. After training the neural network using back propagation the output from the neural network will work as input to the genetic algorithm. These input values will work as seed values for genetic algorithm initialization. The complete flow diagram of the methodology is shown in Figure 3.8.

3.5.3 Flow Chart

The data will help in training the neural network, testing and for efficient optimization. After training the neural network the validation is to be done, in this process, the system output will be compared with the real experimental data to check the algorithm accuracy.

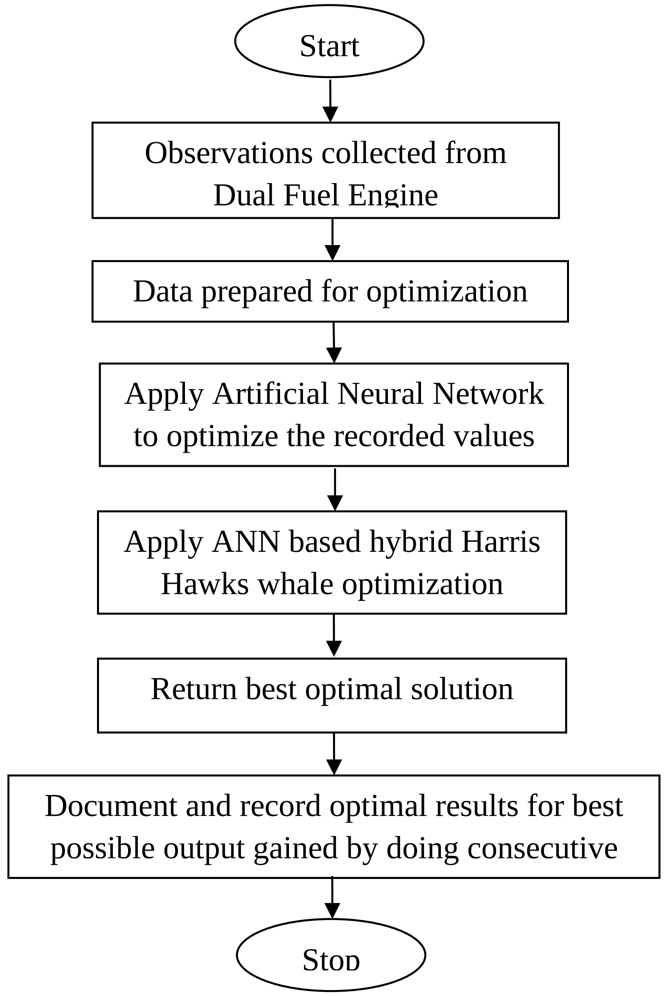


Figure 3.5: Process flow chart

3.6 Artificial Neural Network based hybrid Harris Hawks and Whale Optimization Algorithm (ANNHHOWOA) for optimizing dual fuel engine output characteristics

To find the best possible solution for real engineering problems, utilization of meta-heuristic algorithm has become unavoidable. This motivates to use ANN and apply it to find optimal solutions for input parameters. The learning algorithm is describes as follows:

a) Set values of weights w and bias b.

b) To obtain predicted division of data, all observations are iterated.

c) Calculate values of solutions in each iteration.

d) Calculate L(w,b) where w can be computed as:

1. $w_1 = w_1 - \eta \Delta w_1$
2. $w_2 = w_2 - \eta \Delta w_2$

   …….

   $w_n = w_n - \eta \Delta w_n$

Until the all constraints are fulfilled.

Algorithms that are based on animal behavior are utilized to get best possible solution.

The data acquired from the experimental setup is optimized using ANNHHOWOA hybrid algorithm to find optimal solution to achieve High BTE and Less emission.

3.7 Pseudocode of ANN-hybrid Harris Hawks and Whale Optimization Algorithm

Inputs:

Set and define Input parameters Search agents, current iteration iter, maximum number of iterations T1, population size N and EG for ANN, HHO and WOA.

By using feed forward network calculate all inputs. Along with this also calculate the nearest possible output values.

Initialize population set P_i (i=1,2,3…………,N)

until(t1 < T1)

Find fitness value of Harris Hawk movement for each iteration.

Set parameter A_{rabbit} to define the appropriate location of rabbit.

For each Harris Hawk (P_i)

Do

EP10 = 2rand()-1

K=2(1-rand()) to update energy at initial condition EP_0

Upgrade value of EP1 by using equation (1.4)

Translation from phase of Exploration and phase of Exploitation

if $|EP1| \geq 1$ then

Upgrade location by using equation (1.5)

Upgrade location vector by using equations (1.1) and (1.2)

if $|EP1| < 1$ then

// Soft Encircle to the prey

if($E_{r1} \geq 0.5$ and $|EP1| \geq 0.5$) then

Upgrade position vector by using equation (1.5)

//Hard Encircle

elseif ($E_{r1} \geq 0.5$ and $|EP1| < 0.5$) then

Upgrade position vector by using equation (1.7)

// Soft Encircle of prey with fast dives

elseif ($E_{r1} < 0.5$ and $|EP1| \geq 0.5$) then

upgrade position vector by using equations (1.8) and (1.9)

// Hard Encircle with fast dives

elseif ($E_{r1} < 0.5$ and $|EP1| < 0.5$) then

upgrade position by using equations (1.10) and (1.11)

end end end

By using HHO algorithm, Set initial location of search agents.

Set t1=1

Do

By using objective function calculate every search agent.

Upgrade value of optimal fitness outcome X^*.

Update values of random numbers ze_1,ze_2,ze_3,ze_4.

if(p1<0.5) then

if(A1≤1) then

Update location of current attacking agent by using equation (1.12)

else

Update location of current attacking agent by using equation (1.21)

else

Update location of current attacking agent by using equation (1.16)

until(t1 < T1)

Compute and obtain optimal outcome.

Note and document values of standard deviation, mean, worst and best fitness outcomes.

Document best possible result value obtained after successive uninterrupted trails.

3.7.1 Flow Chart of Proposed Algorithm

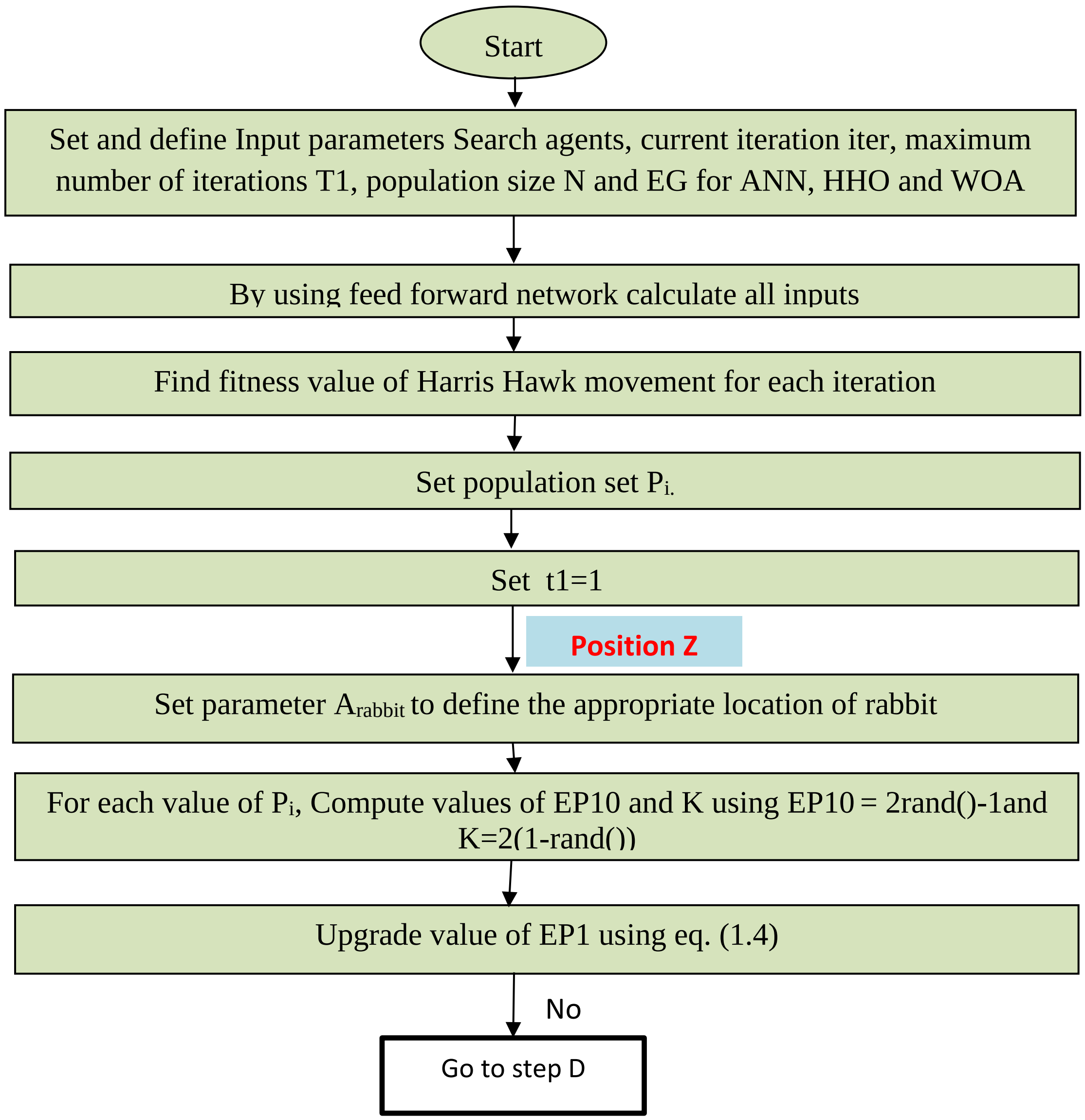


Figure 3.6: Flow chart of proposed ANN-hybrid Harris Hawks and Whale Optimization Algorithm (Initial part1)

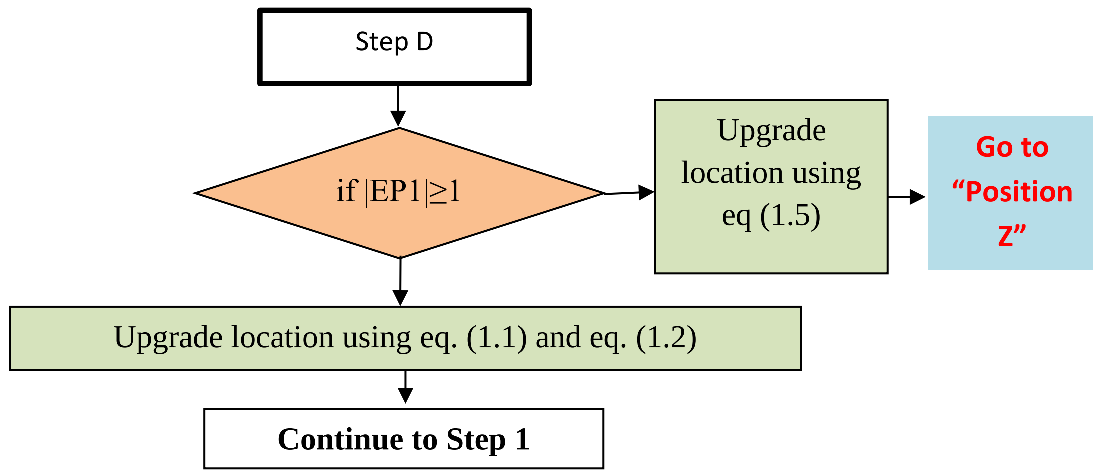


Figure 3.7: Flow chart of proposed ANN-hybrid Harris Hawks and Whale Optimization Algorithm (Initial part2)

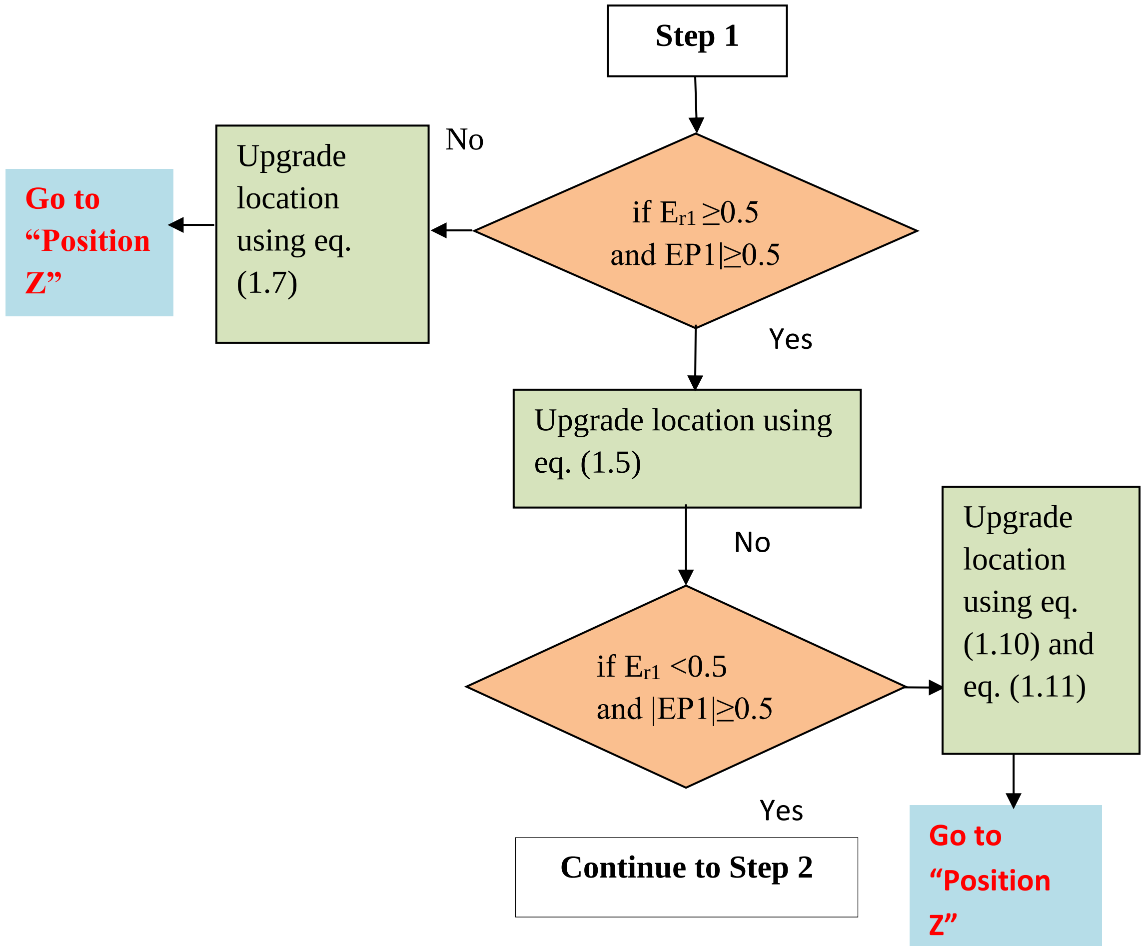


Figure 3.8: Step 1 of Flow chart of proposed ANN-hybrid Harris Hawks and Whale Optimization Algorithm

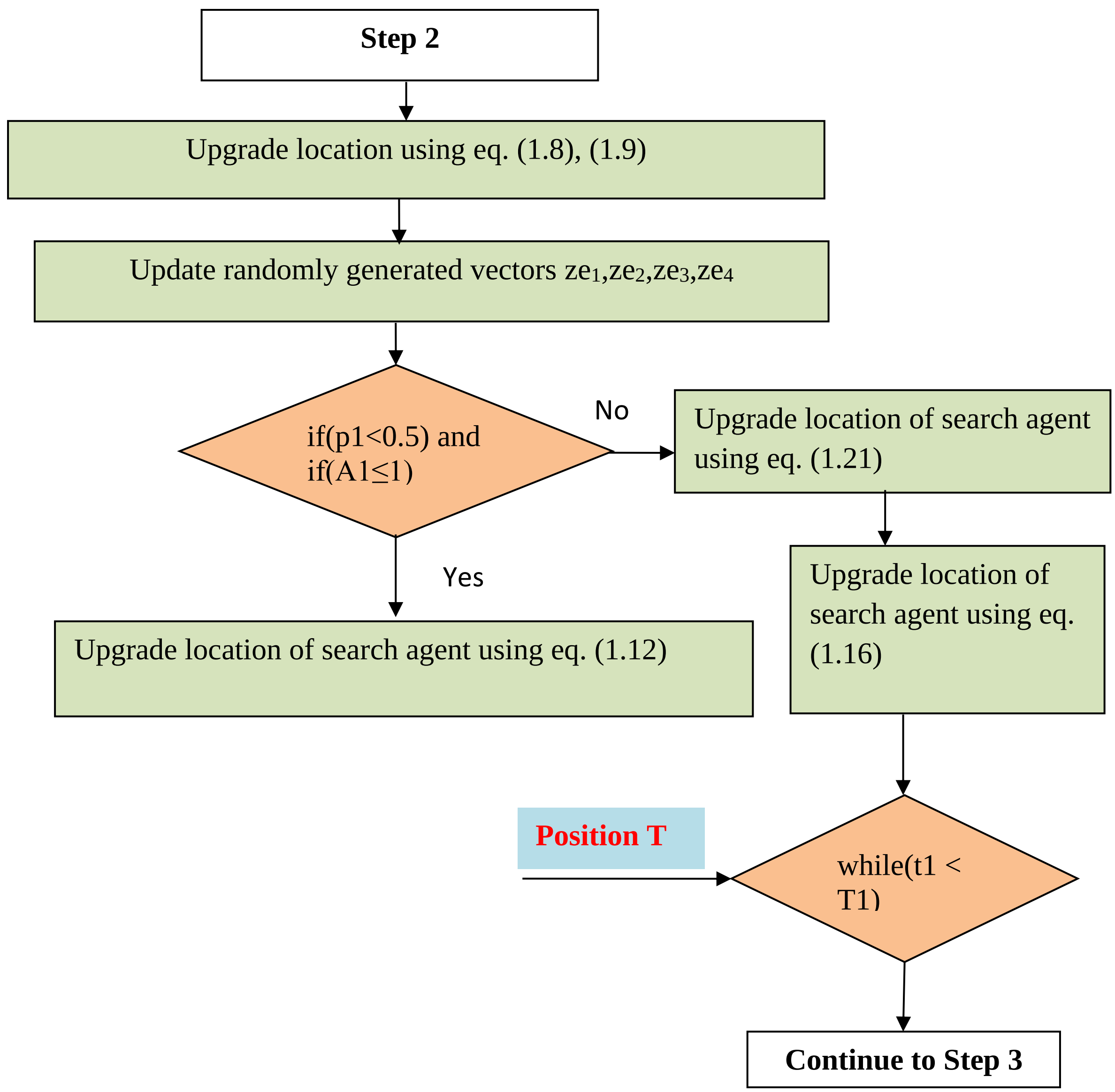


Figure 3.9: Step 2 of Flow chart of proposed ANN-hybrid Harris Hawks and Whale Optimization Algorithm

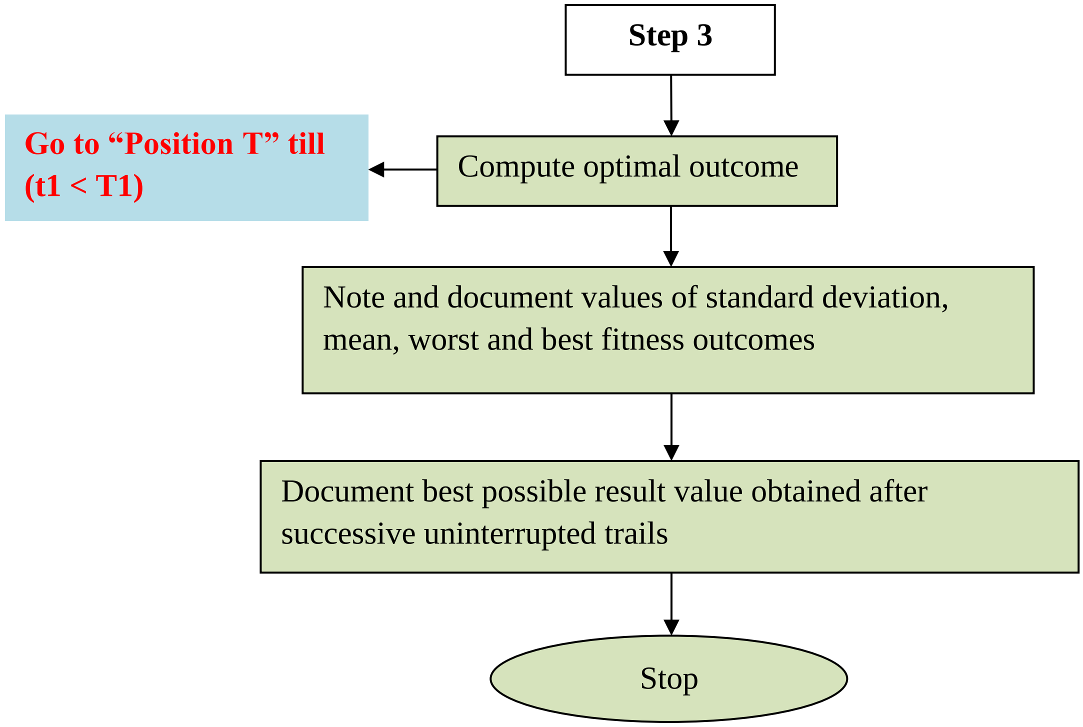


Figure 3.10: Step 3 of Flow chart of proposed ANN-hybrid Harris Hawks and Whale Optimization Algorithm

3.8 Benchmark Functions

Different fixed, unimodel and multimodel [60] benchmark standards are taken into consideration as benchmarks to examine and monitor the utility and competence of hybrid ANNHHOWOA Algorithm to find best possible solution when applied on data gathered from experimental setup.

