MODELLING AND CONTROL OF ELECTRIC MOTOR DRIVES USING NEW CHAOTIC GORILLA TROOPS OPTIMISATION

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Submitted by

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DECLARATION CERTIFICATE

I hereby certify that the work which is being present in the Seminar entitled **"MODELLING AND CONTROL OF ELECTRIC MOTOR DRIVES USING NEW CHAOTIC GORILLA TROOPS OPTIMISATION"** in partial fulfillment of the requirement for the award of degree of Master of Engineering in Power Systems submitted in the Electrical and Instrumentation Engineering Department of Thapar Institute of Engineering and Technology, Patiala is an authentic record of my own work carried out under the guidance of **Dr. Souvik Ganguli**, Assistant Professor, EIED.

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LIST OF ABBREVATIONS

AFT	Ali Baba and 40 thieves
AOA	Arithmetic Optimization Algorithm
AO	Aquila Optimizer
ArOA	Archimedes Optimization Algorithm
AVOA	African Vultures Optimization Algorithm
BWOA	Black Widow Optimization Algorithm
CapSA	Capuchin Search Algorithm
CFA	Chaotic Firefly Algorithm
ChOA	Chimp Optimization Algorithm
ChSA	Chameleon Swarm Algorithm
CGTO	Chaotic Gorilla Troops Optimizer
CGWO	Chaotic Grey Wolf Optimisation
CrySA	Crystal Structure Algorithm
CPSO	Chaotic Particle Swarm Optimisation
COA	Coyote Optimisation Algorithm
DOA	Dingo Optimization Algorithm
FA	Firefly Algorithm
GTO	Gorilla Troops Optimizer
GOA	Grasshopper Optimisation Algorithm
GSA	Gravitational Search Algorithm
GWO	Grey Wolf Optimization
HGS	Hunger Game Search
HHO	Harris Hawks Optimisation
ISA	Interior Search Algorithm
MPA	Marine Predators Algorithm
PSO	Particle Swarm Optimisation
SCA	Sine Cosine Algorithm
SMA	Slime Mold Algorithm
SNS	Social Network Search
WHO	Wild Horse Optimizer
WSO	War Strategy Optimizer

ABSTRACT

In this dissertation, four new sets of chaotic artificial gorilla troop optimizer are created. The position update rule is chaotically varied to yield better performance of the parent technique. There are two controlling parameters in the algorithm which are modified using chaos maps. Both of them are varied together too. Moreover, the position update equation as well as the controlling parameters is altered with the help of chaos maps to get improved performance. A total of ten well-known and widely referenced one-dimensional chaos maps are utilized to develop new chaotic methods. Unimodal and multimodal benchmark functions are used to evaluate the efficacy of the proposed methods. By utilizing the delta operator, it is possible to reduce two induction motor models using this algorithm. Not only the statistical measures of the optimized values are considered for the study but also two popular non-parametric tests have also being carried out to verify the significance of the outcomes thus obtained. The results of the 50 hp and 500 hp induction motor have been presented. A framework for approximating model matching is used in both cases to implement the PID controller. Further an induction motor drive is also modeled and its PI controller is proposed using the unified delta operator. The proposed methods outperform current standard and cutting-edge methods as being evident from their convergence plots as well.

CHAPTER 1

INTRODUCTION

1.1 Background of work

Induction motors are widely used in a wide range of industries due to their ruggedness and robustness. In fact, induction motors make up more than 80% of the motors used in industry. They also require less maintenance. Furthermore, they are easily accessible and reasonably priced [1].

On the other hand, their mathematical models frequently result in overly complicated systems that are difficult to control and operate effectively. They clearly necessitate controllers of higher dimensions. Higher-order controllers obtained for these systems may require additional hardware and not be economically viable. As a result, the order of the original system must be reduced [2].

Delta operator-based modelling and control has a number of advantages over traditional discrete-time systems. As the discrete-time operators cannot handle fast digital data, hence numerical ill-conditioning occurs. The delta domain operator, on the other hand, guarantees fast and accurate computations. There is convergence of discrete delta systems to their continuous time counterparts at very small sampling time, thus providing an integrated modelling approach [3].

Metaheuristic techniques are frequently used to model and control various systems using the delta operator framework [4-6]. In recent years, the use of chaotic metaheuristic techniques to solve engineering problems has grown in popularity. There are many ways to incorporate chaos into metaheuristic techniques. It is a common practice for the position update rule of any algorithm to be randomly varied in order to increase its performance. The overall performance of metaheuristic algorithms can also be improved by modifying some of their parameters using chaos maps. It is possible to use chaos maps in place of random numbers to generate algorithms [7-9].

In recent years, a new metaheuristic method coined as the artificial gorilla troop optimizer (GTO) has been developed, which mimics the social intelligence of gorillas [10]. Algorithms can be made to perform better in a variety of ways. One of the most popular options is the chaotic version. With the help of previously published chaos maps [11], four new sets of chaotic artificial gorilla troop optimizer are proposed in this work. The performance of the GTO algorithm can be improved chaotically by any of the following

- Updating the position equation of the exploitation phase
- Randomly varying two control parameters
- Modifying them together
- Varying two key parameters as well as the update rule.

Higher-dimensional test functions are used to perform initial validation on these algorithms. Unimodal and multimodal test functions are used in this study. Two additional experiments are also conducted out using practical test systems. When modelling and controlling of 50 and 500 hp induction motors, we use these new methods. Further, an induction motor drive is also modelled and controlled using the proposed methods. A combined domain analysis is carried out for the order reduction and the controller design. The statistical measures of the optimal value are also analysed for the test systems. Further, two very popular non-parametric tests viz. the Wilcoxon and Kruskal-Wallis methods [12, 13] are used as an additional support to validate the significance of the outcomes determined.

1.2 Literature review

1.2.1 Review on some recent metaheuristic techniques

A metaheuristic method called the Marine Predators Algorithm (MPA) was presented by Faramarzi *et al*. [14]. It was the ideal encounter rate strategy and biological interaction between carnivore and victim that drove MPA's overall foraging strategy. Hunting and prey catching in marine ecosystems are managed by a set of rules known as the encounter rate strategy.