CHAPTER-4
RESULTS

In this research a hybrid ANN-HHOWOA algorithm is used to validate the data collected from experimental setup. In IC engine our target was to achieve maximum BTE and minimum emissions. To achieve this target for different fuels and at different injection timings we need to use optimization technique. To get the desired target for different inputs we will take the help of ANN-HHOWOA. ANN alone gives the good results if the known input values are used to train the ANN network and reproduce the output of known inputs. At the same time if unknown input values are entered in the system then the result might be, not predictable. To achieve the efficiency for the unknown inputs, meta-heuristic algorithm is a better solution to be used. In this research the hybrid model of ANN-HHOWOA was used to optimize the desired output. In this research the experimental IC engine data is used, the 70% data was utilized to train the network and 30% was used for testing and validating the algorithm. During the validation the result comes out to be 98% accurate, this means the output for different unknown values with the new algorithm achieved nearly 98% accurate. This research will further help the researchers to design the IC engine with different bio-blends to predict the engine output characteristics before designing the actual engine, which further helps in investing huge amount of money.

From the gathered data using experimental setup the graphical relation among various parameters shown as follows:

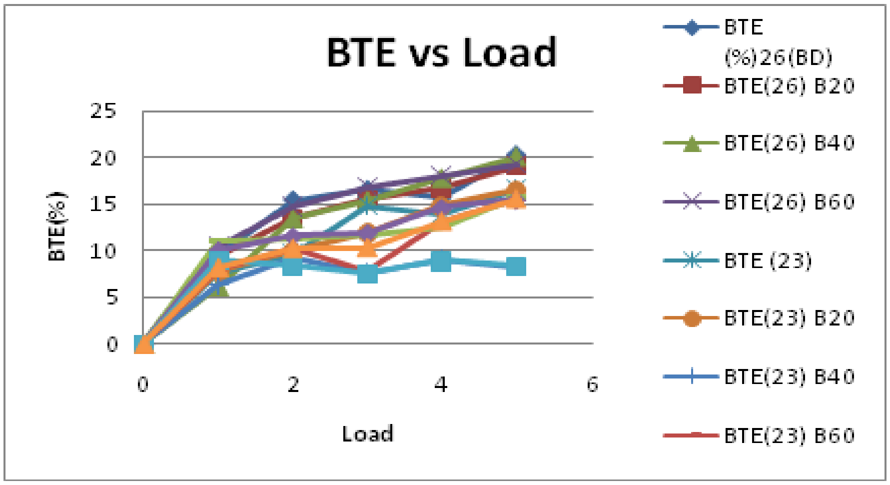


Figure 4.1: Deviation of BTE vs engine Load

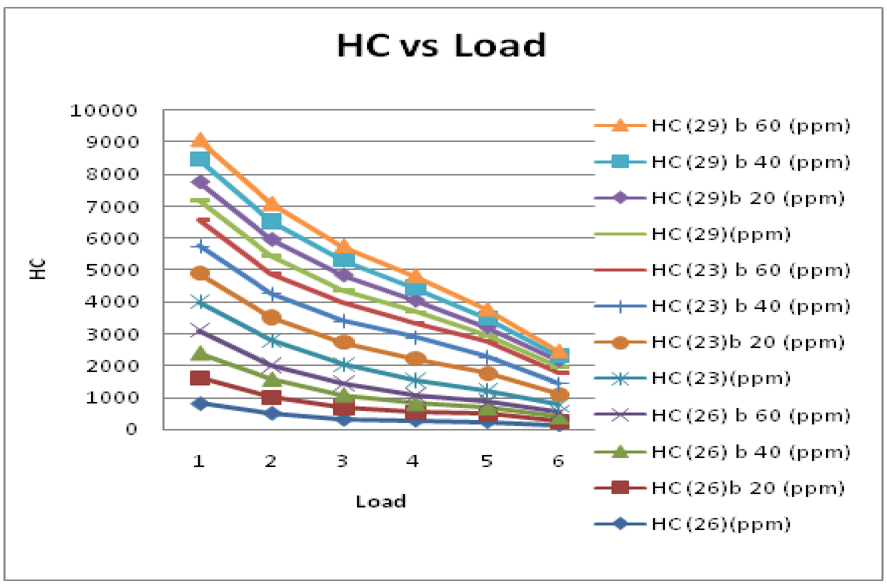


Figure 4.2: Deviation of HC vs engine Load

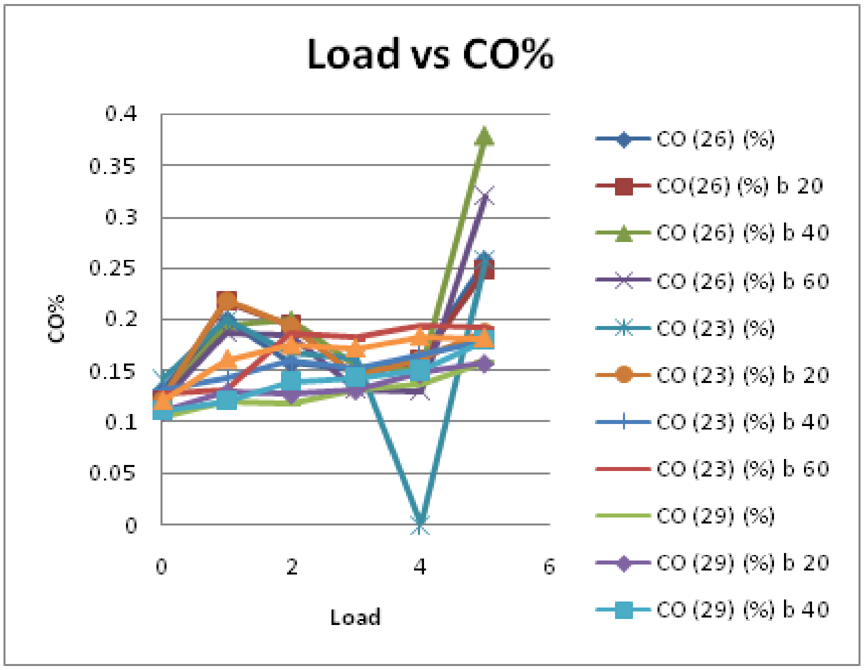


Figure 4.3: Deviation of CO vs engine Load

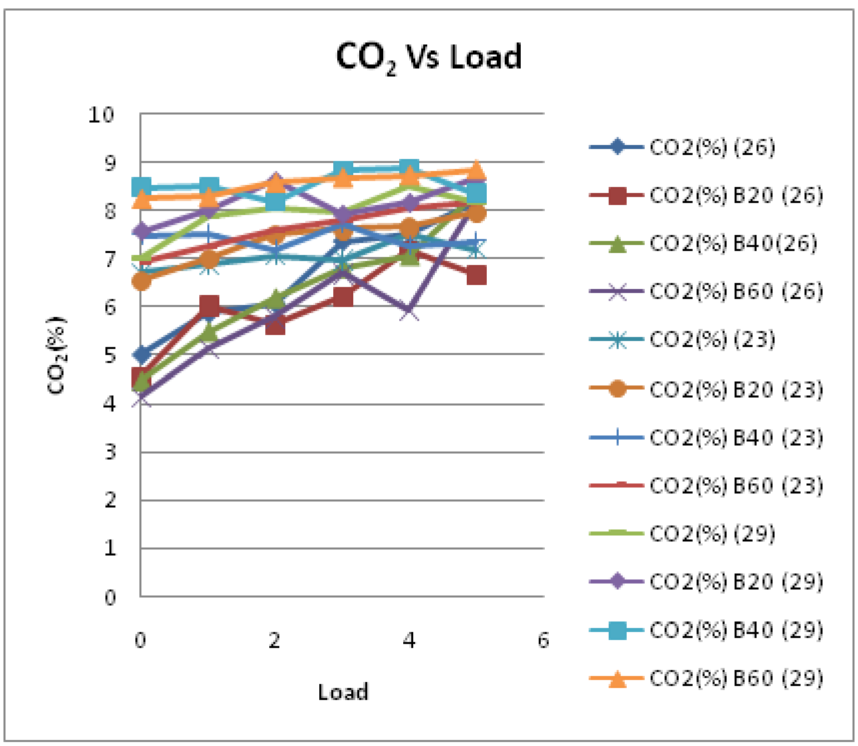


Figure 4.4: Deviation of CO_2 vs engine Load

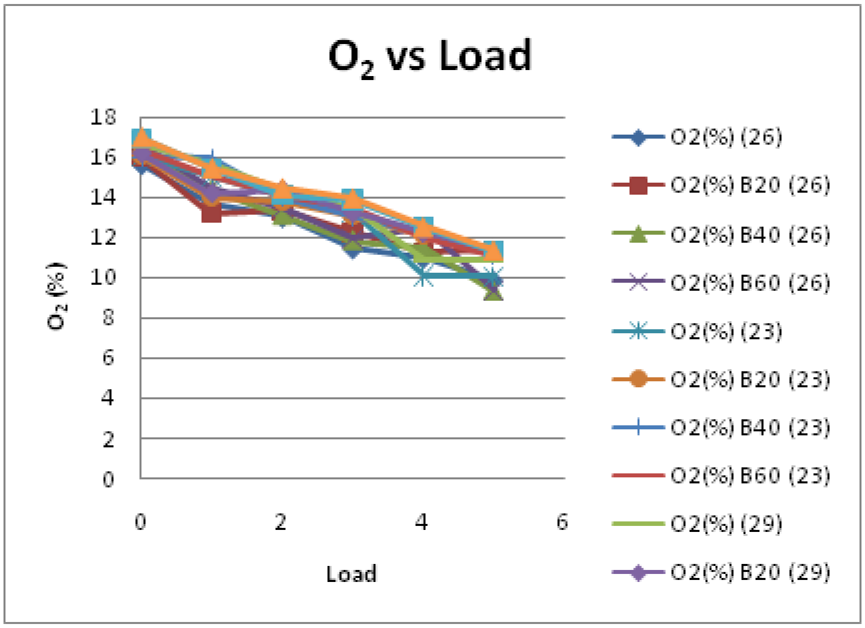


Figure 4.5: Deviation of O_2 vs engine Load

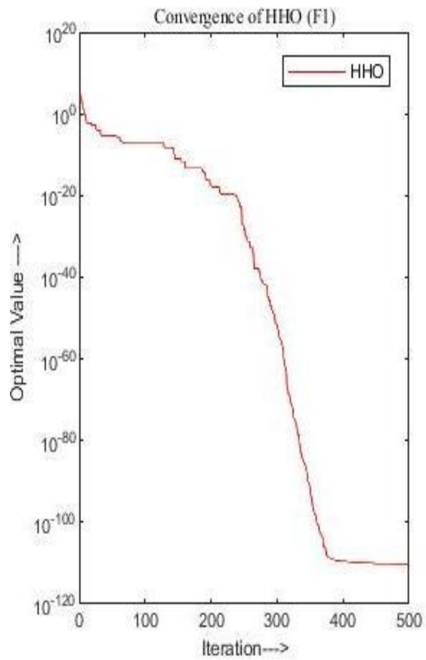
The overall uncertainty is calculated by using succeeding relationship

From the eight hundred observations taken it is concluded that highest BTE is achieved with 26 ^{o} BTDC using normal diesel + biogas. In addition to this, minimum CO level is achieved at 29 ^{o} BTDC using normal diesel + biogas. Furthermore Minimum CO_2 level is achieved at 26 ^{o} BTDC using B60 bio-diesel combination with biogas inlet. Every-time the target of the proposed work is to achieve maximum BTE and minimum emissions. This is possible at different type of fuels and at different BTDC. To solve this problem, optimization is the better solution to achieve the desired targets. The algorithm Artificial Neural Network hybrid Harris Hawks and whale optimization algorithm (ANNHHOWOA) is made and tested to achieve the same. This ANN hybrid approach help in getting the optimal solution to the unknown inputs.

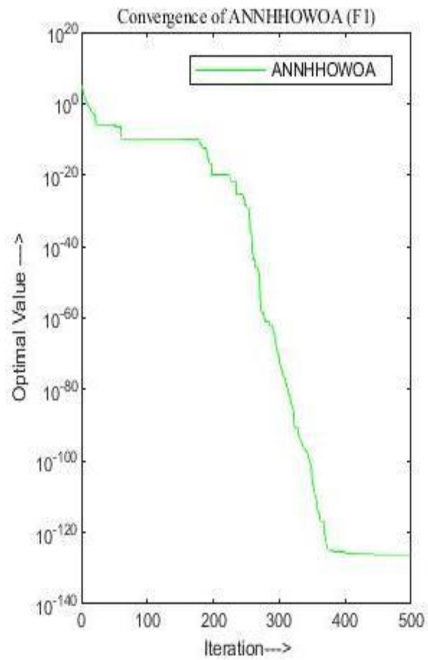
An Artificial Neural Network based hybrid HHOWOA algorithm was designed and used based on previous literature and utilizing the data recorded in the experiments to envisage the performance and emissions characteristics of biogas-biodiesel dual fuel engine. Engine operating load, biodiesel blends and injection timings and biogas flow rate were chosen as the input factors while i) Carbon dioxide ii) HC iii) Carbon monoxide iv) Brake Thermal Efficiency were selected as output targets.

To validate the results obtained and to find the optimal solution, total five hundred trial runs are performed by using ANNHHOWOA algorithm. Best, Average, Worst values, standard deviation values are computed against objective functions. unimodal standard functions from Func1-Func7, multimodel standard functions from Func8-Func11 and fixed functions from Func12-Func20 are considered to endorse the proposed algorithm. The calculated results are then compared with simple HHO algorithm. HHO is considered to be an algorithm that gives better results than the other existing meta heuristic algorithms. From the comparison it can be depicted that hybrid ANNHHOWOA gave better results than HHO.

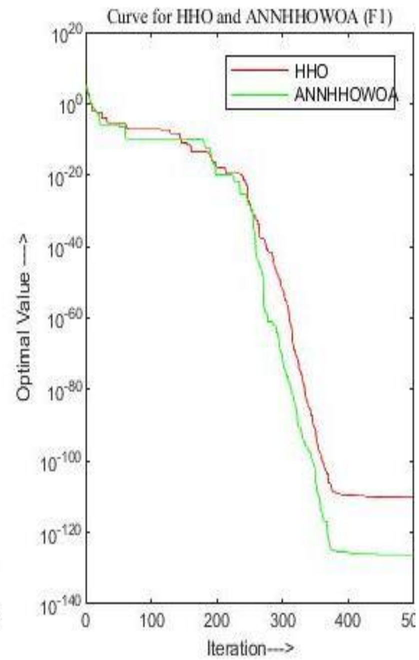
4.1 Convergence Graphs using unimodal benchmark functions



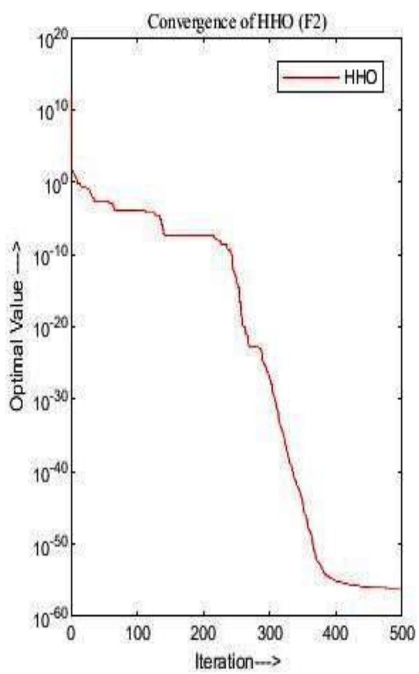
A



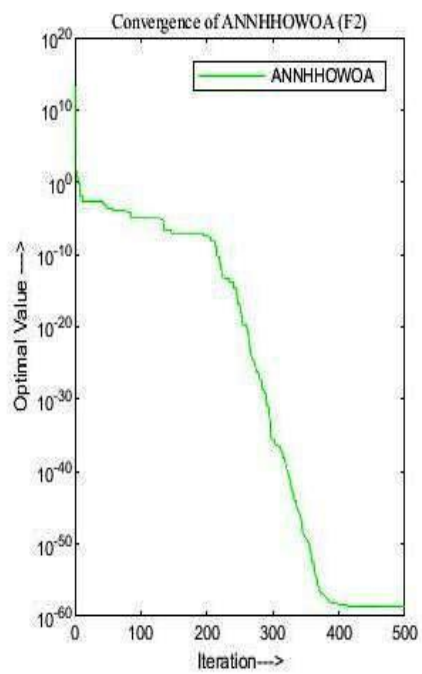
B



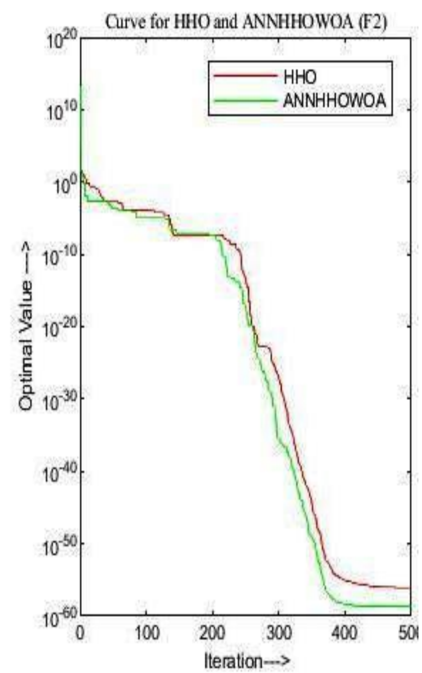
C



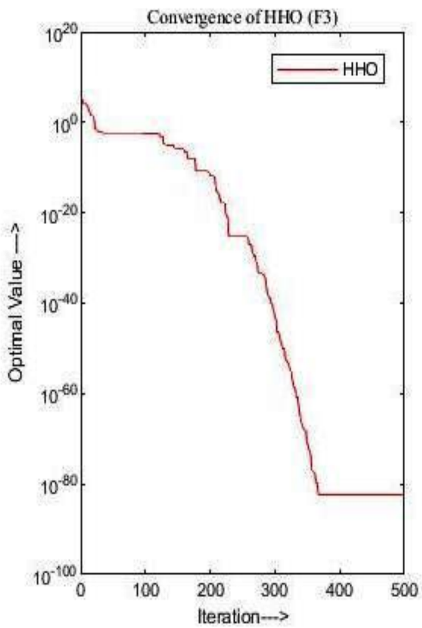
D



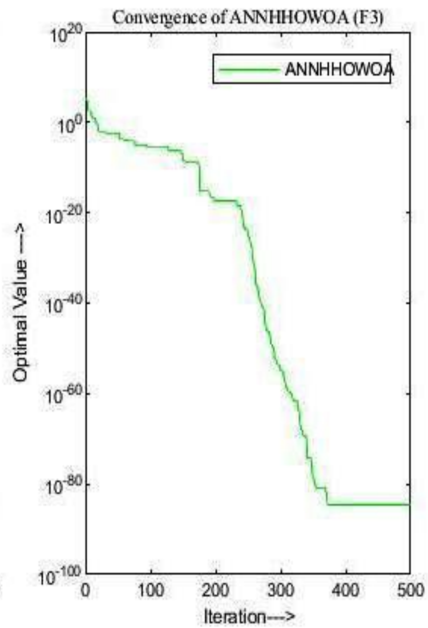
E



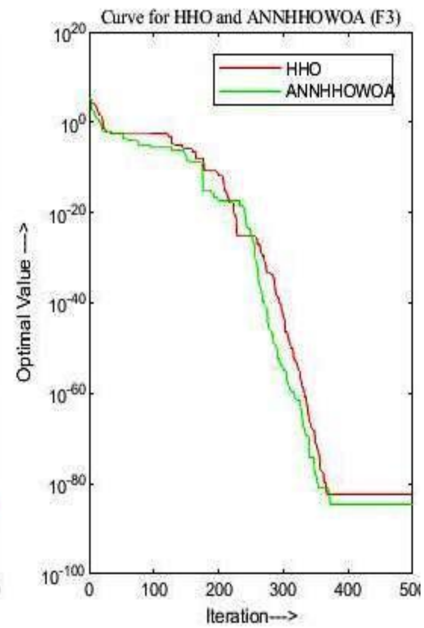
F


Convergence of HHO (F3)
HHO
Optimal Value --->
Iteration--->

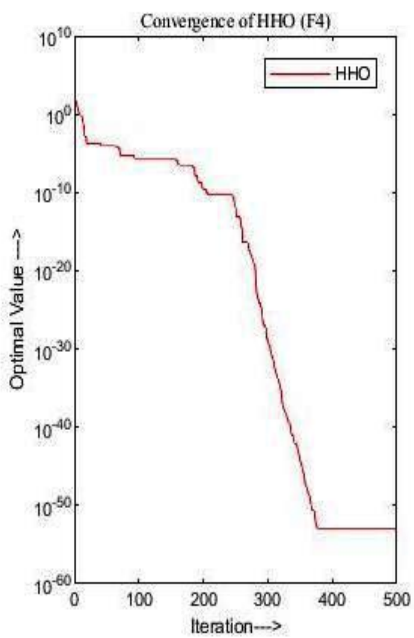
G


Convergence of ANNHHOWOA (F3)
ANNHHOWOA
Optimal Value --->
Iteration--->

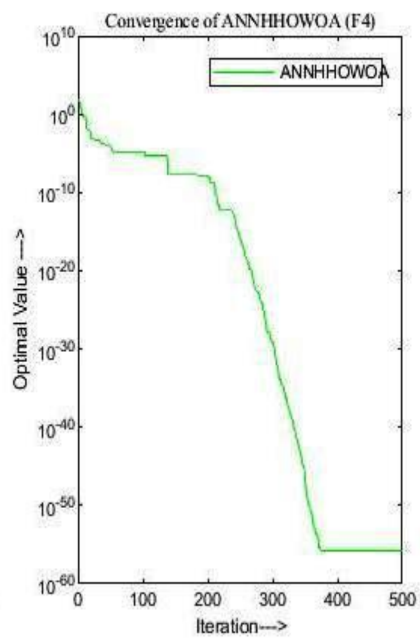
H


Curve for HHO and ANNHHOWOA (F3)
HHO
ANNHHOWOA
Optimal Value --->
Iteration--->

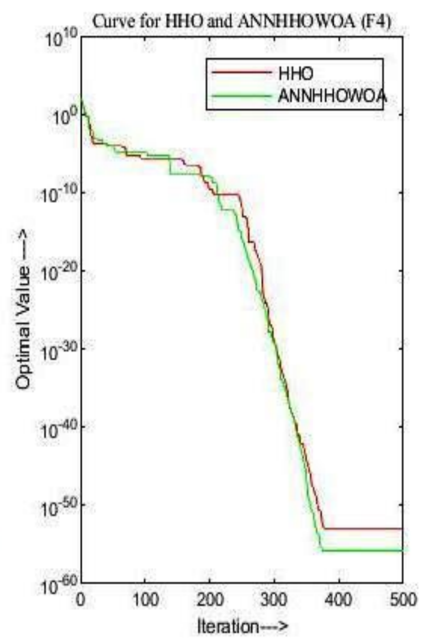
I


Convergence of HHO (F4)
HHO
Optimal Value --->
Iteration--->

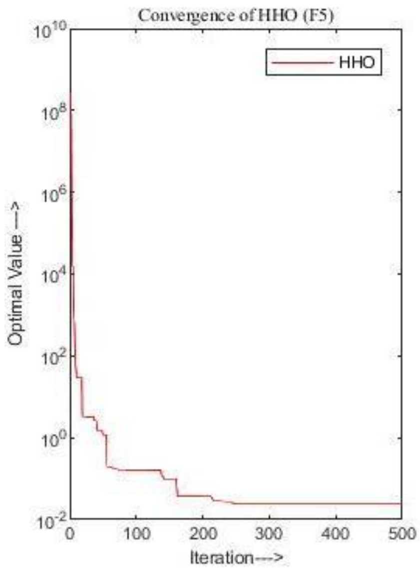
J


Convergence of ANNHHOWOA (F4)
ANNHHOWOA
Optimal Value --->
Iteration--->

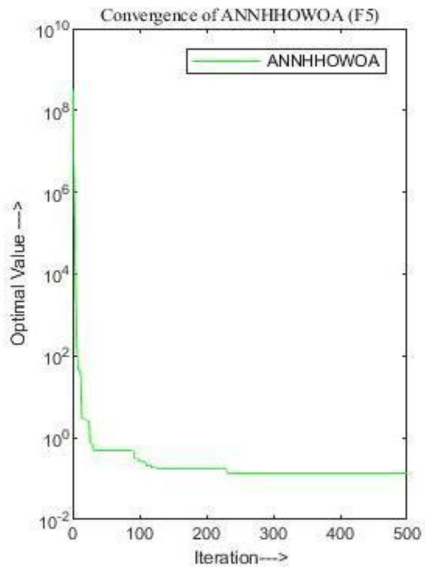
K


Curve for HHO and ANNHHOWOA (F4)
HHO
ANNHHOWOA
Optimal Value --->
Iteration--->

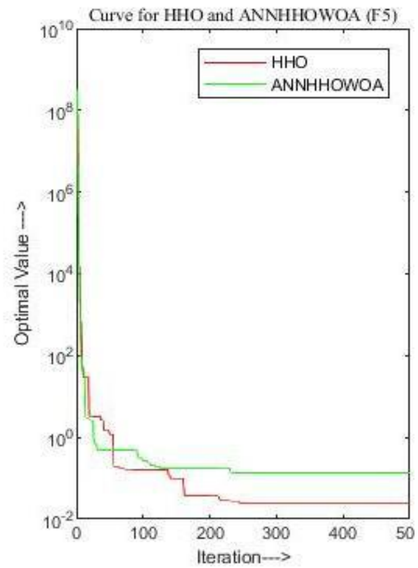
L


Convergence of HHO (F5)
HHO
Optimal Value --->
Iteration--->

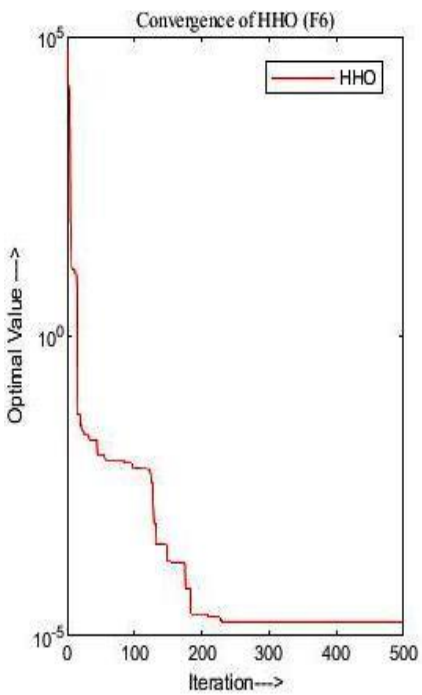
M


Convergence of ANNHHOWOA (F5)
ANNHHOWOA
Optimal Value --->
Iteration--->

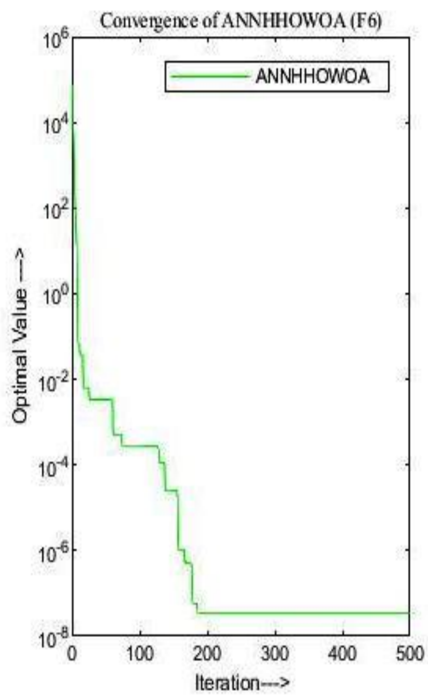
N


Curve for HHO and ANNHHOWOA (F5)
HHO
ANNHHOWOA
Optimal Value --->
Iteration--->

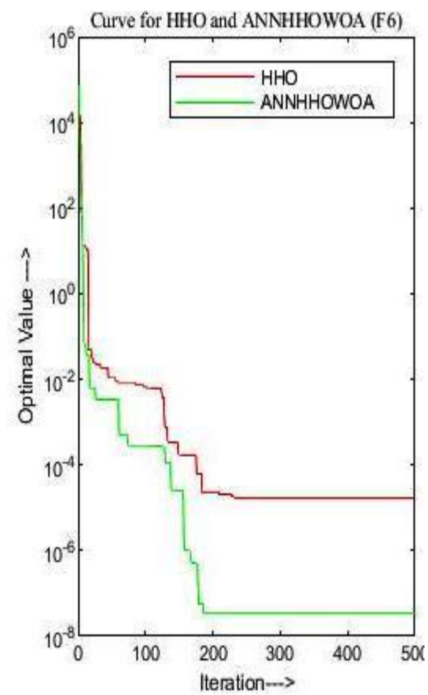
O


Convergence of HHO (F6)
HHO
Optimal Value --->
Iteration--->

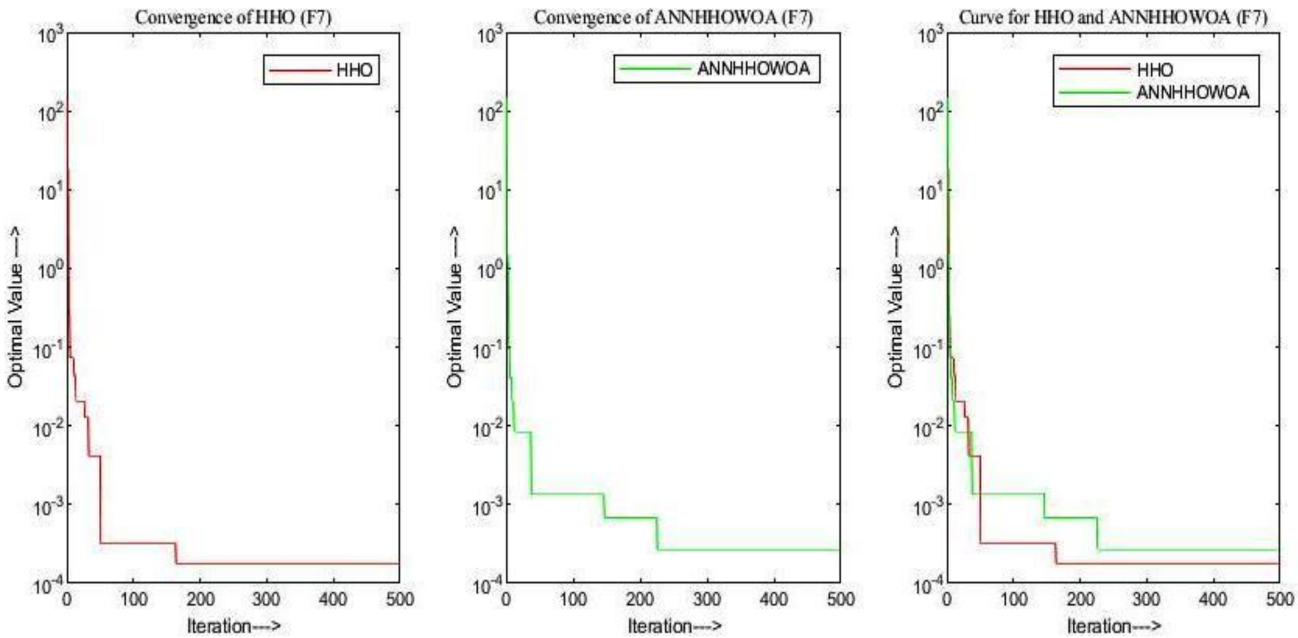
P


Convergence of ANNHHOWOA (F6)
ANNHHOWOA
Optimal Value --->
Iteration--->

Q


Curve for HHO and ANNHHOWOA (F6)
HHO
ANNHHOWOA
Optimal Value --->
Iteration--->

R

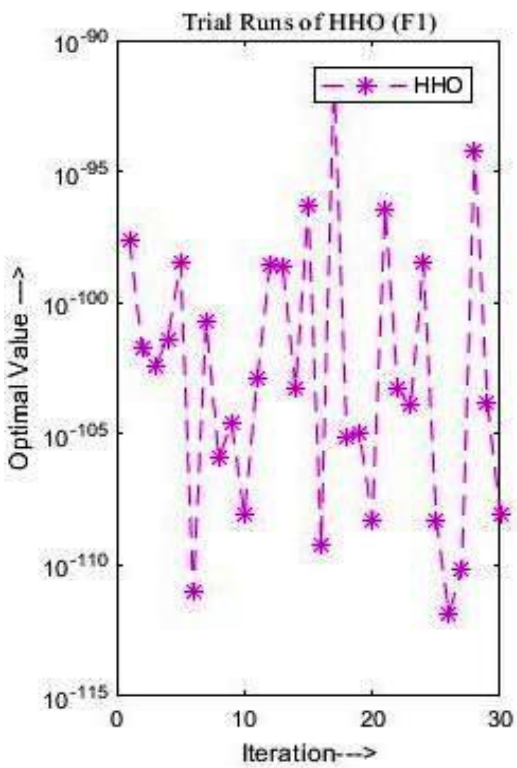


S T U

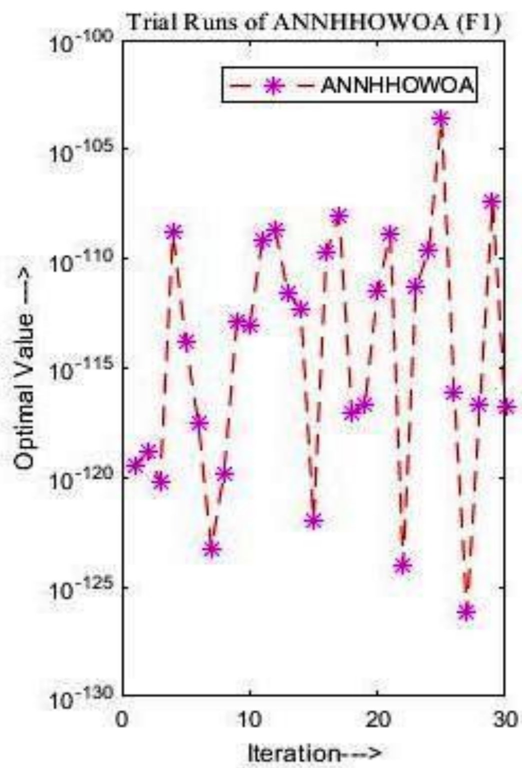
Figure 4.6: Graphs from (A)-(U) shows convergence graphs of HHO, ANNHHOWOA and their comparative graph for unimodal benchmark functions

All these graphs are plotted by taking number of iterations along x-axis and an optimal value generated along y-axis for unimodal benchmark functions. It can be clearly depicted that results generated by ANNHHOWOA are better than HHO.

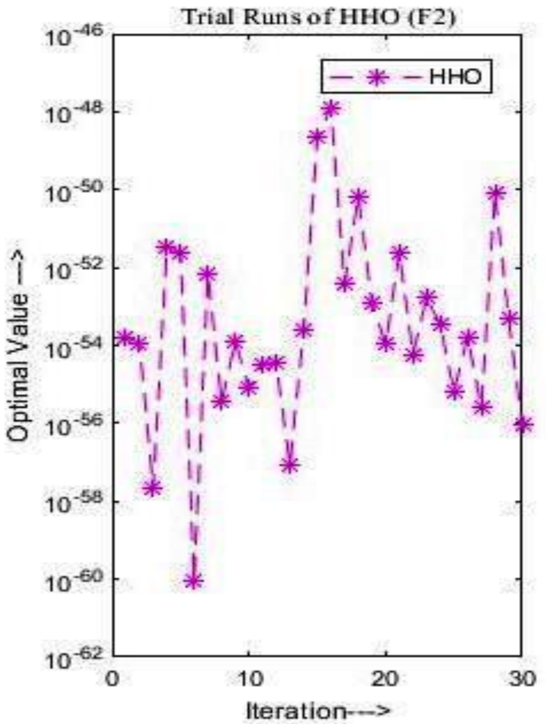
4.2 Graphs of Trail run using unimodal benchmark functions



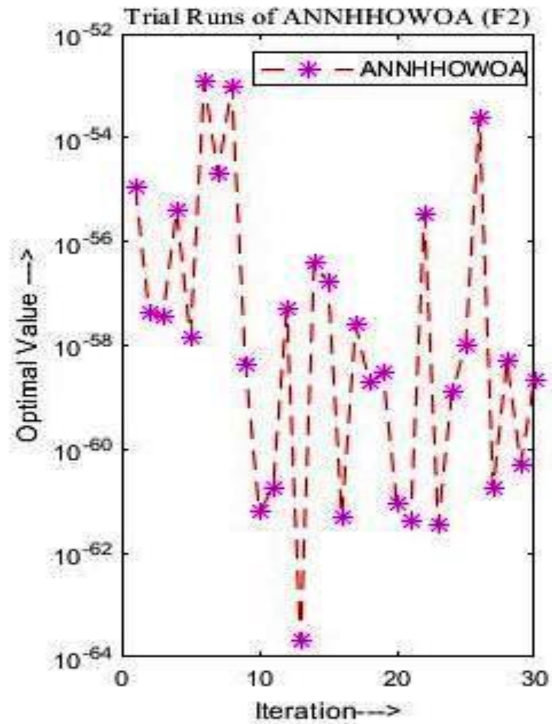
A



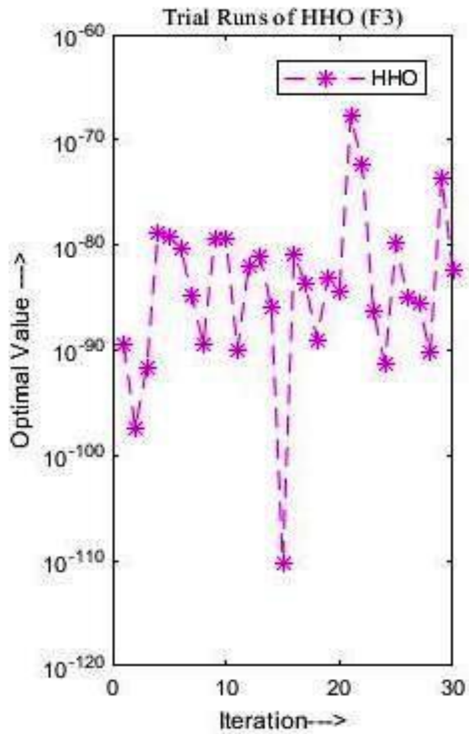
B


Trial Runs of HHO (F2)
HHO
Optimal Value --->
Iteration--->
10^-46
10^-48
10^-50
10^-52
10^-54
10^-56
10^-58
10^-60
10^-62
0
10
20
30

C

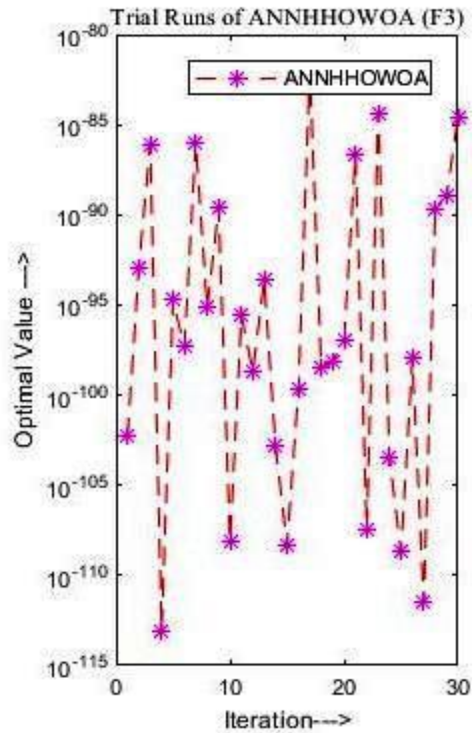

Trial Runs of ANNHHOWOA (F2)
ANNHHOWOA
Optimal Value --->
Iteration--->
10^-52
10^-54
10^-56
10^-58
10^-60
10^-62
10^-64
0
10
20
30

D



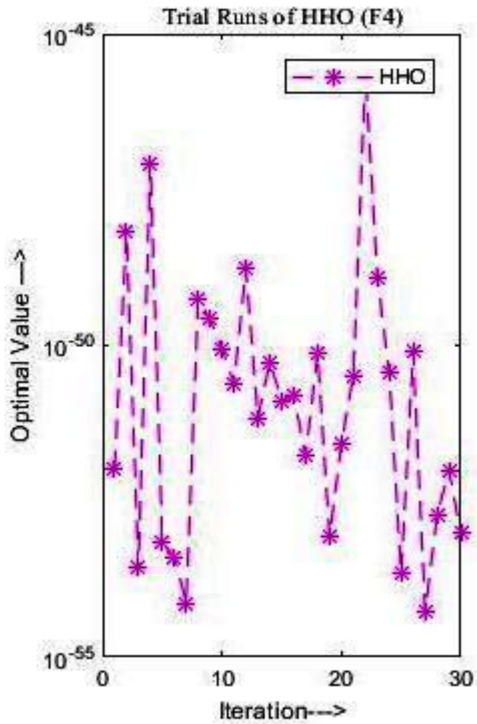
Trial Runs of HHO (F3)
HHO
Optimal Value --->
Iteration--->