Abualigah *et al*. [15] recently described the Arithmetic Optimization Algorithm (AOA), based on arithmetic operation in mathematics. This algorithm made a remarkable contribution in various fields of engineering, like in neural networks, image processing, text and data mining, big data, recourse management, smart home, networking, industry, feature selection, cloud computing, signal demising, other real-world complications.

The Aquila Optimizer (AO) algorithm was proposed by Abualigah *et al*. [16] based on the characteristics of the Aquila's hunting operation. This algorithm was used to solve a wide range of problems, including estimating PV parameters, training neural networks, denoising signals, selecting features, segmenting images, and scheduling tasks in the image processing, text and data mining, big data, resource management, and smart home fields, among others.

Abdollahzadeh *et al.* [17] designed a population-based algorithm for metaheuristic technique with the nomenclature African Vultures Optimization Algorithm (AVOA). This algorithm was developed by keeping various factors like; the way of living, searching for meals, and fighting for the meal by different cultures in the African continent.

Bairwa *et al.* [18] investigated the nature of dingo's life such as social and foraging behaviour and proposed a dingo optimizer (DOA) as a new metaheuristic technique. The whole idea was to suggest this technique that engaged the collaborative and social behaviour of dingoes. The proposed method was inspired from the hunting behaviour of dingoes that contained exploration, encircling, and exploitation.

Braik *et al.* [19] established a novel nature-inspired search optimization algorithm to determine the solution of the constrained and global optimization problems named Capuchin Search Algorithm (CapSA). This algorithm was mainly designed by considering the general behaviour of capuchin monkeys such as wandering for food in the forests, along the riverbanks, around the trees, etc. In this algorithm, the process for finding food of capuchins was carried out. Further, it was extended for bouncing, swinging, and mounting behaviours. Jumping was the main mechanism done by capuchins to jump from shrub to shrub. Some actions which had been done by capuchins like swinging and mounting permitted them to step from the short distances over trees, subdivision of tree, and the top of the tree branches. All these behaviours discussed above finally led to the appropriate solution of global optimization problems.

Talatahari *et al.* [20] proposed a metaheuristic technique inspired by the concept of crystal formation source and applied it adequately via an accurate mathematical model. The authors primarily worked to enhance the efficiency of the model and nature-dependent optimization algorithm, as Crystal Structure Algorithm (CrySA).

Hashim *et al.* [21] introduced an advanced metaheuristic technique for solving the optimization problems termed as Archimedes optimization algorithm (ArOA). This algorithm was encouraged by Archimedes' principle of physics. The method impersonated the guideline of light applied vertically on an item, somewhat or completely inundated in fluid, corresponding to the weight of the displaced fluid**.** The algorithm was effective in some benchmark problems of engineering design.

Naruei *et al.* [22] observed the social life of wild horses and proposed an optimization technique that was encouraged by this observation and named it as wild horse optimizer (WHO).

Generally, horses live in a group with includes a stallion and many mares, colt and filly. Horses have some general habits like mating, leading, dominating, chasing, and grazing. Horses have one special behaviour which differentiates them from other animals. Horse fairness conducts was to such an extent the cubs of the horse before arriving pubescence separate themselves from that group and join another group. This exit was to keep the dad from mating with the offspring. The proposed theory was thus based on the tolerance behaviour of horses.

Braik *et al.* [23] made an algorithm based on the famous story of Ali Baba and 40 thieves where Ali Baba found cave which was full of treasures and named it as Ali Baba and 40 thieves (AFT). The group of 40 thieves would be given an instruction to find the house of Ali Baba. The instruction can be from any member of the group which may not be right every time.

Abdollahzadeh *et al.* [10] introduced a metaheuristic technique based on life of gorillas and the mathematical equations were made and named it as Gorilla Troops Algorithm (GTO). Gorillas preferred to live in groups. Because of silver coloured hair on the back these types of gorillas were called silverback gorilla that can live over 12 years. He was the main leader of the group. Migration of gorillas from one group to other group was very common. To expand their groups they can indulged into fight that may last for few days.

Talatahari *et al.* [24] introduced an algorithm based on the social life, that one person can influence the other person by Imitation, disputation, Innovation, Conversation and named it as Social Network Search (SNS). For example if someone admires Cristiano Ronaldo then whatever he will post on social media then his followers would try to imitate him. By having a good conversation with one or two person, one can influence them. By posting something innovative on social media one can influence other person. If one group admires one thing and other group admires other things, then there will be a dispute between two groups and they can influence other group by presenting the rightful facts.

Hayyolalam *et al.* [25] proposed a meta heuristic technique based on the behavior of black widow spiders and coined it as Black widow optimization algorithm (BWOA). Species which had unsuitable fitness were excluded from the circle due to the stage called cannibalism, so it leads to early and better convergence.

Braik *et al.* [26] proposed the mathematical model based on the life of chameleons which includes their search for food, their 360 degree vision to see the prey and catch them by their long sticky fast tongue and this as Chameleons Swarm Algorithm (ChSA).

Khishe *et al.* [27] proposed a technique which was distinguishable from other social predators as it was based on sexual arousal and individual intelligence of chimps in their group hunting. This technique also reduced the problems like low convergence speed and local optima trapping during high dimensional problems and named it as Chimp Optimisation Algorithm (ChOA).

1.2.2 Review on chaos based metaheuristic algorithms

Gandomi *et al.* [28] introduced chaos into the very famous metaheuristic technique known as Firefly Algorithm (FA) and named it as Chaotic Firefly Algorithm (CFA). This algorithm was based on the characteristics of attraction and flashing of fireflies. 12 chaotic maps were used to adjust the attraction movement of fireflies.

Cai *et al.* [29] used local search chaos in one of the oldest metaheuristic technique known as Particle Swarm Optimization (PSO) and named it as Chaotic Particle Swarm Optimization (CPSO). Iterative and Logistic maps were used in this algorithm to solve the engineering problems.

Kohli *et al.* [30] introduced the chaos theory into the most famous algorithm i.e. Grey Wolf Optimization (GWO) to speed up the convergence speed and coined it as Chaotic Grey Wolf Optimization (CGWO). 10 different chaotic maps were used to validate 13 benchmark functions.