E

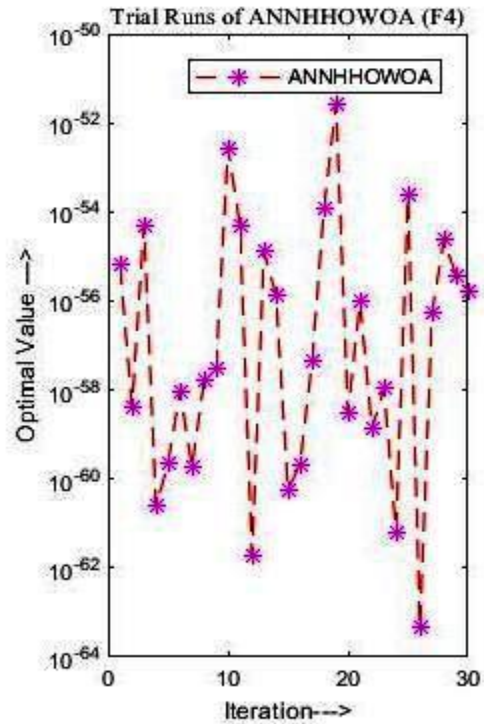


Trial Runs of ANNHHOWOA (F3)
ANNHHOWOA
Optimal Value --->
Iteration--->

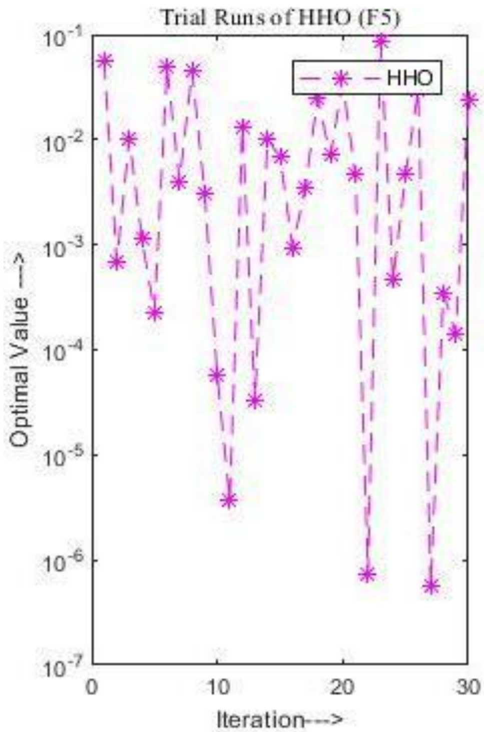
F


Trial Runs of HHO (F4)
HHO
Optimal Value --->
Iteration--->
10^-45
10^-50
10^-55
0
10
20
30

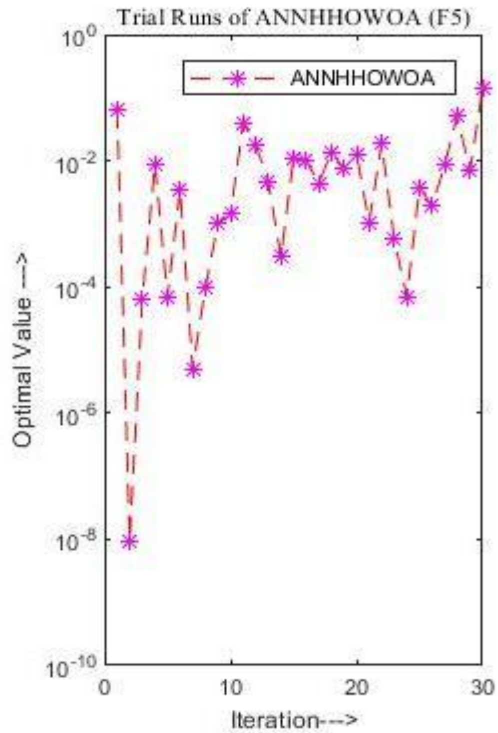
G


Trial Runs of ANNHHOWOA (F4)
ANNHHOWOA
Optimal Value --->
Iteration--->
10^-50
10^-52
10^-54
10^-56
10^-58
10^-60
10^-62
10^-64
0
10
20
30

H

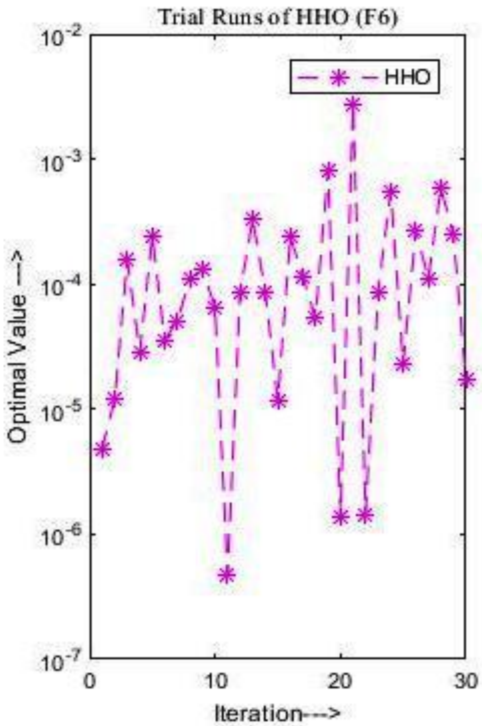


Trial Runs of HHO (F5)
HHO
Optimal Value --->
Iteration--->

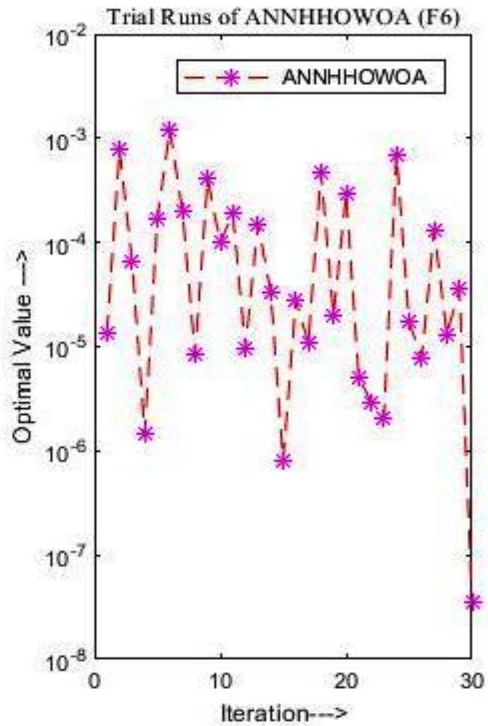


Trial Runs of ANNHHOWOA (F5)
ANNHHOWOA
Optimal Value --->
Iteration--->

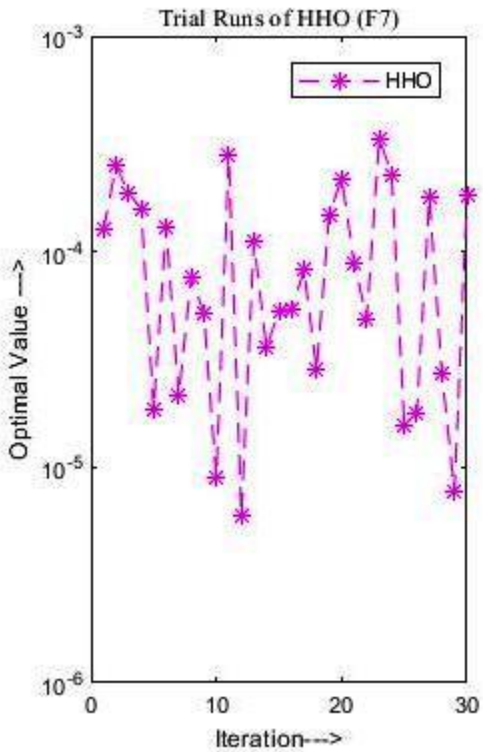
I **J**

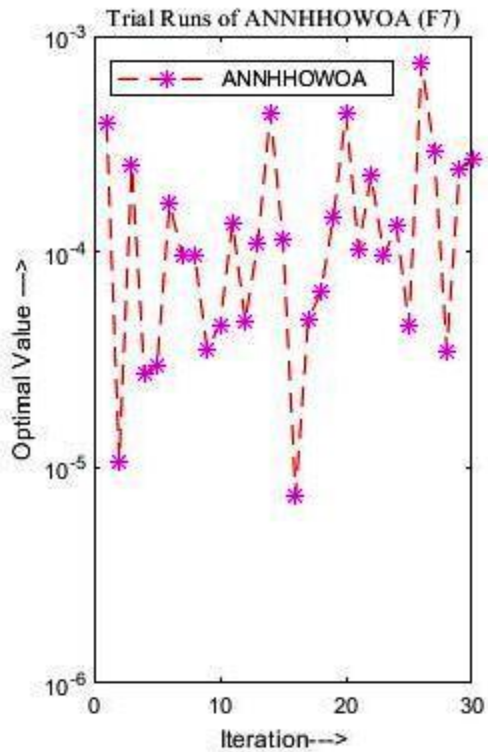

Trial Runs of HHO (F6)
HHO
Optimal Value --->
Iteration--->
10^-2
10^-3
10^-4
10^-5
10^-6
10^-7
0
10
20
30

K


Trial Runs of ANNHHOWOA (F6)
ANNHHOWOA
Optimal Value --->
Iteration--->
10^-2
10^-3
10^-4
10^-5
10^-6
10^-7
10^-8
0
10
20
30

L



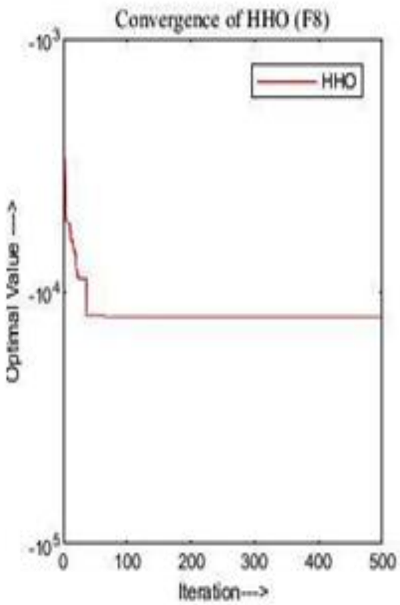


M **N**

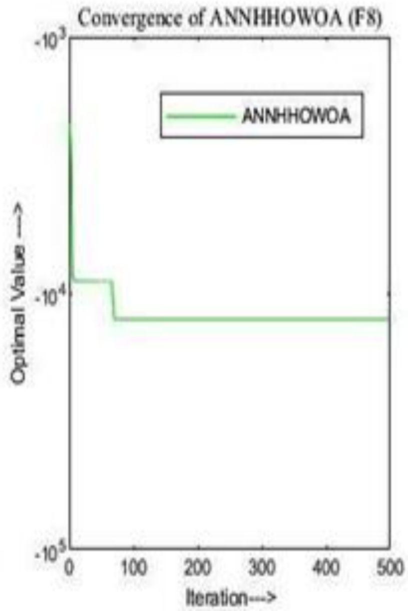
Figure 4.7: Graphs from (A)-(N) represents trial runs performed for HHO, ANNHHOWOA and their comparative graphs for unimodal benchmark functions

The graphs from (A)-(N) are plotted by taking number of iterations along x-axis and an optimal value generated along y-axis for unimodal benchmark functions. It can be clearly depicted that results generated by ANNHHOWOA are better than HHO.

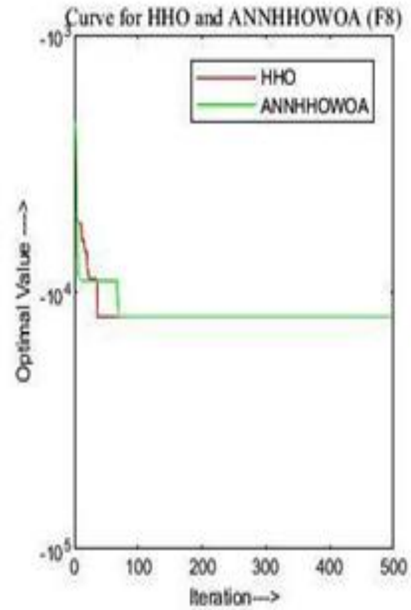
4.3 Convergence Graphs using multimodal benchmark functions



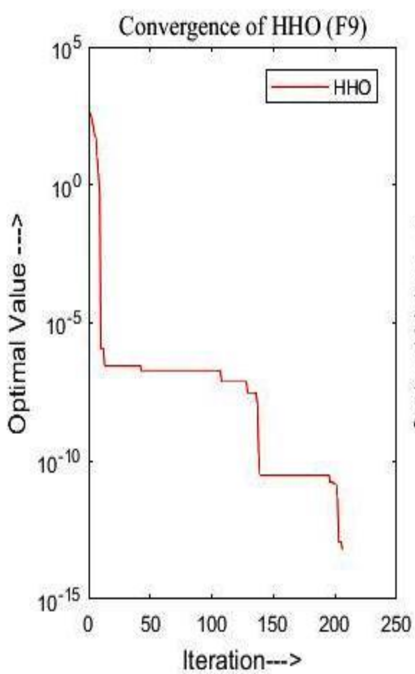
A



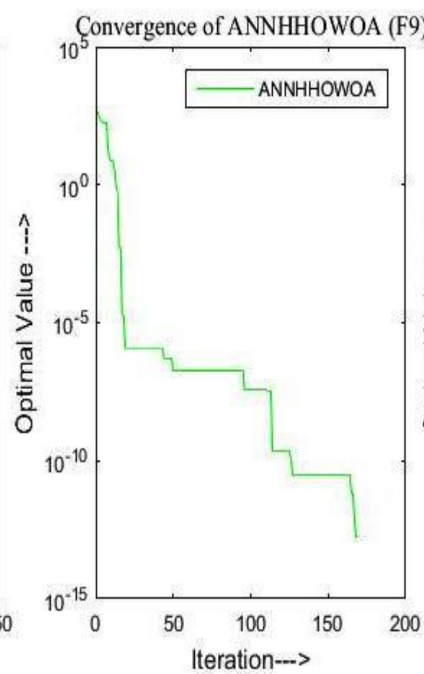
B



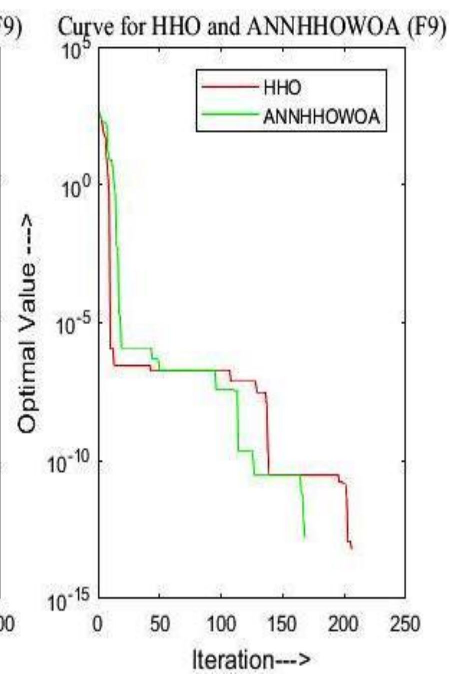
C



D



E



F

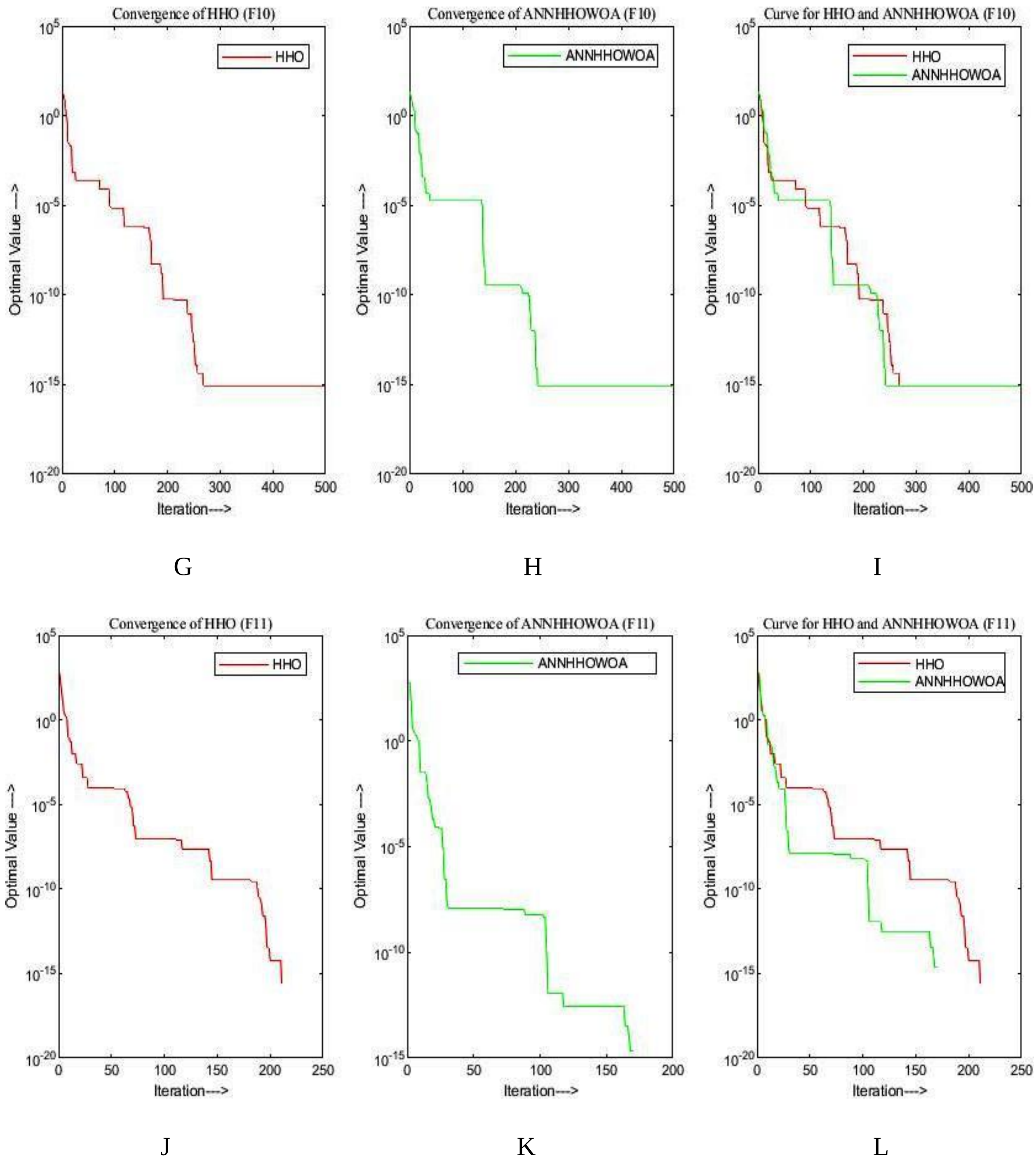
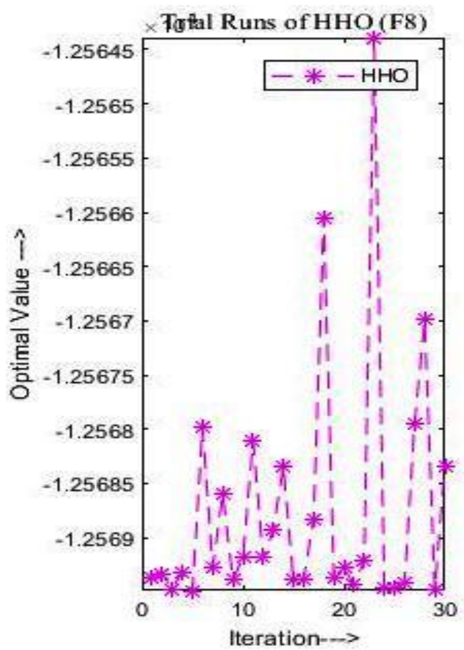


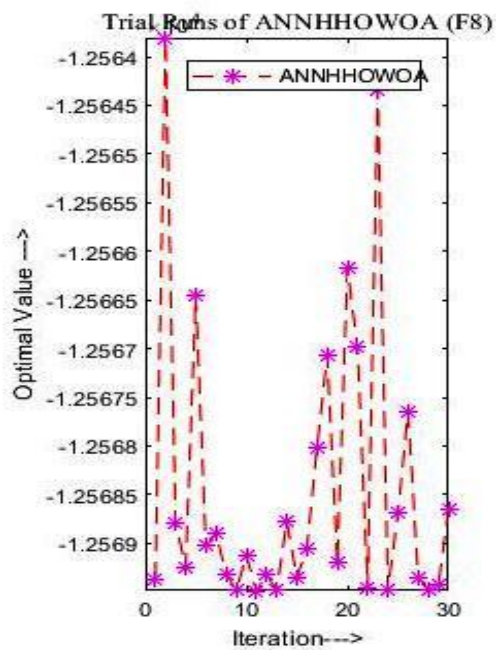
Figure 4.8: Graphs from (A)-(L) represents convergence graphs of HHO, ANNHHOWOA and comparative graph for multimodal benchmark functions

The graphs from (A)-(L) are plotted by taking number of iterations along x-axis and an optimal value generated along y-axis for multimodal benchmark functions. It can be clearly depicted that results generated by ANNHHOWOA are better than HHO.