Arora *et al.* [31] incorporated the chaos feature in Grasshopper Optimization Algorithm (GOA). The GOA was based on the swarming behavior of grasshopper. These maps not only reduced the repulsion and attraction forces between the grasshoppers but also balanced the exploitation and exploration. Among the different maps used in this algorithm, the results showed that circle map had increased the performance of the GOA considerably.

Dhawale *et al.* [32] introduced the sinusoidal chaotic function with the basic slime mould algorithm to enhance the exploitation phase. The Slime Mould Algorithm impersonated the capabilities of a single-cell organism for exploring the minimum paths between food source to search or explore a better solution.

Gezici *et al.* [33] added the 10 different chaotic maps with Harris Hawks Optimization (HHO) to accelerate the convergence speed. HHO is a new metaheuristic algorithm inspired by the cooperative behavior and hunting strategy of Harris Hawk. 15 test functions were used which showed that piece wise map was the most effective one.

Onay *et al.* [34] introduced chaos theory into the Hunger Game Search (HGS) for solving the engineering problems. Non repeatability and ergodicity were the characteristics of chaotic maps. Due to these properties they provided fast convergence speed because of effective scanning of search space in algorithm.

Pierezan *et al.* [35] introduced a Tinkerbell chaotic map into the population based nature inspired metaheuristic technique known as Coyote Optimization Algorithm (COA). This natured inspired algorithm considers the social relations of the coyote proposed to solve single-objective problems.

Ródenas *et al*. [36] introduced the chaotic maps into the qausi-Newton method known as Gravitational Search Algorithm (GSA) to improve the exploitation capabilities of this algorithm.

Arora et al. [37] proposed the chaos theory into Interior Search Algorithm (ISA). In every metaheuristic algorithm there were mainly two problems. The first is the poor convergence speed and second is the entanglement in local minima. So by using the chaos theory we can eliminate these two problems. ISA is a metaheuristic technique based on beautification of mirrors and object.

Liang *et al.* [38] used the opposition based learning strategy and chaotic local search strategy to balance exploitation and exploration capabilities for the simple Sine Cosine Algorithm (SCA). SCA was a metaheuristic technique based on the cosine and sine function.

1.2.3 Modelling and control in the delta domain (with metaheuristic techniques)

Ganguli *et al.* [3] proposed a hybrid firefly technique to reduce single-input single-output systems taking the benefit of the combined domain of analysis. Sum of square error (SSE) was taken up as the error function to optimize the unknown parameters of the lower-order model. Three constraints were also utilized to determine the parameters.

Ganguli *et al.* [39] further extended their work to develop generalized reduced models for multi-input multi-output systems in the delta operator framework. A new set of hybrid firefly algorithms were used for the purpose. Two additional constraints like matching of time and frequency domain parameters were imposed apart from dc gain matching, stability and minimum-phase features.

Ganguli *et al.* [40] also proposed reduction techniques for fractional order systems through a constrained optimization approach. A host of new algorithms were utilized for comparison with the proposed technique. Non-parametric tests along with statistical measures are performed to justify the significance of the method.

Ganguli *et al.* [6] even developed control scheme in the delta domain for five different test systems. An approximate model matching (AMM) technique was adopted for the same. An arbitrary reference model of desired specification was taken up to match up with the controlled plant. The sum of square error (SSE) was considered as the objective to determine the unknown controller parameters.

Ganguli *et al.* [4] took up the modelling and control of permanent magnet synchronous motor (PMSM) drive in the unified domain applying a hybrid firefly method. A constrained optimization rule was employed to reduce the model. Further, a PI controller was developed for the reduced plant model.

1.3 Research Gaps

From the literature, it is found that many new metaheuristic algorithms have been developed by the researchers in the recent past. It is also observed that artificial gorilla troop optimizer (GTO) is one such interesting method that can be employed to solve diverse engineering problems. Since the algorithm is relatively new, several modifications of it are being developed by the researchers. One of the obvious variations viz. the chaos embedded GTO is missing in the literature. Hence, four new propositions of the chaos based GTO approach will be attempted in this dissertation.

There are several popular choices for the error minimization carried out in reduced order modelling. Integral of square error (ISE) and sum of square error (SSE) are the popularly widely employed as per literature records [3, 39-40]. The integral of time-weighted absolute error (ITAE) criterion will however exhibit relatively small overshoot to some input response with good damped oscillations. Moreover, it has better selectivity as well. Thus, ITAE will be chosen as an objective function in this work to obtain the unknown parameters of the lower-order system.

The exact model matching (EMM) [41] and the approximation model matching (AMM) [42] techniques are used to synthesise controllers applying the Truxal approach. The controller so built by EMM does not guarantee its implementation in hardware. This is the main flaw of exact model matching: Thus, approximate model matching may prove to be a viable alternative in which model order reduction scheme as proposed above can be applied to develop control scheme in the delta domain.

A new application field involving identification and control of converter fed electric drives in the delta domain may also be thought of. Though literature supports modelling and control of electric drives in both the continuous and discrete-time domain, nevertheless practically no work in electric drives has been examined utilizing the delta operator technique. Thus, order reduction and proper controller design in the delta operator framework might be devised for induction motor and drives, in particular employing new chaotic metaheuristic algorithms.

1.4 Objective of research work

Based on the identified gaps in research, the objectives of the proposed work carried out in this dissertation are described as follows:

- To develop new chaotic versions of gorilla troop optimizer and its validation using unimodal and multi-modal benchmark functions
- Reduced order modelling and control of induction motors in the unified delta domain
- Model and control induction motor drive in the delta operator framework.

1.5 Organization of the dissertation

The remaining dissertation is arranged as per the statements provided below.

Chapter 2 discusses the problem of model diminution and controller implementation along with its solution using the delta operator framework.

Chapter 3 proposes four sets of new chaotic versions of the gorilla troop optimizer (GTO).

Chapter 4 presents the results of these newly developed chaotic gorilla troop optimizer on few benchmark test functions, two induction motor models and one practical induction motor drive model. Further, the main inferences and future propositions are also addressed in this chapter.

CHAPTER 2

PROBLEM FORMULATION

2.1 Introduction

In this chapter, the problem of order diminution and controller realization in the combined domain of analysis using delta operator is discussed. Modelling and control in the unified domain instead of regular discrete-time systems has several advantages. The discrete-time operators cannot handle high speed digital data and thus results in numerical ill-conditioning. The delta domain operator however takes care of high-speed computation with increased numerical stability. Further, the discrete-delta systems at high sampling limit convergences to its continuous-time counterpart thus giving a unified modelling approach. The rest of chapter is organized in the following manner. In Section 2.2, the basics of the delta operator is deliberated. Section 2.3 discusses about the model reduction process in the delta domain. Further, the steps of the delta operator-based controller synthesis are described in Section 2.4. Finally concluding remarks are addressed in Section 2.5 along with directions for Chapter 3.

2.2 Basics of delta operator

The delta-operator, an alternate modelling technique of the discrete-time system [43] is defined as

$$\delta = \frac{q-1}{\Delta} \tag{2.1}$$

as per the time-domain analysis. Here Δ denotes the sampling period while q is the forward shift operator. Operating δon a differential signal $x(t)$ results in

$$\delta x(t) = \frac{x(t+\Delta)-x(t)}{\Delta} \tag{2.2}$$

It can be found that

$$\lim_{\Delta\to 0} \delta x(t) = \frac{d}{dt}x(t) \tag{2.3}$$

which indicate the resemblance of the discrete-time δ -operator with the continuous-time differential operator $\frac{d}{dt}$ at a fast sampling rate.

Similar relation applies for the complex domain as well. The delta transform operator is denoted by γ and is given by

$$\gamma = \frac{z-1}{\Delta} \tag{2.4}$$

2.3 Problem statement for order reduction

Let us suppose that the transfer function of the higher-order system using the delta operator be defined by

$$G_\delta(\gamma) = \frac{N_{k-1}(\gamma)}{D_k(\gamma)} = \frac{\sum_{i=0}^{k-1} b_i \gamma^i}{\sum_{i=0}^{k} a_i \gamma^i} \tag{2.5}$$

where a_i and b_i are the coefficients of the denominator and the numerator polynomials respectively. $G_\delta(\gamma)$ is considered as irreducible such that the numerator and denominator do not have any factors in common. The prime objective here is to determine a lower-order model of order $r(r < k)$ in such a manner that it preserves all the fundamental properties of the higher order system and denoted below by

$$G_{R\delta}(\gamma) = \frac{N_{r-1}(\gamma)}{D_r(\gamma)} = \frac{\sum_{i=0}^{r-1} d_i \gamma^i}{\sum_{i=0}^{r} c_i \gamma^i} \tag{2.6}$$

The constraints involved to obtain this fixed-structured reduced system are as follows:

- Equalling the dc gain
- Assuring stability
- Preserving the minimum phase characteristics.

Thus, the problem of order reduction needs to be solved using a constrained optimization-based approach. There are several popular choices for the error minimization carried out in reduced order modelling. Integral of square error (ISE) and sum of square error (SSE) are the popularly widely employed as per literature records [3, 39-40]. The integral of time-weighted absolute error (ITAE) criterion will however exhibit relatively small overshoot to some input response with good damped oscillations. Moreover, it has better selectivity as well. Thus, ITAE is chosen as an objective function in this work to find out the unknown parameters of the reduced system. The difference or error value is constituted from the pseudo random binary sequence (PRBS) based responses of original system and fixed structured reduced system with unknown numerator and denominator coefficients. The constraints discussed above also need to be satisfied in order to determine a suitable lower-order model.

2.4 Controller synthesis formulation

This work also employs approximate model matching (AMM) [42] for controller synthesis. It is preferred over exact model matching (EMM) [41] because EMM does not ensure the hardware realization of the controller. Below is a generalised stepwise procedure for controller tuning in the delta domain.

Step-1: Select a general controller represented by

$$C_\delta = \frac{\beta_0+\beta_1\gamma+\cdots+\beta_r\gamma^r}{\alpha_0+\alpha_1\gamma+\cdots+\gamma^r} \tag{2.7}$$

Step-2: Make a choice for the standard reference model that meets certain required specifications.

Step-3: Determine the output response considering unity feedback and compare it with the response of the reference model.

Step-4: Find the sum of square error (SSE) determined by the difference between the output of the reference model to that of the controlled plant in closed-loop mode.

Step-5: Optimize this SSE by applying the proposed heuristic method. As a result, the controller coefficients i.e. β_i and α_i are obtained within specified search limits.

However, for the sake of simplicity a PID controller is realized for 50 hp and 500 hp induction motor models while a PI controller is conceptualized for an induction motor drive.

2.5 Concluding remarks

The delta operator is introduced in this chapter. Their advantages over the conventional discrete-time shift operator are also narrated. The problem for model reduction and controller synthesis in the delta operator is also addressed. In Chapter 3, the chaotic gorilla troop optimizer (CGTO) is proposed which is utilized not only reduce the higher-order systems but also help to tune the controller parameters in the delta domain by leveraging the benefits of AMM. For comparison, the GTO method, as well as a number of standard heuristic approaches, is employed.

CHAPTER 3

PROPOSED METHODS

3.1 Introduction

In this dissertation, four new sets of chaotic version of gorilla troop optimizer are developed. In the first set, the position equation of the parent algorithm is updated using different one-dimensional chaotic maps. In the second set, two parameters are altered by chaotic maps. In the third set, both of these parameters are together varied using chaotic maps. In the fourth set, the position update rules as well as the controlling parameters are modified to improve upon the performance of the basic technique. Ten popular and widely cited chaotic maps are considered to develop new chaotic algorithms. The mathematical modelling of gorilla troop optimizer is deliberated in Section 3.2. The description of the suggested methods and their nomenclatures are provided in Sections 3.3-3.6.The efficacy of these proposed techniques will be tested in Chapter 4.