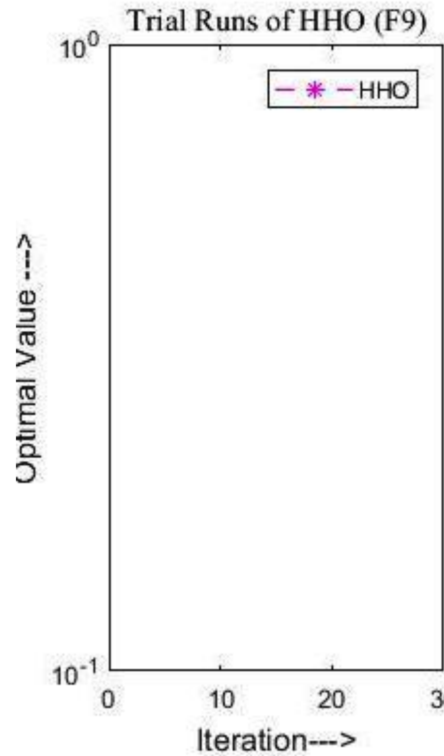
4.4 Graphs of Trail run using multimodal benchmark functions



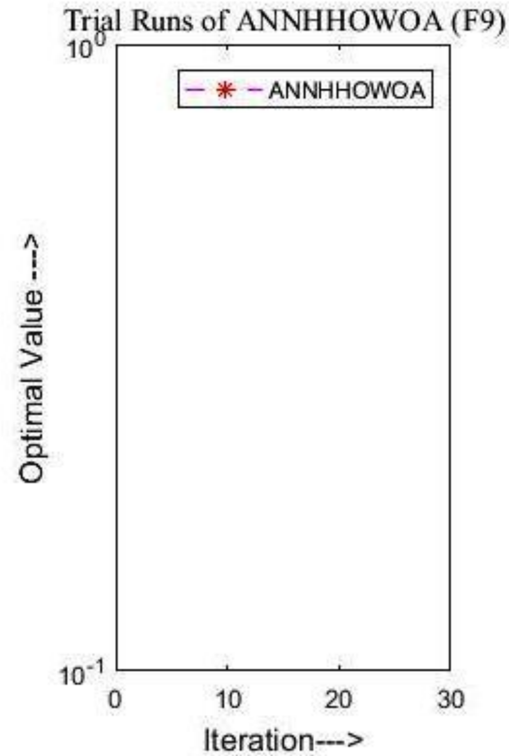
A



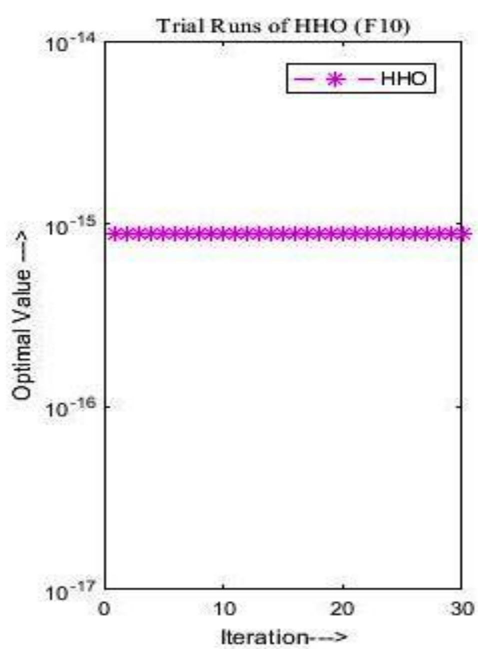
B


Trial Runs of HHO (F9)
HHO
Optimal Value --->
Iteration--->
10^0
10^-1
0
10
20
30

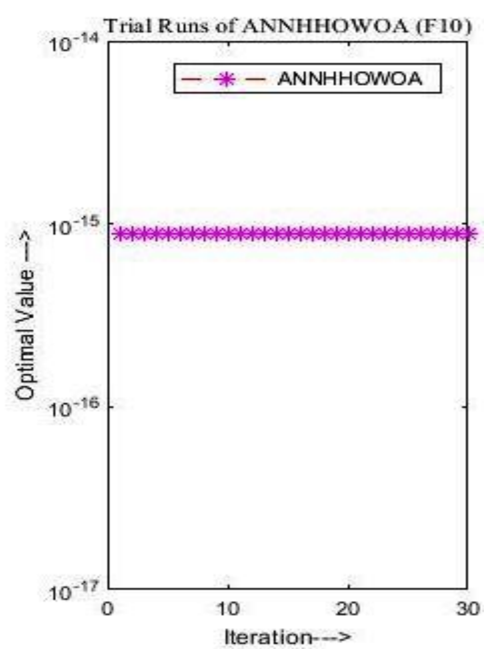
C


Trial Runs of ANNHHOWOA (F9)
ANNHHOWOA
Optimal Value --->
Iteration--->
10^0
10^-1
0
10
20
30

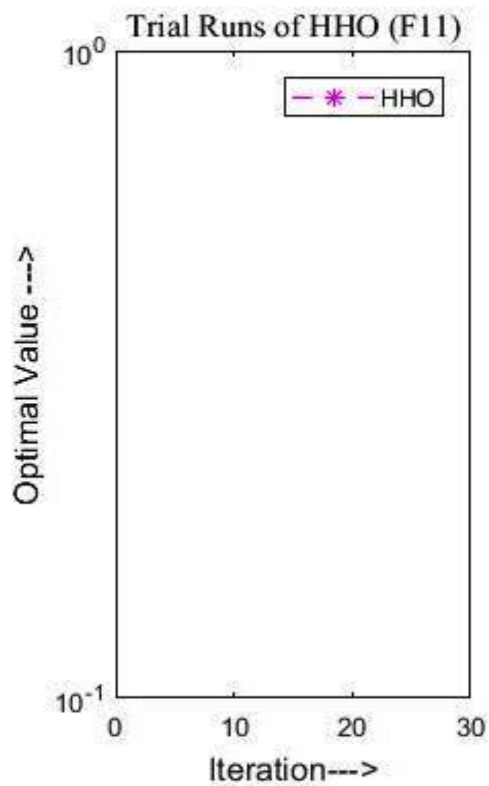
D


Trial Runs of HHO (F10)
HHO
Optimal Value --->
Iteration--->
10^-14
10^-15
10^-16
10^-17
0
10
20
30

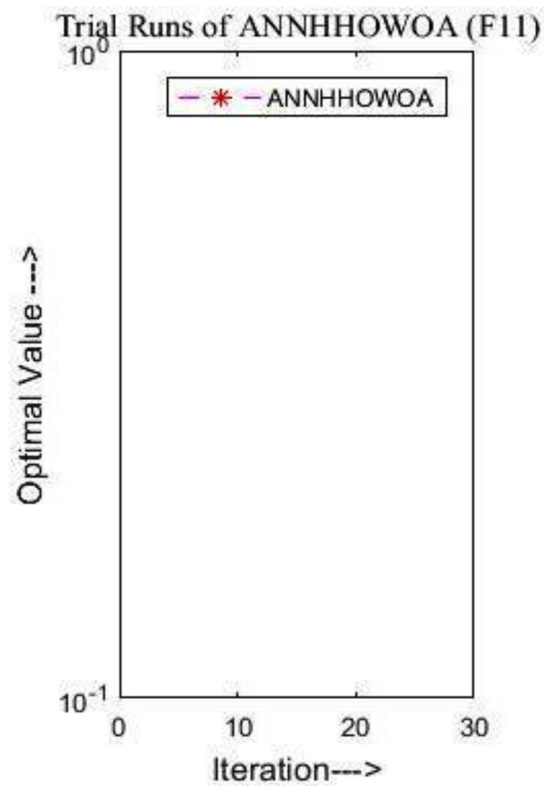
E


Trial Runs of ANNHHOWOA (F10)
ANNHHOWOA
Optimal Value --->
Iteration--->
10^-14
10^-15
10^-16
10^-17
0
10
20
30

F



G

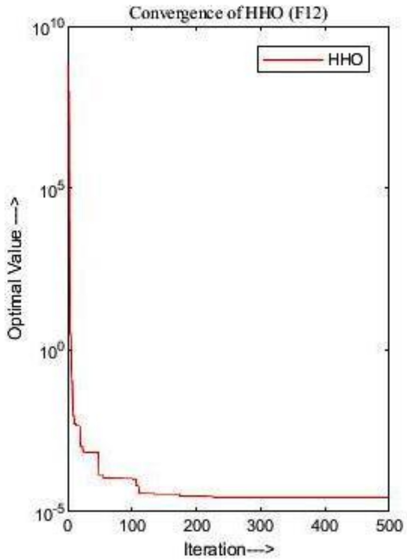


H

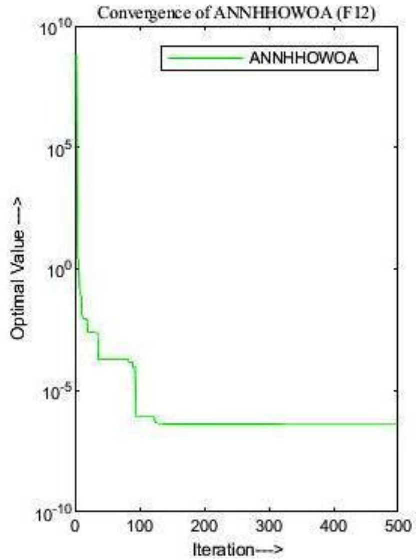
Figure 4.9: Graphs (A)-(H) represents trial runs done using HHO, ANNHHOWOA and comparative graphs for multimodal benchmark functions

The graphs from (A)-(H) are plotted by taking number of iterations along x-axis and an optimal value generated along y-axis for multimodal benchmark functions. It can be clearly depicted that results generated by ANNHHOWOA are better than HHO.

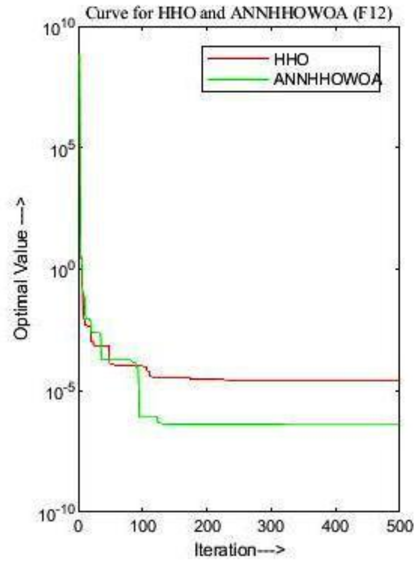
4.5 Convergence Graphs using fixed benchmark functions