3.2 Artificial gorilla troop optimizer (GTO)

Artificial gorilla troop optimization, popularly coined as GTO, was developed by Abdollahzadeh *et al.* [10] utilizing the social intelligence behaviour of the gorillas as a model. During the algorithm's exploration phase, three distinct operators are employed. In order to increase GTO investigation, the first operator migrates to an unknown location. This shifts the balance of exploration and exploitation in favour of the second operator. The GTO's ability to discover new optimization spaces is greatly enhanced by the third operator in the exploration process: migration toward a well-known location. The exploration phase of the GTO technique is thus governed by three strategies stated by Eqn. (1) narrated below.

$$\mathrm{gx}(\mathrm{t}+1)=\begin{cases}(\mathrm{ul}-\mathrm{ll})\times a_1+\mathrm{lb}, & \mathrm{rand}<\mathrm{P},\\ (a_2-c)\times x_r(t)+l\times \mathrm{h}, & \mathrm{rand}\geq 0.5,\\ x(i)-l\times\left(\mathrm{l}\times\left(\mathrm{x(t)}-\mathrm{g}x_r(t)\right)+a_3\times\left(\mathrm{x(t)}-\mathrm{g}x_r(t)\right)\right), & rand<0.5\end{cases} \tag{3.1}$$

where *x(t)* and *gx(t+1)* reprsent the present gorilla position and the candidate position vector of the gorilla in the succeeding *'t'* iteration, respectively, while *rand, a1, a2, and a3* denote random numbers ranging between 0 and 1. The parameter *'P'* represents the probability of choosing the migration strategy to an unrecognized position and must lie between 0–1 before the optimization operation. Last but not the least, the parameters x_r and gx_r demonstrate a single member of the gorillas represented from the whole population and one of the vectors of gorilla candidate positions that can be randomly designated, respectively. ll and ul represent respectively the lower and upper limits of the decision variables. The variables c, l and h in Eqn. (1) are represented by Eqns. (3.2), (3.4), and (3.5) as

$$c = f \times \left(1 - \frac{iteration}{Max\_iteration}\right) \tag{3.2}$$

$$\mathrm{f} = \cos(2 \times \mathrm{a}_4) + 1 \tag{3.3}$$

$$\mathrm{l} = \mathrm{c} \times \mathrm{L} \tag{3.4}$$

$$\mathrm{h} = \mathrm{z} \times \mathrm{x(t)} \tag{3.5}$$

$$\mathrm{z} = [-\mathrm{c}, \mathrm{c}] \tag{3.6}$$

where the symbols *iteration* and *Max_iteration* represent respectively the present iteration count and the total iteration number of the optimization process, whereas the symbols *cos* and *a4* signify the cosine function and random number between 0-1, respectively. Moreover, the notations l and z denote random values lying in the range of [−1, 1] and [−c, c], respectively. In contrast to the exploration part, two operators are used in the exploitation phase, greatly improving search performance. In this way, the algorithm's exploitation phase is depicted with the help equation (3.7) given below.

$$\mathrm{gx(t+1)} = \mathrm{l} \times \mathrm{m} \times (\mathrm{x(t)} - \mathrm{x}_{\mathrm{silverback}}) + \mathrm{x(t)} \tag{3.7}$$

Here, x*(t)* represents the position vector corresponding to the gorilla, while $x_{silverback}$ denotes the silverback gorilla position vector giving rise to the optimal solution. In this Eqn. (3.7), m is narrated as

$$\mathrm{m} = \left(\left|\frac{1}{\mathrm{n}}\sum_{\mathrm{i}=1}^{\mathrm{n}} g\mathrm{x}_{\mathrm{i}}(\mathrm{t})\right|^{\mathrm{G}}\right)^{\frac{1}{\mathrm{G}}} \tag{3.8}$$

gxi (t) depicts the position of each candidate gorilla in iteration t, whereas n represents the number of gorillas present. Thus, *G* stands for

$$\mathrm{G} = 2^{l} \tag{3.9}$$

where *'l'* can be determined by Eqn. (3.4). The other strategy of the exploitation phase to compete for adult females is mathematically formulated as

$$\mathrm{gx(i)} = \mathrm{x_{silverback}} - (\mathrm{x_{silverback}} \times \mathrm{q} - \mathrm{x(t)} \times \mathrm{q}) \times \mathrm{a} \tag{3.10}$$

$$\mathrm{q} = 2 \times \mathrm{a_5} - 1 \tag{3.11}$$

q denotes the impact force, given in Eqn. (3.11), while the symbol r_5 stands for the random numbers in the range [0, 1]. Moreover,

$$\mathrm{a} = \beta \times \mathrm{e} \tag{3.12}$$

Here, the coefficient 'a' constitutes a vector that assesses the amount of violence for any rivalry. Thus, it can be determined with Eqn. (3.12) and e denotes

$$\mathrm{e} = \begin{cases} \mathrm{n_1}, & \mathrm{rand} \geq 0.5, \\ \mathrm{n_2}, & \mathrm{rand} < 0.5. \end{cases} \tag{3.13}$$

Further in Eqn. (3.12), the parameter β is a user defined value before the manoeuvring of the optimization occurs, while e is simulates the effect of violence on the dimension of the solutions.

3.3 Problem method-1

The position update Eqn. (3.10) in the exploitation phase of the GTO algorithm is chaotically varied using one-dimensional chaotic maps bringing about significant improvement in the outcome of the original GTO algorithm. The proposed nomenclatures for the algorithms are defined by chaotic gorilla troop optimizer (CGTO). The chaotic maps taken up for the study are shown in Table 3.1.

Table 3.1. Standard chaotic maps

Map Name	Definition
Chebyshev map	$z_{k+1} = \cos(k \cos^{-1}(z_k))$
Circle map	$z_{k+1} = z_k + \mathrm{b} - (\mathrm{a} - 2\pi)\sin(2\pi z_k) mod(1)$
Gauss map	$z_{k+1} = \begin{Bmatrix} 0 & z_k = 0 \\ 1/z_k mod(1) & otherwise \end{Bmatrix}$
Iterative map	$z_{k+1} = \sin(a\pi/z_k)$

Logistic map	$z_{k+1} = az_k(1 - z_k)$
Piecewise map	$z_{k+1} = \begin{cases} \frac{z_k}{P} & 0 \leq z_k < P \\ \frac{z_k - P}{0.5 - P} & P \leq z_k < 0.5 \\ \frac{1 - P - z_k}{0.5 - P} & 0.5 \leq z_k < 1 - P \\ \frac{1 - z_k}{P} & 1 - P \leq z_k < 1 \end{cases}$
Sine map	$z_{k+1} = \frac{a}{4}\sin(\pi z_k)$
Singer map	$z_{k+1} = \mu(7.86z_k - 23.31z_k^2 + 28.75z_k^3 - 13.3028.75z_k^4$
Sinusoidal map	$z_{k+1} = az_k^2 \sin(\pi\, z_k)$
Tent map	$z_{k+1} = \begin{cases} \frac{z_k}{0.7} z_k < 0.7 \\ \frac{10}{3}(1 - z_k) \quad z_k \geq 0.7 \end{cases}$

Accordingly, the proposed CGTO algorithms are numbered as per their chaotic map number, as discussed in Table 3.2.

Table 3.2. Nomenclature of the different CGTOs

Nomenclature of algorithm	Variation in the algorithm	Chaotic map used
CGTO-01	Position	Chebyshev Map
CGTO-02	Position	Circle Map
CGTO-03	Position	Gauss Map
CGTO-04	Position	Iterative Map
CGTO-05	Position	Logistic Map
CGTO-06	Position	Piece wise Map

CGTO-07	Position	Sine Map
CGTO-08	Position	Singer Map
CGTO-09	Position	Sinusoidal Map
CGTO-10	Position	Tent Map

3.4 Proposed method-2

There are two controlling parameters in the parent artificial gorilla troop optimization technique which contribute significantly to the performance of the algorithm. They are denoted in the algorithm by 'ω' and 'P' respectively. Replacing them by chaotic maps greatly influence the results of the GTO algorithm. Ten chaotic maps, widely accepted in the literature, are considered in this chapter as shown in Table 3.1. The proposed methods are prescribed as chaos inspired gorilla troop optimizer denoted by ChAGTO in this work. Thus the algorithms are numbered from ChAGTO-1 to ChAGTO-20 as per parameter variations and chaos map used. These are formally presented in Table 3.3.

Table 3.3. Names of the various CGTOs

Names of algorithm	Parameter variation	Chaotic map
ChAGTO-01	ω	Chebyshev Map
ChAGTO-02	ω	Circle Map
ChAGTO-03	ω	Gauss Map
ChAGTO-04	ω	Iterative Map
ChAGTO-05	ω	Logistic Map
ChAGTO-06	ω	Piece wise Map
ChAGTO-07	ω	Sine Map
ChAGTO-08	ω	Singer Map

ChAGTO-09	ω	Sinusoidal Map
ChAGTO-10	ω	Tent Map
ChAGTO-11	P	Chebyshev Map
ChAGTO-12	P	Circle Map
ChAGTO-13	P	Gauss Map
ChAGTO-14	P	Iterative Map
ChAGTO-15	P	Logistic Map
ChAGTO-16	P	Piece wise Map
ChAGTO-17	P	Sine Map
ChAGTO-18	P	Singer Map
ChAGTO-19	P	Sinusoidal Map
ChAGTO-20	P	Tent Map

3.5 Proposed method-3

Here, both the algorithm parameters referred to as $'\omega'$ and *'P'* are replaced with chaotic maps Both of them are incorporated into this algorithm in order to produce even better outcomes. In this dissertation, once again the ten chaotic maps in Table 3.1 are examined. We refer to the proposed approaches as CAGTO, which stands for chaos-inspired artificial gorilla troop optimizer. Accordingly, the algorithms are numbered one through ten in the order in which the parameters and chaos map are varied. Table 3.4 displays the data in a formal manner.

Table 3.4. Nomenclature of the proposed CAGTO methods

Nomenclature of proposed methods	Changes in the algorithm	Chaotic maps utilized
CAGTO-01	P & ω	Chebyshev Map
CAGTO-02	P & ω	Circle Map

CAGTO-03	P & ω	Gauss Map
CAGTO-04	P & ω	Iterative Map
CAGTO-05	P & ω	Logistic Map
CAGTO-06	P & ω	Piece wise Map
CAGTO-07	P & ω	Sine Map
CAGTO-08	P & ω	Singer Map
CAGTO-09	P & ω	Sinusoidal Map
CAGTO-10	P & ω	Tent Map

3.6. Proposed method-4

In this technique, the position update rule Eqn. (3.10) in the exploitation phase of the GTO algorithm as well as the two controlling parameters $'\omega'$ and $'P'$ are chaotically modified using one-dimensional chaotic maps bringing about significant improvement in the outcome of the original GTO algorithm. The proposed nomenclatures for the algorithms are defined by chaotic gorilla troop optimizer (ChGTO). Accordingly, the proposed ChGTO algorithms are numbered as per their chaotic map number, as discussed in Table 3.5.

Table 3.5 Different names for the proposed ChGTO methods

Nomenclature of algorithm	Variations in the algorithm	Chaos maps used
ChGTO-01	P, ω, and position	Chebyshev Map
ChGTO-02	P, ω, and position	Circle Map
ChGTO-03	P, ω, and position	Gauss Map

ChGTO-04	P, ω, and position	Iterative Map
ChGTO-05	P, ω, and position	Logistic Map
ChGTO-06	P, ω, and position	Piece wise Map
ChGTO-07	P, ω, and position	Sine Map
ChGTO-08	P, ω, and position	Singer Map
ChGTO-09	P, ω, and position	Sinusoidal Map
ChGTO-10	P, ω, and position	Tent Map

3.6 Conclusions

Four different sets of the chaotic gorilla troop optimizer are constructed in this chapter. Using various one-dimensional chaotic maps, the parent algorithm's position equation is changed in the first set. In the second set, chaotic maps change two parameters. In the third set, chaotic maps are used to jointly vary these two parameters. To enhance the functionality of the fundamental technique, the fourth set modifies the regulating parameters as well as the position update rules. To create new chaotic algorithms, ten well-known and frequently quoted chaotic maps are taken into consideration.