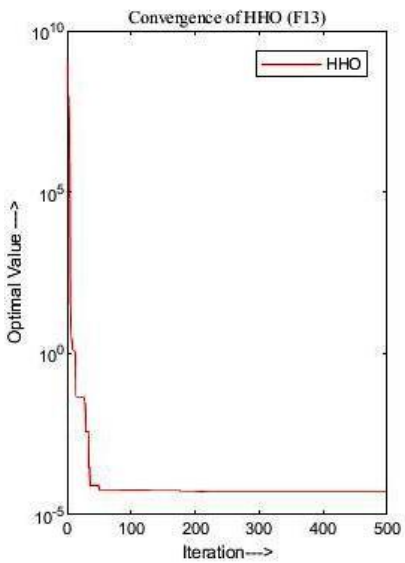
A



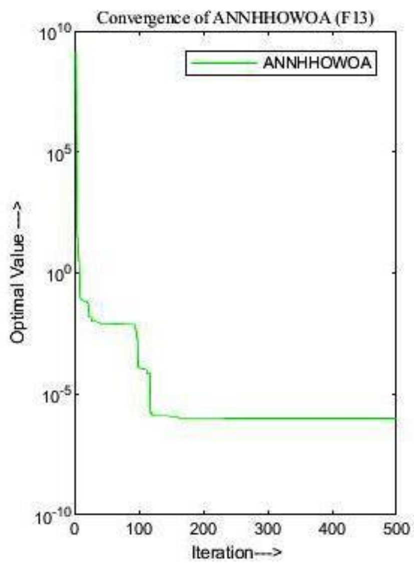
B



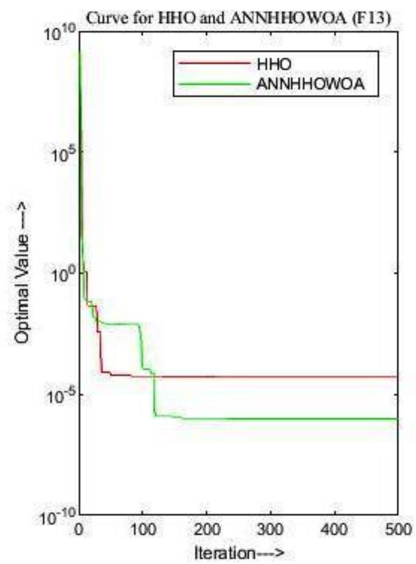
C



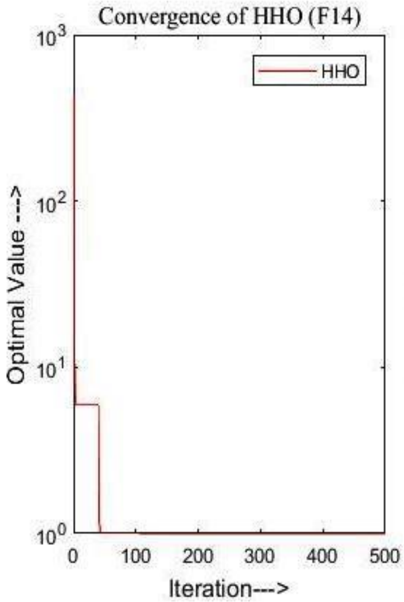
D



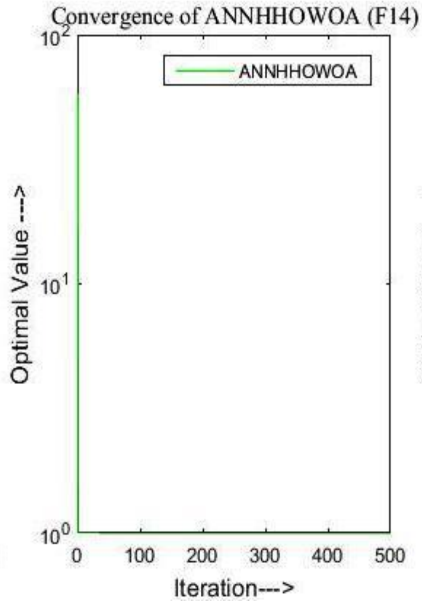
E



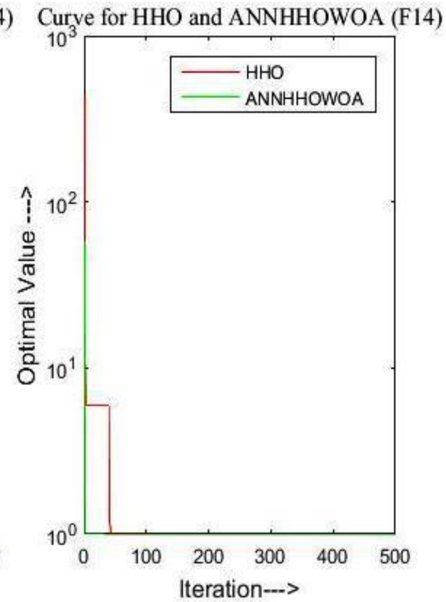
F


Convergence of HHO (F14)
HHO
Optimal Value --->
Iteration--->

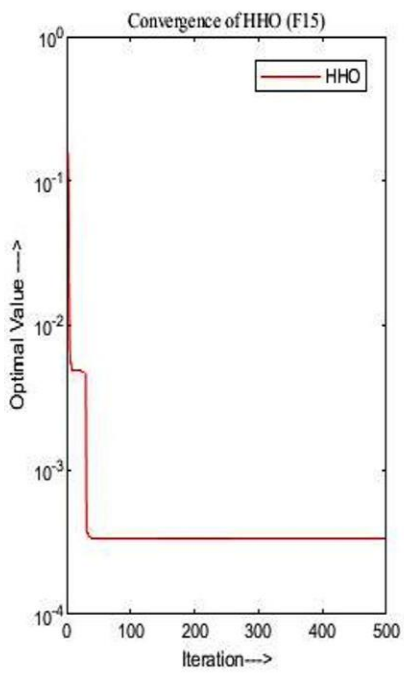
G


Convergence of ANNHHOWOA (F14)
ANNHHOWOA
Optimal Value --->
Iteration--->

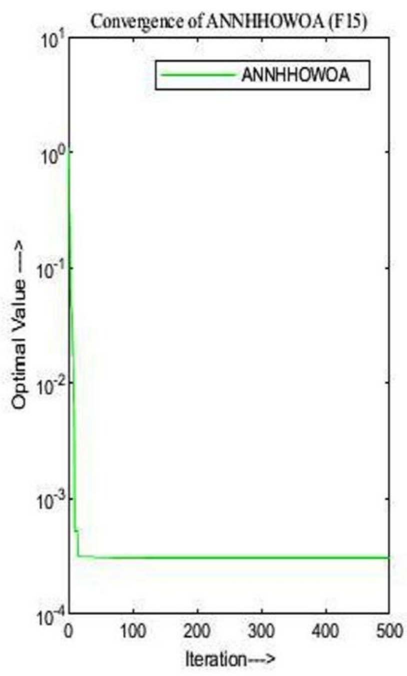
H


Curve for HHO and ANNHHOWOA (F14)
HHO
ANNHHOWOA
Optimal Value --->
Iteration--->

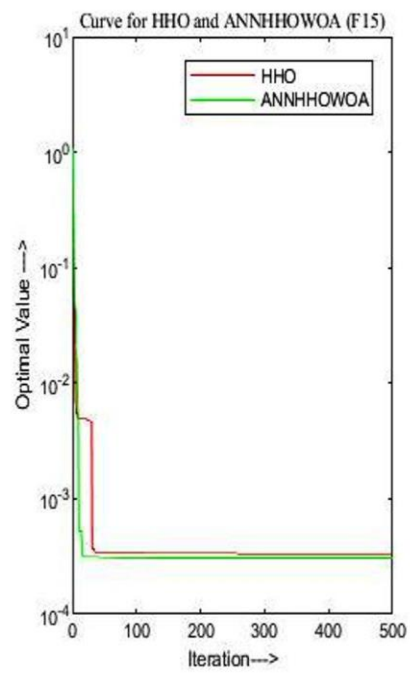
I


Convergence of HHO (F15)
HHO
Optimal Value --->
Iteration--->

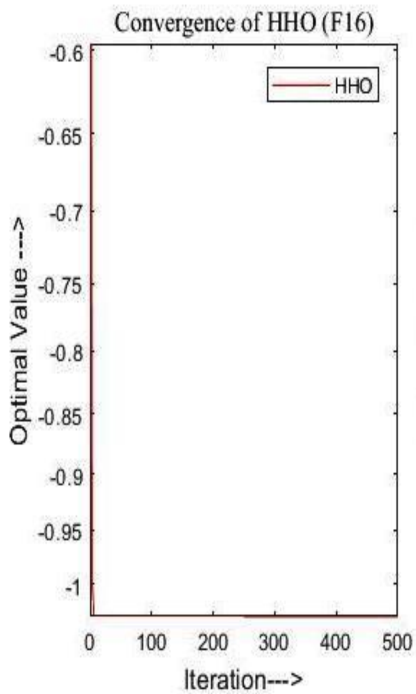
J


Convergence of ANNHHOWOA (F15)
ANNHHOWOA
Optimal Value --->
Iteration--->

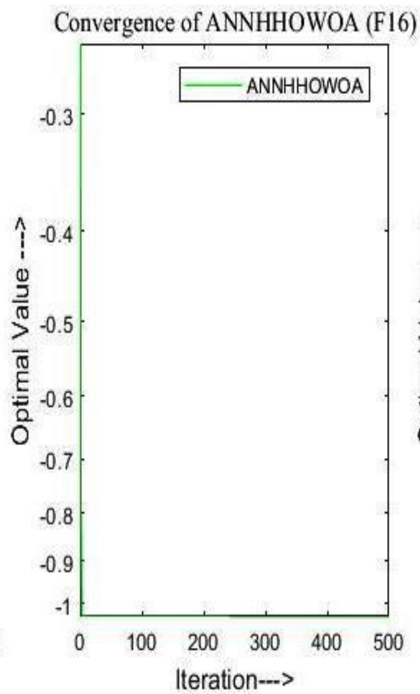
K


Curve for HHO and ANNHHOWOA (F15)
HHO
ANNHHOWOA
Optimal Value --->
Iteration--->

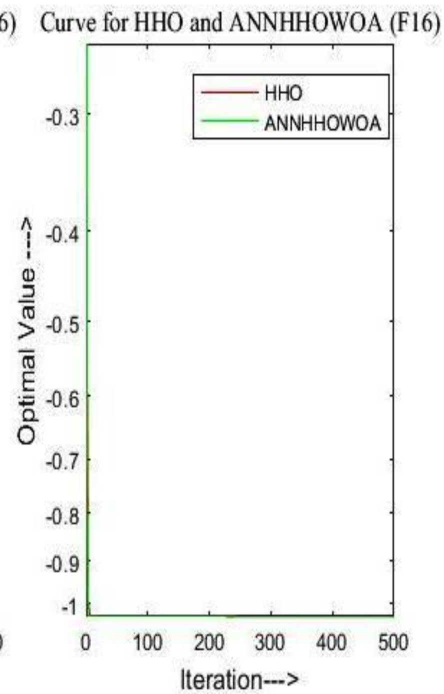
L


Convergence of HHO (F16)
HHO
Optimal Value --->
Iteration--->

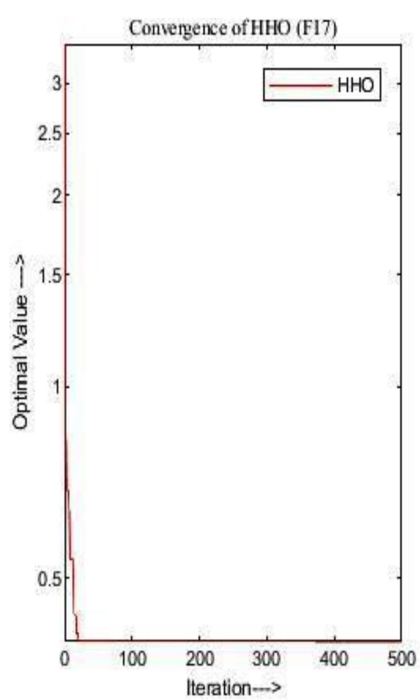
M


Convergence of ANNHHOWOA (F16)
ANNHHOWOA
Optimal Value --->
Iteration--->

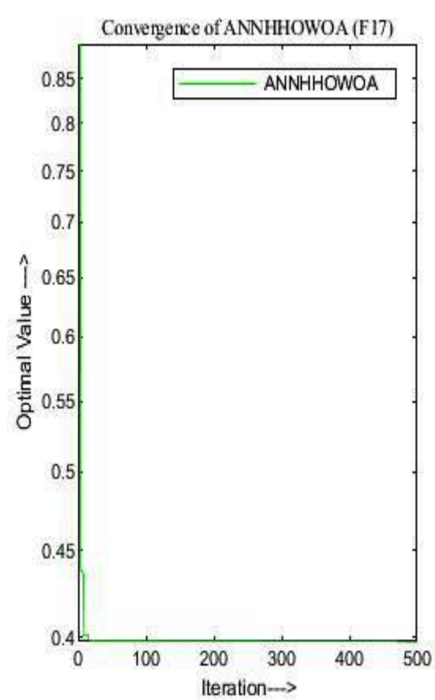
N


Curve for HHO and ANNHHOWOA (F16)
HHO
ANNHHOWOA
Optimal Value --->
Iteration--->

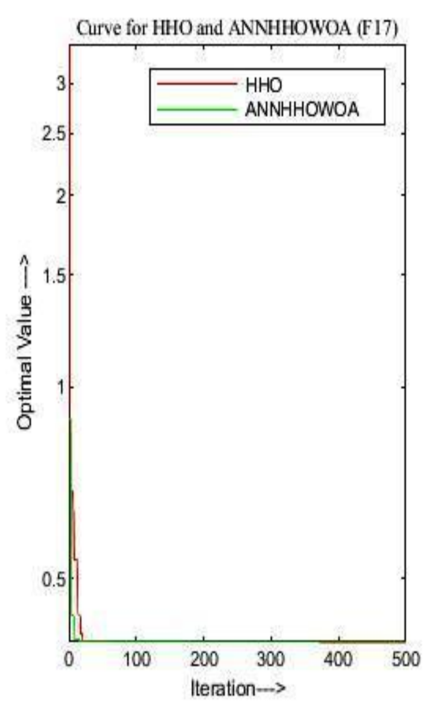
O


Convergence of HHO (F17)
HHO
Optimal Value --->
Iteration--->

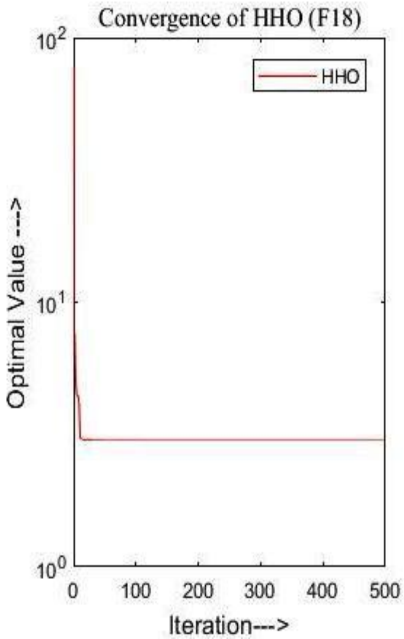
P


Convergence of ANNHHOWOA (F17)
ANNHHOWOA
Optimal Value --->
Iteration--->

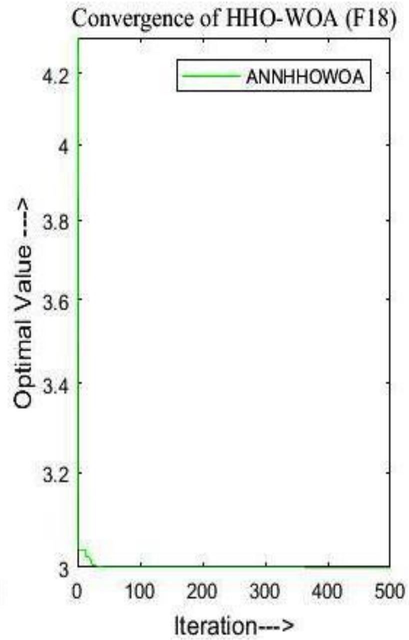
Q


Curve for HHO and ANNHHOWOA (F17)
HHO
ANNHHOWOA
Optimal Value --->
Iteration--->

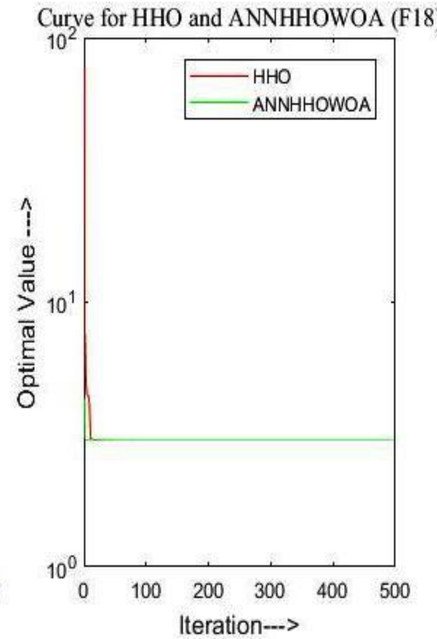
R


Convergence of HHO (F18)
HHO
Optimal Value --->
Iteration--->

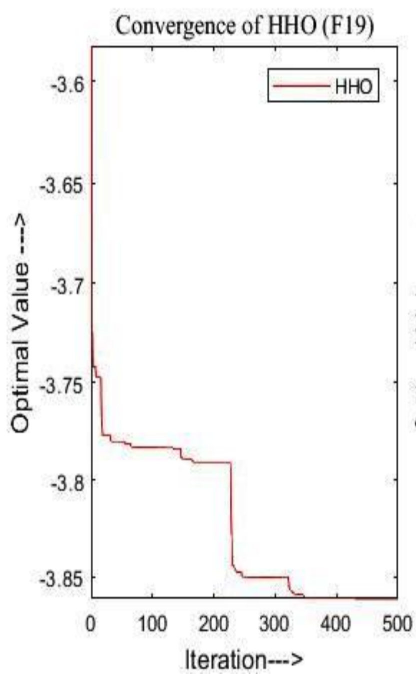
S


Convergence of HHO-WOA (F18)
ANNHHOWOA
Optimal Value --->
Iteration--->

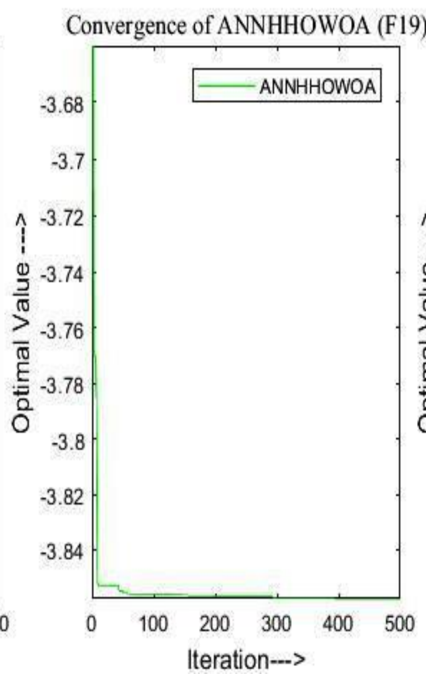
T


Curve for HHO and ANNHHOWOA (F18)
HHO
ANNHHOWOA
Optimal Value --->
Iteration--->

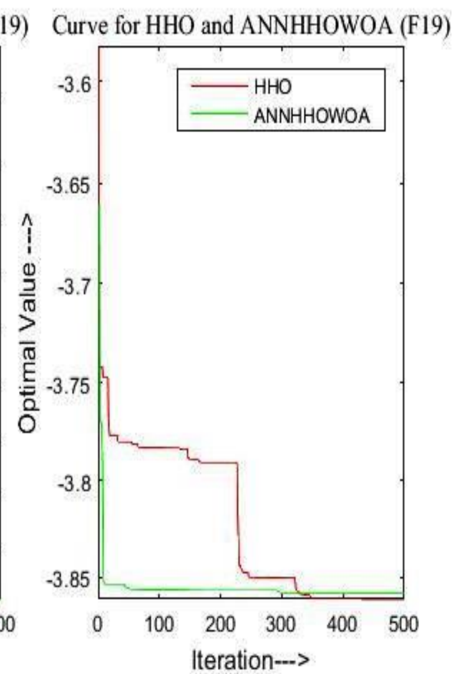
U


Convergence of HHO (F19)
HHO
Optimal Value --->
Iteration--->

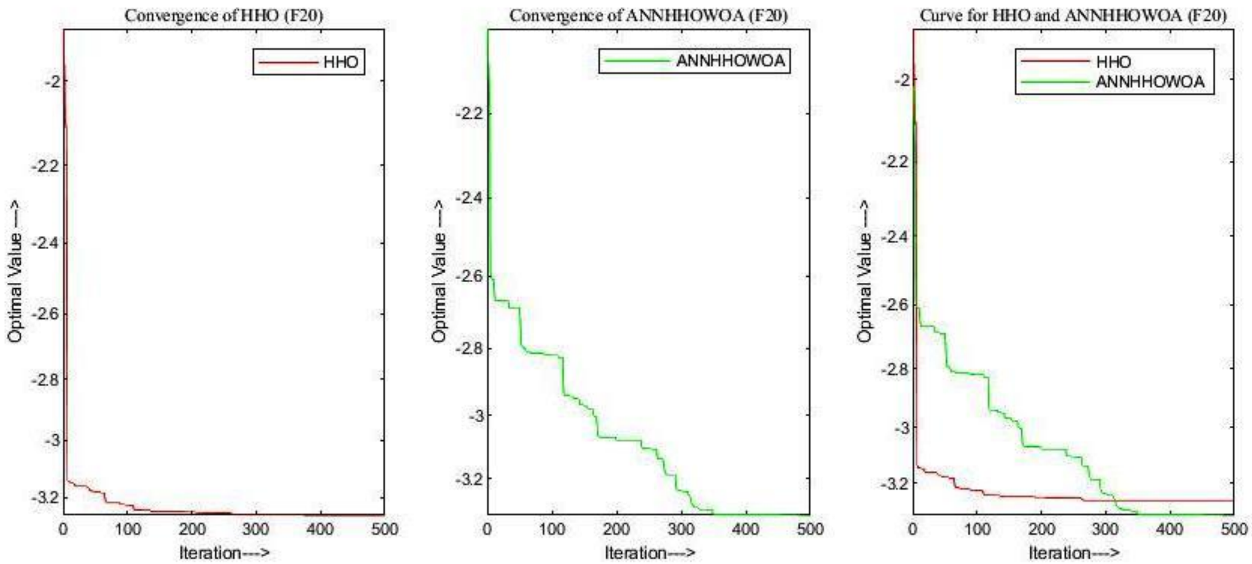
V


Convergence of ANNHHOWOA (F19)
ANNHHOWOA
Optimal Value --->
Iteration--->

W


Curve for HHO and ANNHHOWOA (F19)
HHO
ANNHHOWOA
Optimal Value --->
Iteration--->

X

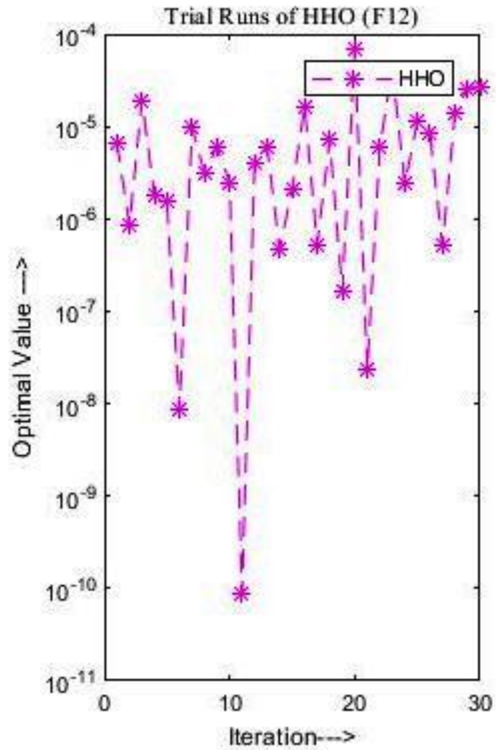


Y Z A1

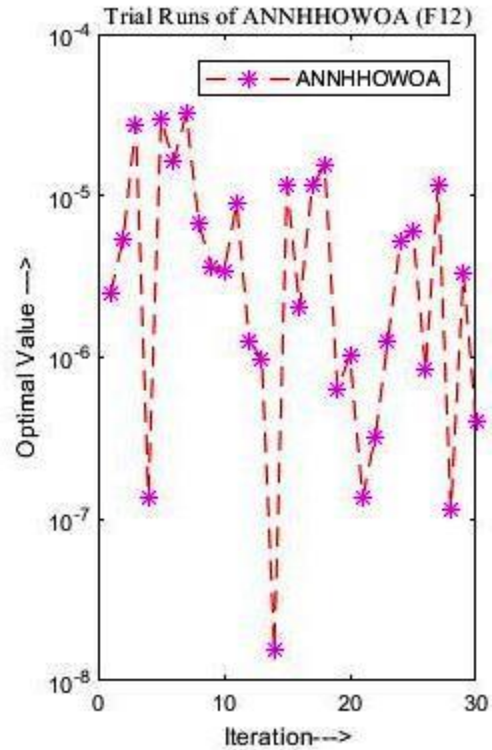
Figure 4.10: Graphs from (A)-(A1) represents convergence graphs of HHO, ANNHHOWOA and comparative graph for fixed benchmark functions

The graphs from (A)-(A1) are plotted by taking number of iterations along x-axis and an optimal value generated along y-axis for fixed benchmark functions. It can be clearly depicted that results generated by ANNHHOWOA are better than HHO.

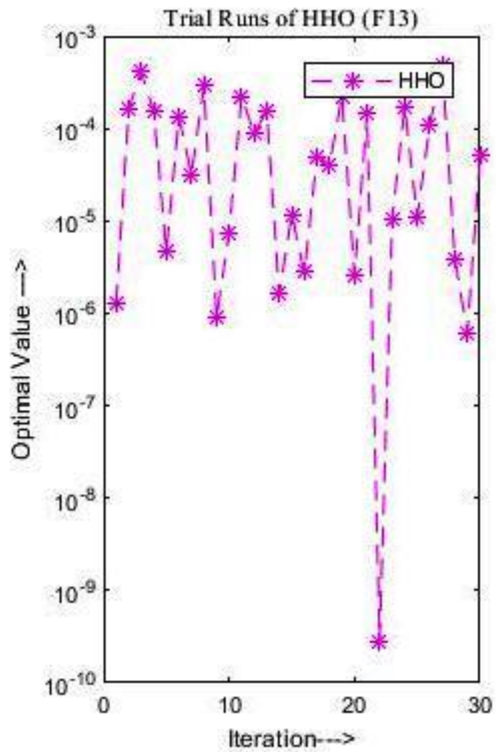
4.6 Graphs of Trail run using fixed benchmark functions



A

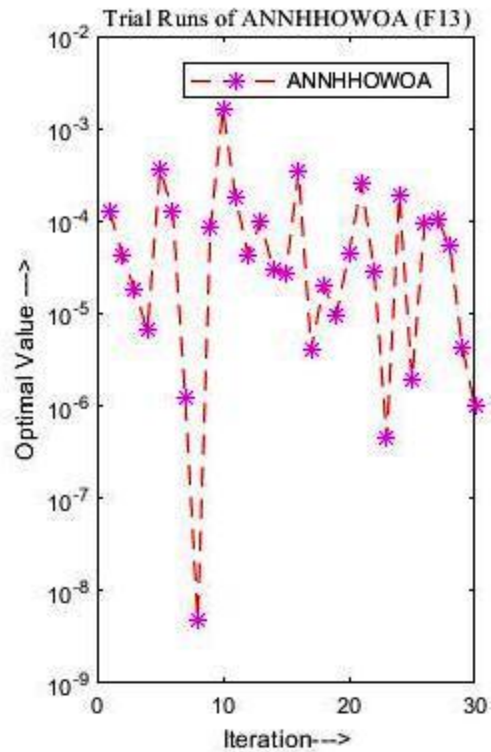


B



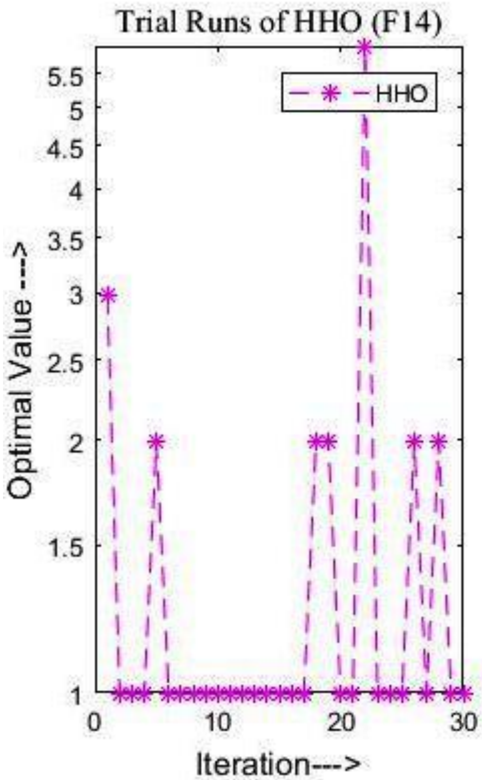
Trial Runs of HHO (F13)
HHO
Optimal Value --->
Iteration--->

C

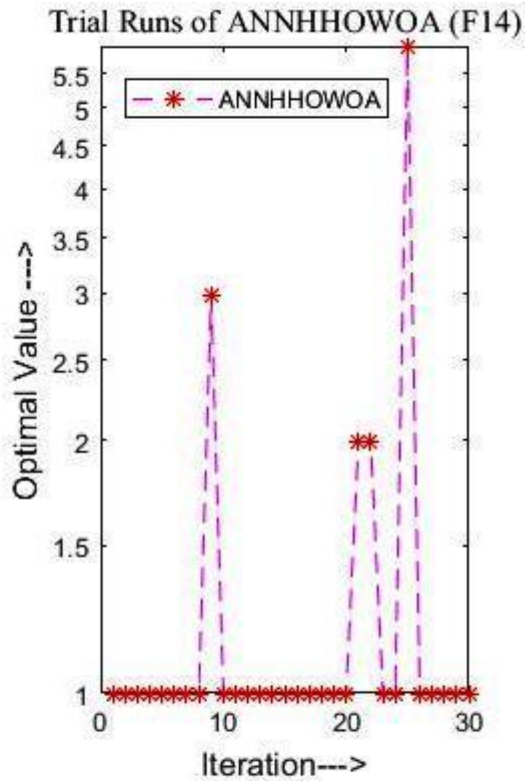


Trial Runs of ANNHHOWOA (F13)
ANNHHOWOA
Optimal Value --->
Iteration--->

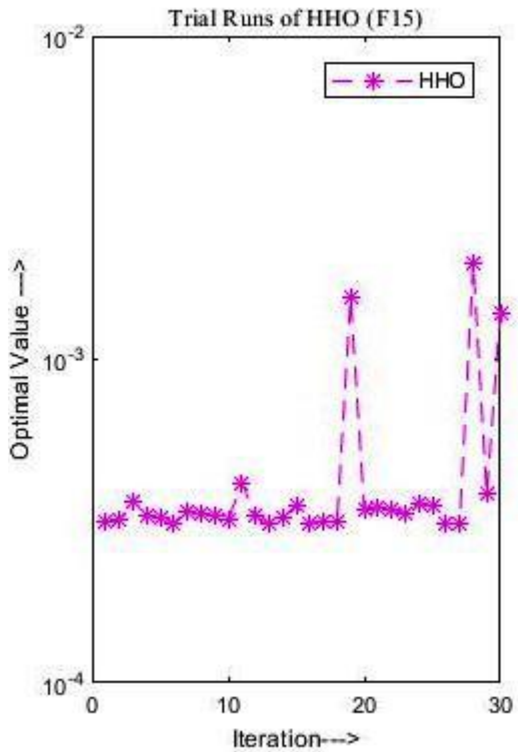
D


Trial Runs of HHO (F14)
HHO
Optimal Value --->
Iteration--->
5.5
5
4.5
4
3.5
3
2.5
2
1.5
1
0
10
20
30

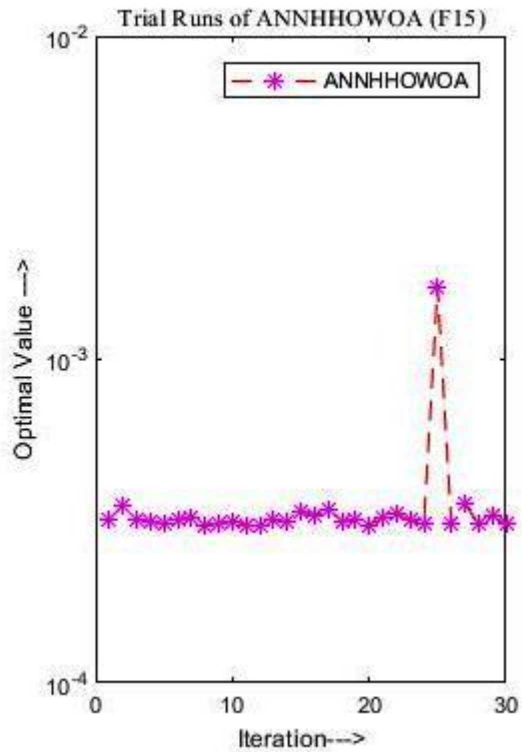
E


Trial Runs of ANNHHOWOA (F14)
ANNHHOWOA
Optimal Value --->
Iteration--->
5.5
5
4.5
4
3.5
3
2.5
2
1.5
1
0
10
20
30