In the next chapter, two types of test functions namely; unimodal and multi-modal will be applied to validate the efficacy of the proposed techniques, A 50 hp induction motor model will be also reduced and further its controller is designed utilizing the benefit of delta operator with the help of these proposed algorithms. Finally, a practical test system of induction motor drive will be taken up for the purpose of order reduction and controller synthesis. The controller realization in both cases will be carried out using approximate model matching framework. The convergence speed and accuracy of the proposed techniques are expected to be better as compared to the standard and latest methods. The statistical measures of the optimal values will be analysed for the test systems, accounting for the best outcome as well as stability of the proposed algorithms. Non-parametric tests will further be conducted to verify the significance of the proposed approaches. Thus the results in all experimentations performed show great promise.

CHAPTER 4

RESULTS AND DISCUSSIONS

4.1 Introduction

In this chapter, the four novel chaotic versions of the gorilla troop optimizer developed in the previous chapter are now being applied primarily on three test systems. First of all, unimodal and multimodal test functions are used to evaluate the effectiveness of the suggested techniques. By utilizing the delta operator, it is possible to reduce two induction motor models using this algorithm. Not only the statistical measures of the optimized values are considered for the study but also two popular non-parametric tests have also being carried to validate the significance of the outcomes. A framework for approximating model matching is used in both cases to implement the PID controller. In terms of convergence speed and accuracy, the proposed methods outperform current standard and cutting-edge methods. Last but not the least, an induction motor drive is taken up for the purpose of order reduction and controller synthesis. The controller realization in this case is carried out using approximate model matching framework. Thus the results in all experimentations performed show great promise.

4.2 Simulation results for proposed method-1

Experiment 1: To test the efficacy of the proposed methods, two types of test functions viz. unimodal and multi-modal are considered for experimentation. Two unimodal test functions while three multi-modal test benchmarks are taken for the study. The mathematical descriptions of these test functions are available in Table 4.1. Their search domain and ideal optimum values are also specified. F1 and F2 considered are unimodal functions while F3, F4 and F5 represent the multi-modal test functions. In each of these test functions, hundred decision variables are optimized. The population size and the maximum number of iterations are considered as 30 and 500 for these test problems. This means that the number of function evaluations (NFE) is $30 \times 500 = 15{,}000$ which is quite competitive in terms of number of decision variables considered for the study.

Table 4.1. Benchmark functions

Function descriptions	Dimension	Search domain	f_{min} value
$f_1(z) = \sum_{i=1}^{n} z_i^2$	100	[-100, 100]	0
$f_2(z) = \sum_{i=1}^{n-1} \left[100\left(z_{i+1} - z_i^2\right)^2 + (z_i - 1)^2\right]$	100	[-30,30]	0
$f_3(z) = 20\, exp\left(-0.2\sqrt{\frac{1}{n}\sum_{i=1}^{n} z_i^2}\right) - exp\left(\frac{1}{n}\sum_{i=1}^{n} cos(2\pi z_i)\right) + 20 + e$	100	[-32,32]	0
$f_4(z) = \frac{\pi}{n}\left\{10\, sin(\pi z_1) + \sum_{i=1}^{n-1}(z_i - 1)^2[1 + 10\, sin^2(\pi z_{i+1})] + (z_n - 1)^2\right\} + \sum_{i=1}^{n}\mu(z_i, 10, 100, 4) y_i = 1 + \frac{z_i + 1}{4}$ $\mu(z_i, a, k, m) = \begin{cases} k(z_i - a)^m & z_i > a \\ 0 & -a < z_i < a \\ k(-z_i - a)^m & z_i < -a \end{cases}$	100	[-50,50]	0

$f_5(z) = 0.1\left\{sin^2(3\pi z_1) + \sum_{i=1}^{n}(z_i-1)^2[1+sin^2(3\pi z_i+1)] + (z_n-1)^2[1+sin^2(2\pi z_n)]\right\} + \sum_{i=1}^{n}\mu(z_i,5,100,4)$	100	[-50,50]	0

These test functions are optimized using the proposed techniques. Further, the algorithms like Gorilla Troop Optimizer (GTO), Marine Predator Algorithm (MPA), Black Widow Optimization Algorithm (BWOA), Chimp Optimization Algorithm (ChOA), Chameleon Swarm Algorithm (ChSA), Dingo Optimization Algorithm (DOA), Slime Mould Algorithm (SMA), Wild Horse Optimizer (WHO), and War Strategy Optimizer (WSO) are applied for comparison. The convergence plots of the test functions (F1-F5) are displayed in Figure 4.1-4.5.