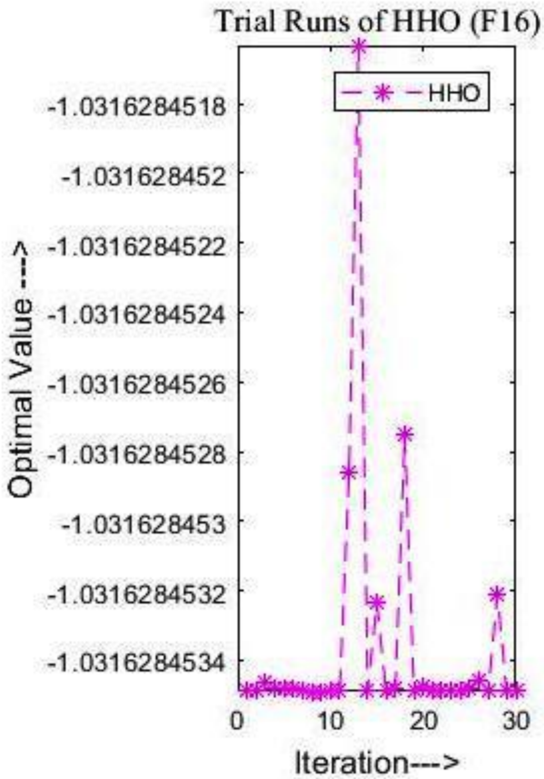
F


Trial Runs of HHO (F15)
HHO
Optimal Value --->
Iteration--->
10-2
10-3
10-4
0
10
20
30

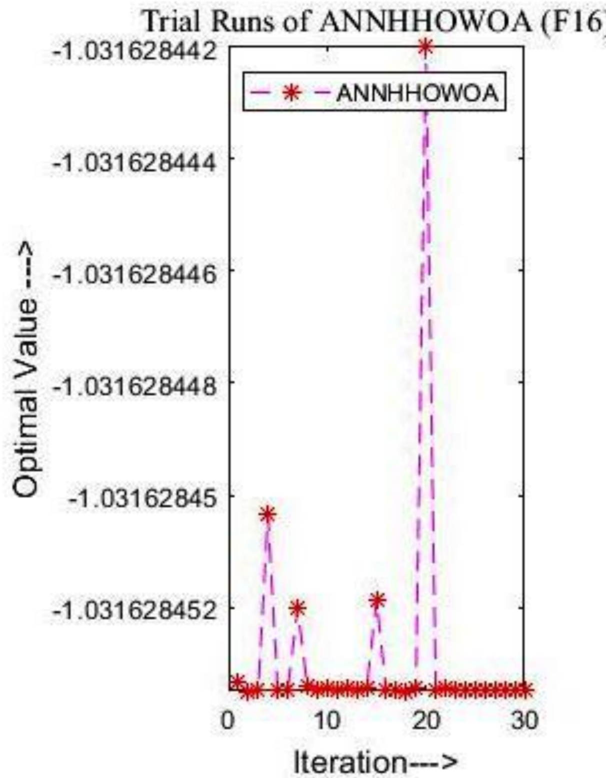
G


Trial Runs of ANNHHOWOA (F15)
ANNHHOWOA
Optimal Value --->
Iteration--->
10-2
10-3
10-4
0
10
20
30

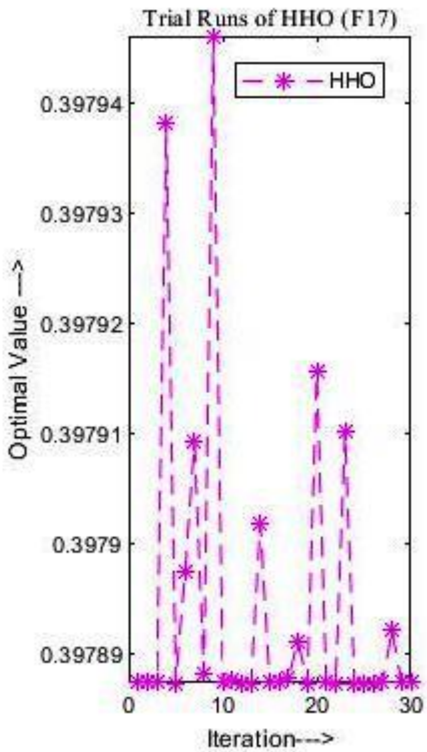
H


Trial Runs of HHO (F16)
HHO
-1.0316284518
-1.031628452
-1.0316284522
-1.0316284524
-1.0316284526
-1.0316284528
-1.031628453
-1.0316284532
-1.0316284534
Optimal Value --->
0
10
20
30
Iteration--->

I

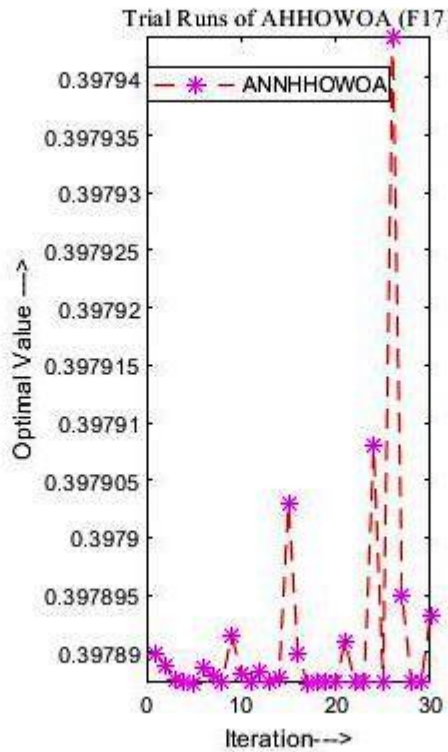

Trial Runs of ANNHHOWOA (F16)
ANNHHOWOA
-1.031628442
-1.031628444
-1.031628446
-1.031628448
-1.03162845
-1.031628452
Optimal Value --->
0
10
20
30
Iteration--->

J



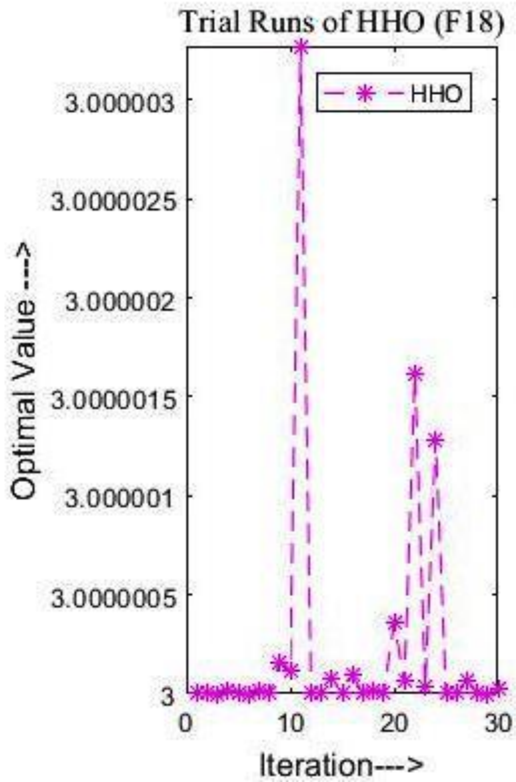
Trial Runs of HHO (F17)
HHO
Optimal Value --->
0.39794
0.39793
0.39792
0.39791
0.3979
0.39789
0
10
20
30
Iteration--->

K

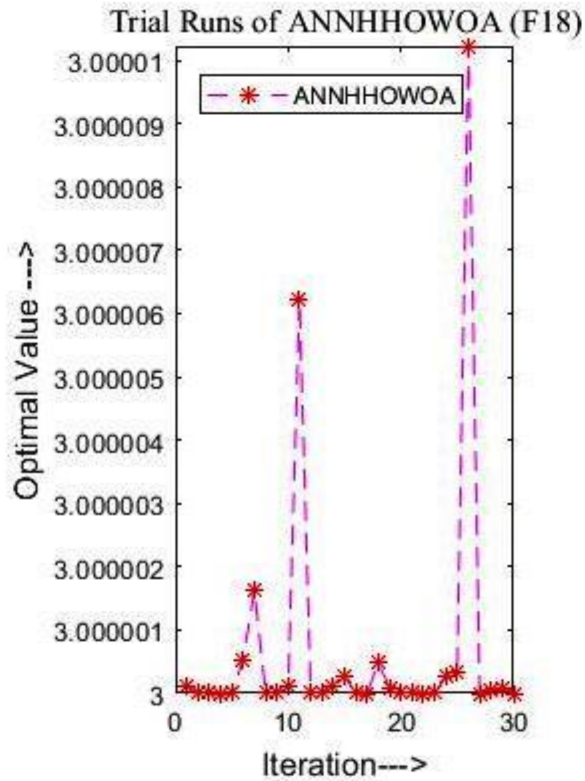


Trial Runs of AHHOWOA (F17)
ANNHHOWOA
Optimal Value --->
0.39794
0.397935
0.39793
0.397925
0.39792
0.397915
0.39791
0.397905
0.3979
0.397895
0.39789
0
10
20
30
Iteration--->

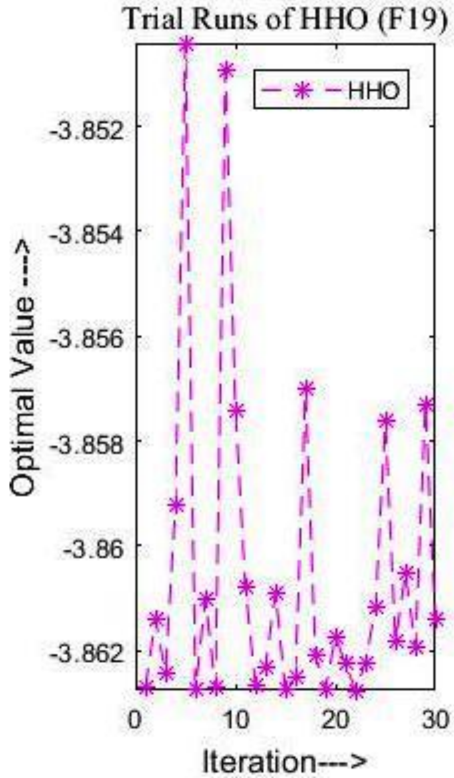
L


Trial Runs of HHO (F18)
HHO
Optimal Value --->
Iteration--->
3.000003
3.0000025
3.000002
3.0000015
3.000001
3.0000005
3
0
10
20
30

M

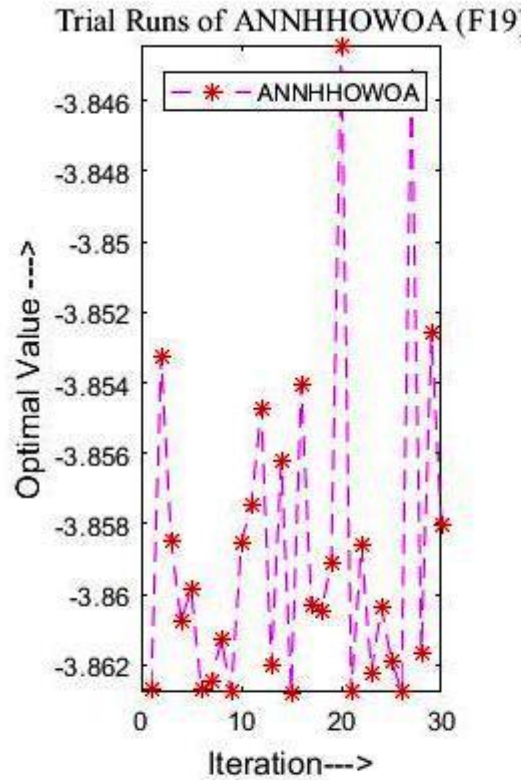

Trial Runs of ANNHHOWOA (F18)
ANNHHOWOA
Optimal Value --->
Iteration--->
3.00001
3.000009
3.000008
3.000007
3.000006
3.000005
3.000004
3.000003
3.000002
3.000001
3
0
10
20
30

N



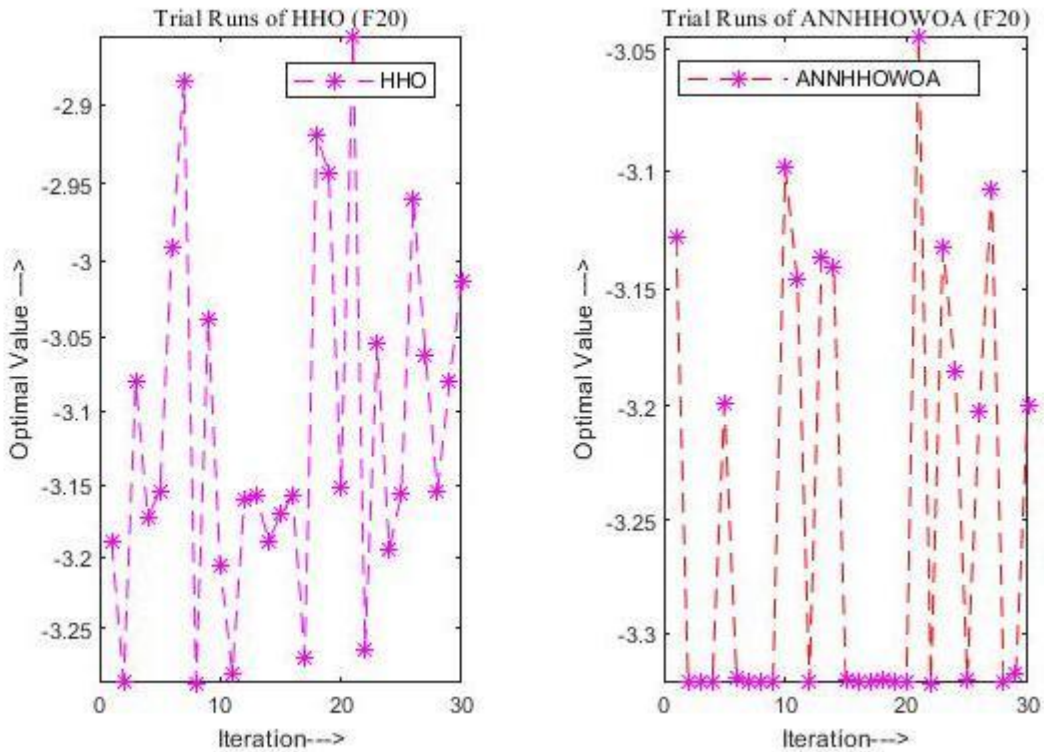
Trial Runs of HHO (F19)
HHO
-3.852
-3.854
-3.856
-3.858
-3.86
-3.862
Optimal Value --->
0
10
20
30
Iteration--->

O



Trial Runs of ANNHHOWOA (F19)
ANNHHOWOA
-3.846
-3.848
-3.85
-3.852
-3.854
-3.856
-3.858
-3.86
-3.862
Optimal Value --->
0
10
20
30
Iteration--->

P



Q R

Figure 4.11: Graphs from (A)-(R) represents trial runs performed for HHO, ANNHHOWOA and comparative graphs for fixed benchmark functions

The graphs fron (A)-(R) are plotted by taking number of iterations along x-axis and an optimal value generated along y-axis for fixed benchmark functions. It can be clearly depicted that results generated by ANNHHOWOA are better than HHO.

Table 4.1: Results of time taken by multimodal, unimodal and fixed benchmark functions using hybrid ANNHHOWOA algorithm for computing best and worst fitness, mean, median, and p-value standard deviation.

Function	Parameters					
	Mean	SD	Best Fitness	Worst Fitness	Median	p-value
Func1	9.56E-106	5.24E-105	6.94E-127	2.87E-104	5.00E-114	3.25E-01
Func2	8.28E-55	2.82E-54	2.02E-64	1.22E-53	7.62E-59	1.18E-01

Func3	4.08E-84	2.22E-83	8.66E-114	1.22E-82	8.08E-98	3.23E-01
Func4	1.00E-53	4.91E-53	4.54E-64	2.69E-52	3.71E-58	2.73E-01
Func5	1.43E-02	2.77E-02	9.42E-09	1.36E-01	4.47E-03	8.28E-03
Func6	1.70E-04	2.86E-04	3.58E-08	1.22E-03	3.10E-05	2.91E-03
Func7	1.63E-04	1.67E-04	7.38E-06	7.53E-04	1.06E-04	9.17E-06
Func8	-1.26E+04	1.52E+00	-1.26E+04	-1.26E+04	-1.26E+04	2.05E-115
Func9	0.00	0.00	0.00	0.00	0.00	0.00
Func10	8.88E-16	0.00	8.88E-16	8.88E-16	8.88E-16	0.00
Func11	0.00	0.00	0.00	0.00	0.00	0.00
Func12	7.01E-06	9.05E-06	1.56E-08	3.20E-05	3.36E-06	2.06E-04
Func13	1.31E-04	2.98E-04	4.75E-09	1.62E-03	4.33E-05	2.25E-02
Func14	3.66E-04	2.47E-04	3.08E-04	1.67E-03	3.18E-04	5.82E-09
Func15	-1.03E+00	3.10E-09	-1.03E+00	-1.03E+00	-1.03E+00	6.42E-249
Func16	3.98E-01	1.09E-05	3.98E-01	3.98E-01	3.98E-01	4.60E-134
Func17	1.20E+01	1.29E+01	3.00E+00	3.00E+01	3.00E+00	2.05E-05
Func18	-3.25E+00	9.33E-02	-3.32E+00	-3.04E+00	-3.32E+00	1.68E-46
Func19	-5.44E+00	1.35E+00	-1.04E+01	-5.09E+00	-5.09E+00	1.01E-19
Func20	-5.49E+00	1.37E+00	-1.05E+01	-5.13E+00	-5.13E+00	1.22E-19

Table 4.2: Results of time taken by hybrid ANNHHOWOA algorithm to find optimal solution.

	Time (in Seconds)		
Function	**Best Time**	**Mean Time**	**Worst Time**
Func1	5.00E-02	8.00E-02	3.10E-01
Func2	5.00E-02	7.00E-02	1.90E-01
Func3	2.20E-01	2.40E-01	3.40E-01
Func4	5.00E-02	6.00E-02	8.00E-02
Func5	8.00E-02	9.00E-02	1.10E-01
Func6	5.00E-02	7.00E-02	9.00E-02
Func7	1.30E-01	1.60E-01	2.30E-01
Func8	8.00E-02	1.00E-01	2.70E-01
Func9	6.00E-02	8.00E-02	1.40E-01
Func10	6.00E-02	8.00E-02	1.40E-01
Func11	8.00E-02	1.00E-01	3.30E-01
Func12	3.10E-01	3.70E-01	7.30E-01

Func13	3.30E-01	3.70E-01	4.40E-01
Func14	5.00E-02	9.00E-02	3.00E-01
Func15	5.00E-02	9.00E-02	2.80E-01
Func16	5.00E-02	8.00E-02	2.20E-01
Func17	5.00E-02	6.00E-02	1.40E-01
Func18	6.00E-02	9.00E-02	3.30E-01
Func19	9.00E-02	1.30E-01	4.70E-01
Func20	0.09	0.14	0.42

In the Table 4.1 and Table 4.2 Func1-Func20 refers to unimodel, multimodel and fixed benchmarks functions.

The computed results show that rather than using standalone meta-heuristic algorithms to find optimal solution, ANN based hybrid approach performed better.

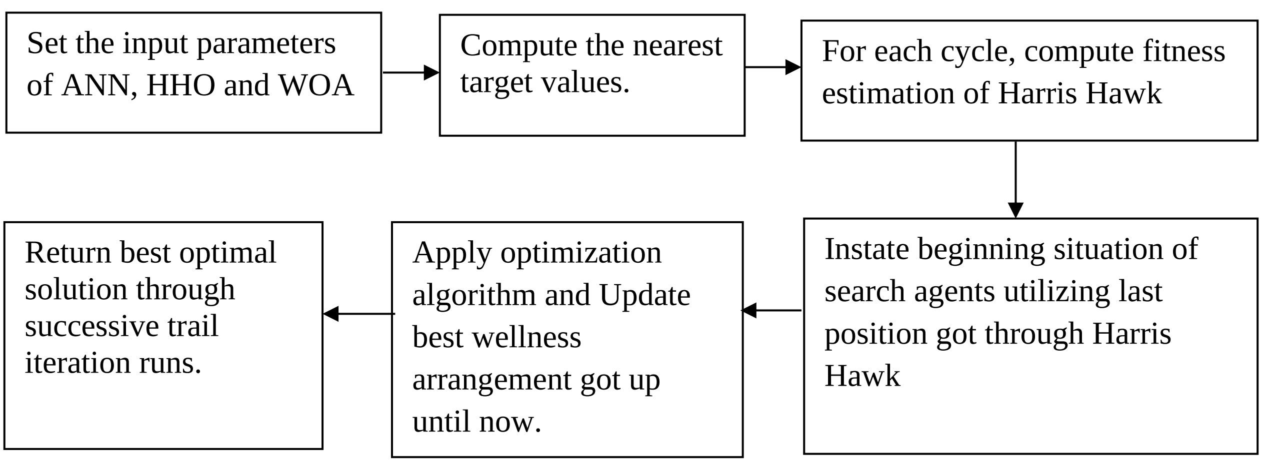


Figure 4.12: Working steps of ANN-hybrid HHO and WOA

To approve the outcomes produced by the calculation, 500 emphasis runs are contemplated to defeat the stochastic idea of anticipated ANN-HHOWOA calculation and every target work has been evaluated for best, average, worst values and standard deviation. So as to endorse the period of utilization by the suggested calculation, unimodal benchmark capacities, multimodel benchmark works and fixed benchmark capacities are considered.

These outcomes are contrasted and HHO which is considered as a calculation that furnishes better solutions when contrasted and others as of considering meta-heuristics calculations recognized in recent times.

ANN-HHOWOA algorithm resulted in significant outcomes in contrast to HHO which reflects even enhanced results than HHO.

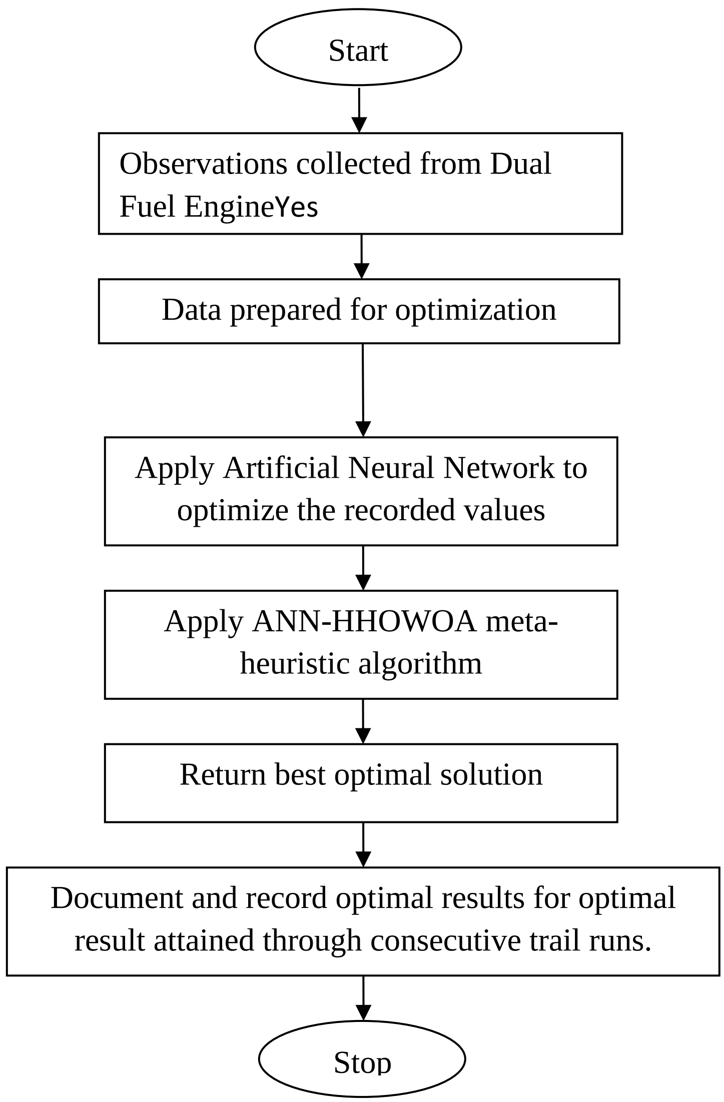


Figure 4.13: Validation and verification work flow

4.7 Comparative analysis of hybrid ANNHHOWOA algorithm with other hybrid algorithms

From the comparison tables Table 4.3, Table 4.4 and Table 4.5 of hybrid algorithms, we can conclude that the hybrid ANNHHOWOA is performing better as compared to others hybrid algorithms in terms of SD and MEAN value calculation. Moreover the -ve value depicts that the optimal solution of that value is achieved with less iterations and with least time taken to get optimal slution.

Table 4.3: Results of values of Mean and SD calculated using hybrid ANNHHOWOA algorithm and other hybrid algorithms for Unimodal Benchmark Function

Algorithms	Parameters	Unimodal Benchmark Functions						
		F1	**F2**	**F3**	**F4**	**F5**	**F6**	**F7**
hHHO-PSO	**Mean**	0.00	0.00	0.00	0.00	1.00E-02	0.00	0.00
	SD	0.00	0.00	0.00	0.00	1.00E-02	0.00	0.00
hHHO-GWO	**Mean**	0.00	0.00	0.00	0.00	2.00E-02	0.00	0.00
	SD	0.00	0.00	0.00	0.00	2.00E-02	0.00	0.00
hHHO-SCA	**Mean**	0.00	0.00	0.00	0.00	1.00E-02	0.00	0.00
	SD	0.00	0.00	0.00	0.00	2.00E-02	0.00	0.00
hGWO-SA	**Mean**	3.11E-59	9.54E-35	4.70E-15	1.32E-14	2.71E+01	6.18E-01	NA
	SD	7.27E-59	9.39E-35	1.29E-14	2.50E-14	1.01E+00	3.36E-01	NA
hANNHHOWOA	**Mean**	9.56E-106	8.28056E-55	4.07758 E-84	1.002 59E-53	1.43E-02	1.70E-04	1.63E-04
	SD	5.24E-105	2.81517E-54	2.22006 E-83	4.90939 E-53	2.77E-02	2.86E-04	1.67E-04

Table 4.4: Results of values of Mean and SD calculated using hybrid ANNHHOWOA algorithm and other hybrid algorithms for Multimodal Benchmark Functions

Algorithms	Parameters	Multimodal Benchmark Functions					
		F8	**F9**	**F10**	**F11**	**F12**	**F13**
hHHO-PSO	**Mean**	-1.26E+04	0.00	8.88E-16	0.00	1.13E-05	1.00E-04
	SD	9.47E-01	0.00	0.00	0.00	1.50E-05	2.00E-04
hHHO-GWO	**Mean**	-1.26E+04	0.00	8.88E-16	0.00	NA	NA
	SD	1.04E+00	0.00	0.00	0.00	NA	NA
hHHO-SCA	**Mean**	-1.26E+04	0.00	8.88E-16	0.00	1.13E-05	1.00E-04
	SD	7.67E-01	0.00	0.00	0.00	1.50E-05	2.00E-04
hGWO-SA	**Mean**	-5.92E+03	2.18E-01	1.51E-14	1.45E-01	4.58E-01	NA
	SD	7.54E+02	1.19E+00	1.87E-15	2.17E-01	2.45E-01	NA
hANNHHOWOA	**Mean**	-1.26E+04	0.00	8.88E-16	0.00	7.01E-06	1.00E-04
	SD	1.52E+00	0.00	0.00	0.00	9.05E-06	3.00E-04

Table 4.5: Results of values of Mean and SD calculated using hybrid ANNHHOWOA algorithm and other hybrid algorithms for Fixed Dimension Benchmark Functions

Algo rithms	Para meters	Fixed Dimension Benchmark Function						
		F14	F15	F16	F17	F18	F19	F20
hHHO-PSO	Mean	1.36E+00	3.94E-04	-1.03E+00	3.98E-01	3.00E+00	-3.86E+00	-3.10E+00
	SD	1.26E+00	2.20E-04	4.80E-09	3.49E-05	5.28E-07	3.41E-03	1.03E-01
hHHO-GWO	Mean	1.26E+00	3.44E-04	-1.03E+00	3.98E-01	3.00E+00	-3.86E+00	-3.11E+00
	SD	9.32E-01	3.14E-05	3.97E-10	1.86E-05	2.65E-07	4.30E-03	1.21E-01
hHHO-SCA	Mean	1.26E+00	3.45E-04	-1.03E+00	3.98E-01	3.00E+00	-3.86E+00	-3.09E+00
	SD	4.47E-01	4.03E-05	1.80E-09	2.15E-05	9.98E-07	3.00E-03	1.09E-01
hGWO-SA	Mean	4.32E-03	-1.03E+00	3.98E-01	3.00E+00	NA	NA	NA
	SD	8.16E-03	1.05E-08	9.90E-06	5.74E-06	NA	NA	NA
hANNHHOWOA	Mean	3.66E-04	-1.03E+00	3.98E-01	1.20E+01	-3.25E+00	-5.44E+00	-5.49E+00
	SD	2.47E-04	3.10E-09	1.09E-05	1.29E+01	9.33E-02	1.35E+00	1.37E+00

4.8 Trial Runs performed to optimize the results generated by IC engine using ANNHHOWOA algorithm

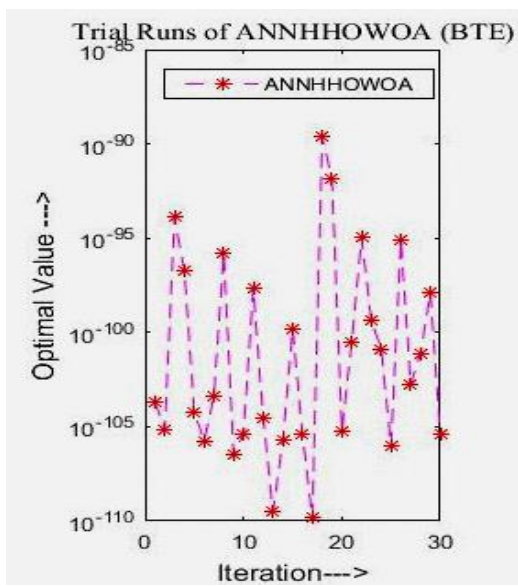


Figure 4.14: Trial runs to achieve optimal BTE using ANN-HHOWOA

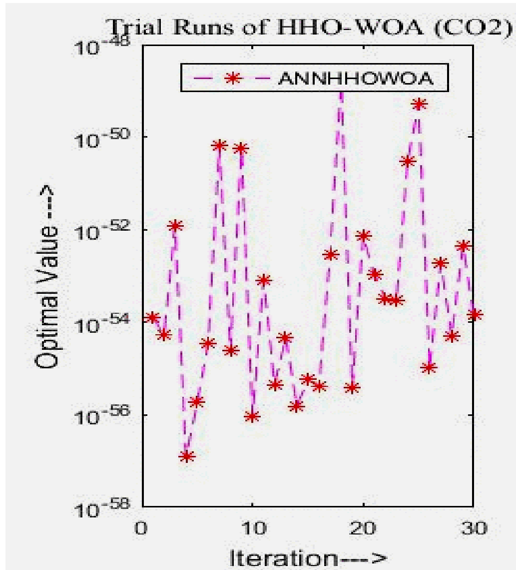


Figure 4.15: Trial runs to achieve optimal CO_2using ANN-HHOWOA

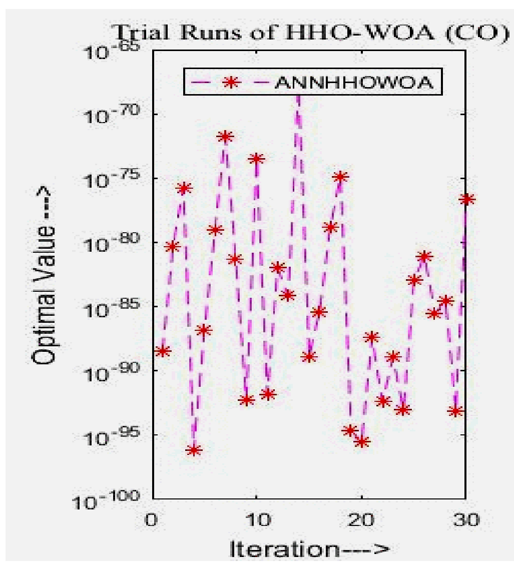


Figure 4.16: Trial runs to achieve optimal CO using ANN-HHOWOA

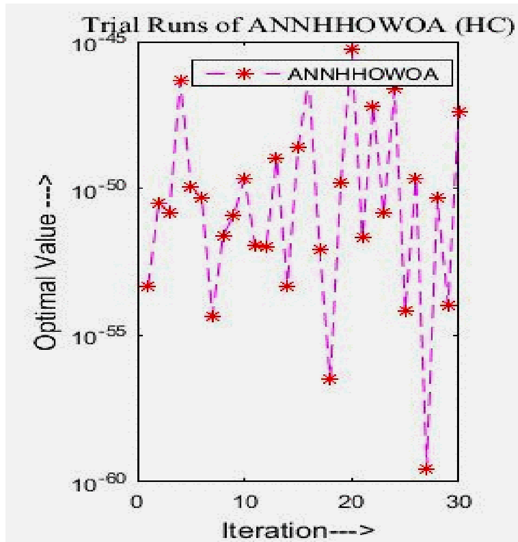


Figure 4.17: Trial runs to achieve optimal HC using ANN-HHOWOA

These graphs are generated by executing code of hybrid HHOWOA algorithm on MATLAB. Simulation time to achieve optimal output parameters using hybrid ANN-HHOWOA is graphically shown as:

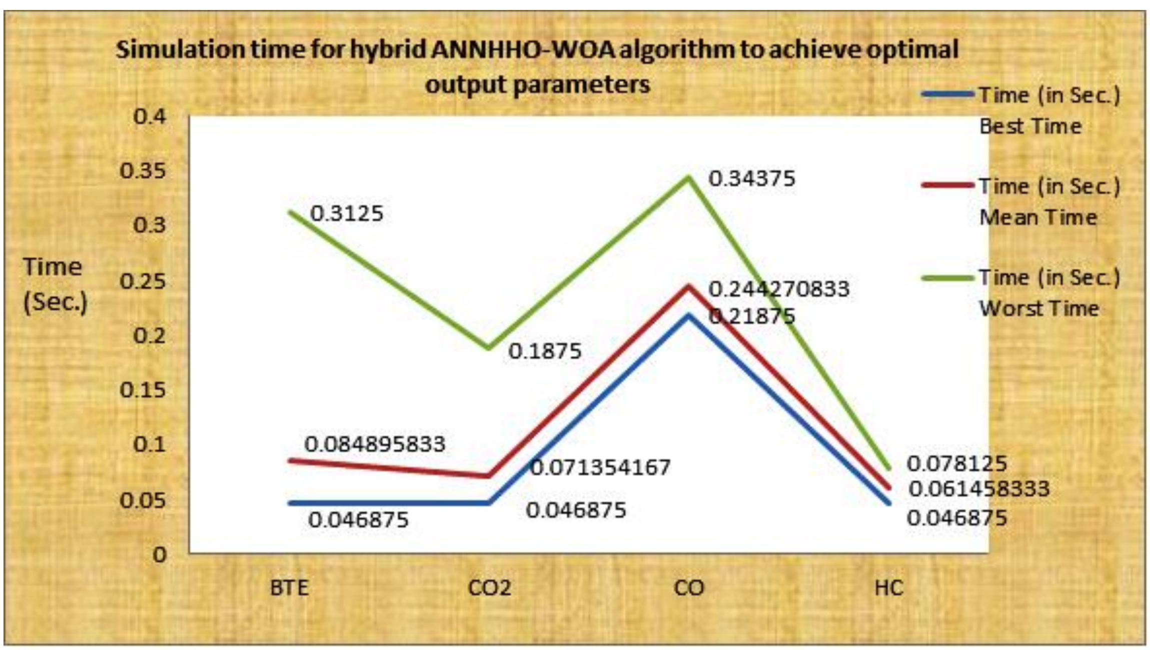


Figure 4.18: Simulation time graph to achieve optimal output

To experimentally validate the results by using ANN-HHOWOA algorithm, it is clearly visible from Figure 4.14-4.17 that the optimal solution of the desired target is achieved with in 30 trial runs. Seventy percent of data is used for training fifteen percent for testing and fifteen percent is used for validation. It has been concluded that Artificial Neural Network based hybrid Harris Hawks and whale optimization algorithm (ANN-HHOWOA) algorithm gave remarkable results with classification rate 98.6667% which is much better than other meta-heuristic algorithms.

After applying ANN based hybrid Harris Hawks and whale optimization algorithm (ANN-HHOWOA) on the gathered input data from the experimental setup of dual fuel engine, the optimal solution is obtained which also leads to find better classification rate of 98.6667%. This is graphically shown as:

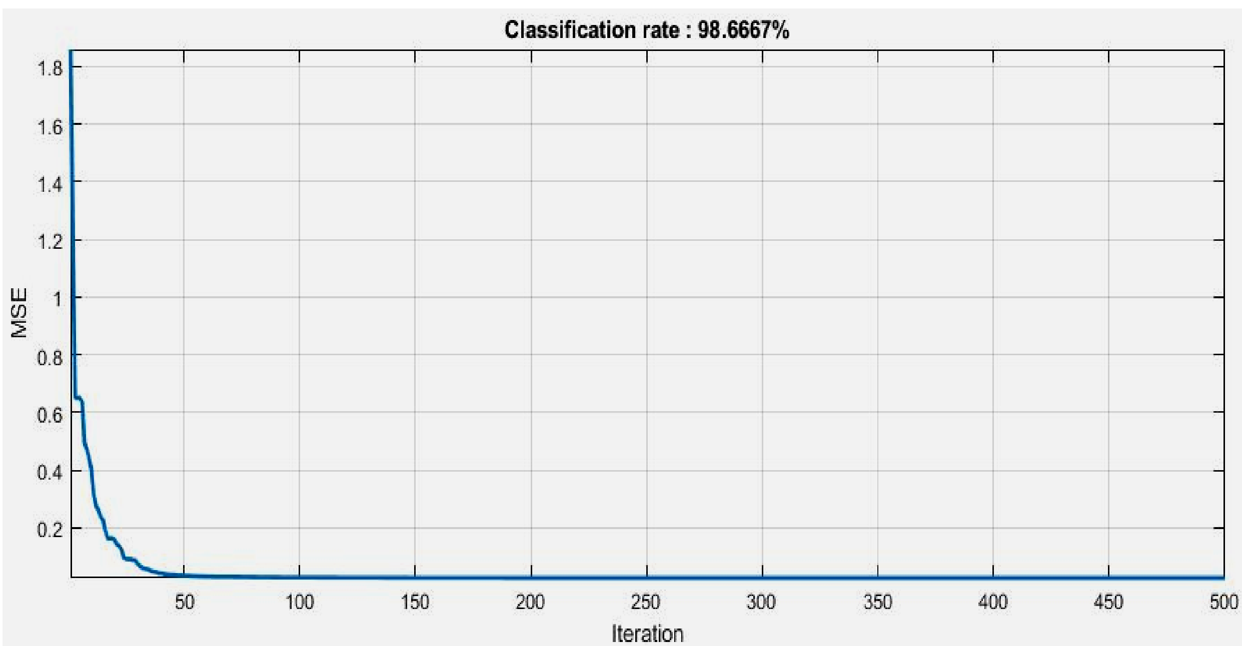


Figure 4.19: Graph depicting classification rate to achieve optimal results

Prediction done by algorithm depicts that we can achieve 98.6667% target value if the new engine is invented or the existing engine is modified efficiently. The target value refers to high BTE and less emissions. To attain the best possible outcome of the output parameters using modern hybrid ANN-HHOWOA algorithm, values of worst time, mean time and best time are shown in Table 4.2.

4.9 Critical Observations from Obtained Results

In dual fuel engine main purpose is to achieve high BTE and minimum emissions. From the observations taken it is concluded that highest BTE is achieved with 26^o BTDC using normal diesel + biogas. In addition to this, minimum CO level is achieved at 29^o BTDC using normal diesel + biogas. Furthermore Minimum CO_2 level is achieved at 26^o BTDC using B60 bio-diesel combination with biogas inlet. Every-time the target of the proposed work is to achieve maximum BTE and minimum emissions. This is possible at different type of fuels and at different BTDC. To solve this problem, optimization is the better solution to achieve the desired targets. The algorithm Artificial Neural Network hybrid Harris Hawks and whale optimization algorithm (ANNHHOWOA) is created and tested to achieve the same. This ANN hybrid approach help in getting the optimal solution to the unknown inputs.

To experimentally validate the results by using ANNHHOWOA algorithm, 30 trial runs are performed on objective functions of gathered data to find optimal solution. Seventy percent of data is used for training fifteen percent for testing and fifteen percent is used for validation. It has been concluded that Artificial Neural Network hybrid Harris Hawks and whale optimization algorithm (ANNHHOWOA) algorithm gave remarkable results with classification rate 98.6667% which is much better than other meta-heuristic algorithms.

After applying ANN based Artificial Neural Network hybrid Harris Hawks and whale optimization algorithm (ANNHHOWOA) on the gathered input data from the experimental setup of dual fuel engine, the optimal solution is obtained which also leads to find better classification rate of 98.6667%.

CHAPTER-5

CONCLUSION AND FUTURE SCOPE

5.1 Conclusion

An existing diesel engine has been improved so that it could operate on dual fuels. For a dual fuel engine, data against the primary fuel and secondary fuel is gathered to improve Brake Thermal Efficiency. The investigations were performed by using IC diesel engine. Mixtures of rice bran biodiesel and biogas were used as primary fuel under dual fuel working mode. Experimental examination analysis was conducted on a conventional diesel engine with rice bran biodiesel blends as basic fuel and biogas under dual fuel operational mode. To optimize the gathered data to the nearest possible accurate value and to find classification rate, the experimental data was given as an input to Artificial Neural Network hybrid Harris Hawks and whale optimization algorithm. Load given to engine i.e. engine load, biodiesel blends, and injection timings were considered as input parameters. Without spending huge amount of money to manufacture and invent a new mechanical hardware, Performance of dual fuel engine working on various bio fuels is tested by using this algorithm**.**

5.2 Future Scope

For future, instead of investing huge amount in research by designing new engine for new bio-fuel or other type of fuels and for checking response characteristics of engine the proposed methodology can be used to get expected outcomes. Before the researchers invest huge amount of money to design a new engine, this will help them to predict and estimate BTE and emissions. Furthermore, Artificial Neural Network based hybrid Harris Hawks and whale optimization algorithm will help in achieving the target which Government has set for BS5, BS6 or even more. The usage of hybrid ANN-HHOWOA model helps in reducing effort, time and cost evolved in designing of engine hardware.

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