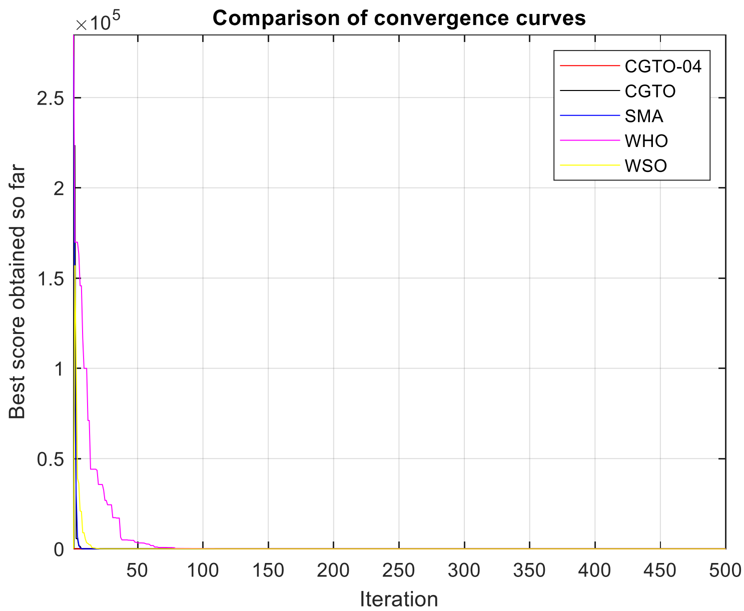

Fig. 4.1. Convergence plots of test function F1

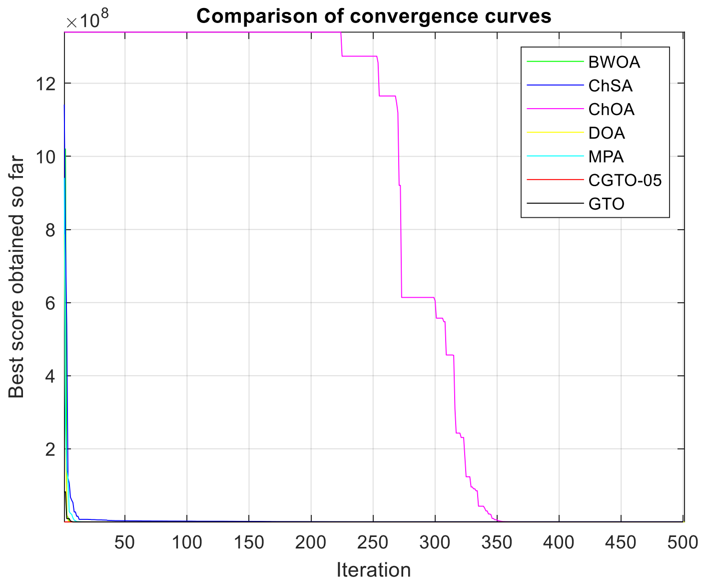

Fig. 4.2. Convergence plots of test function F2

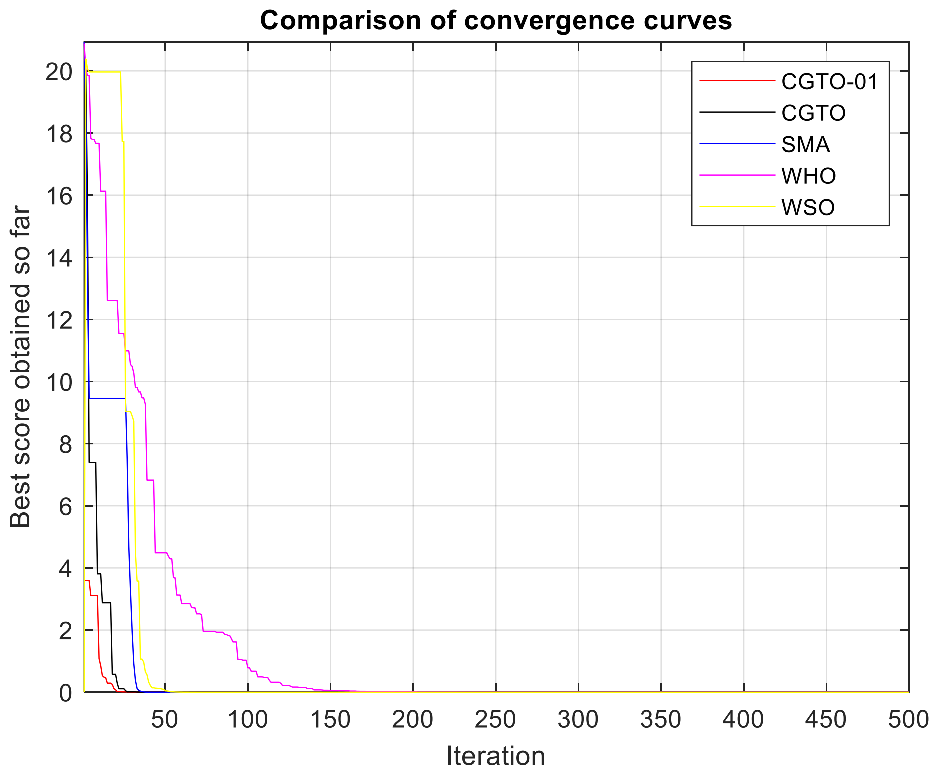

Fig. 4.3. Convergence plots of test function F3

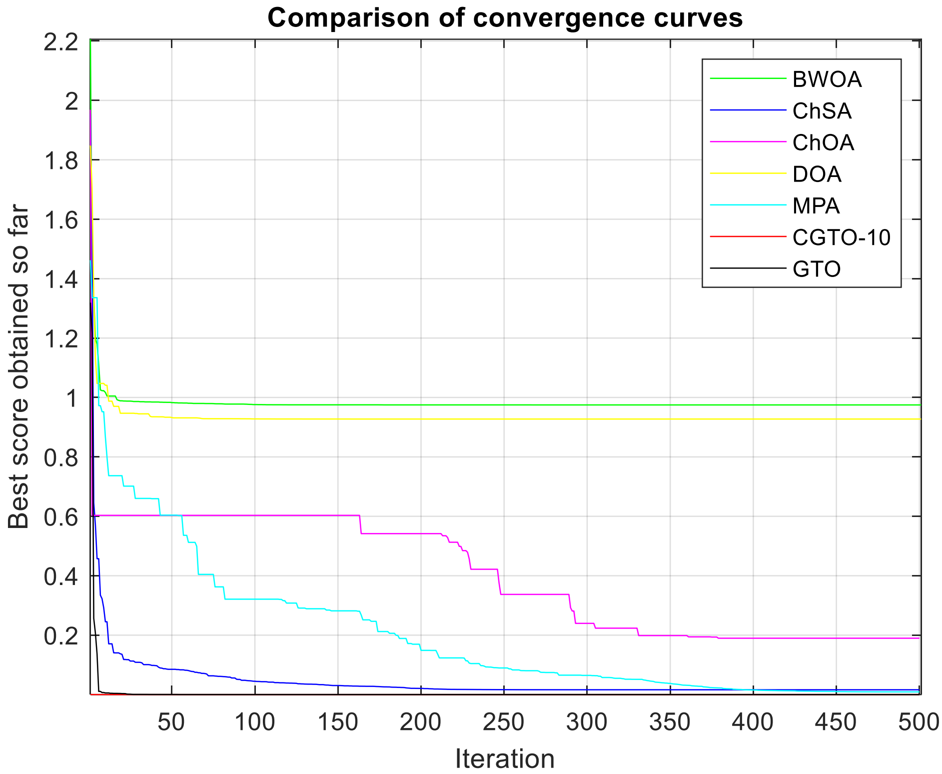

Fig. 4.4. Convergence plots of test function F4

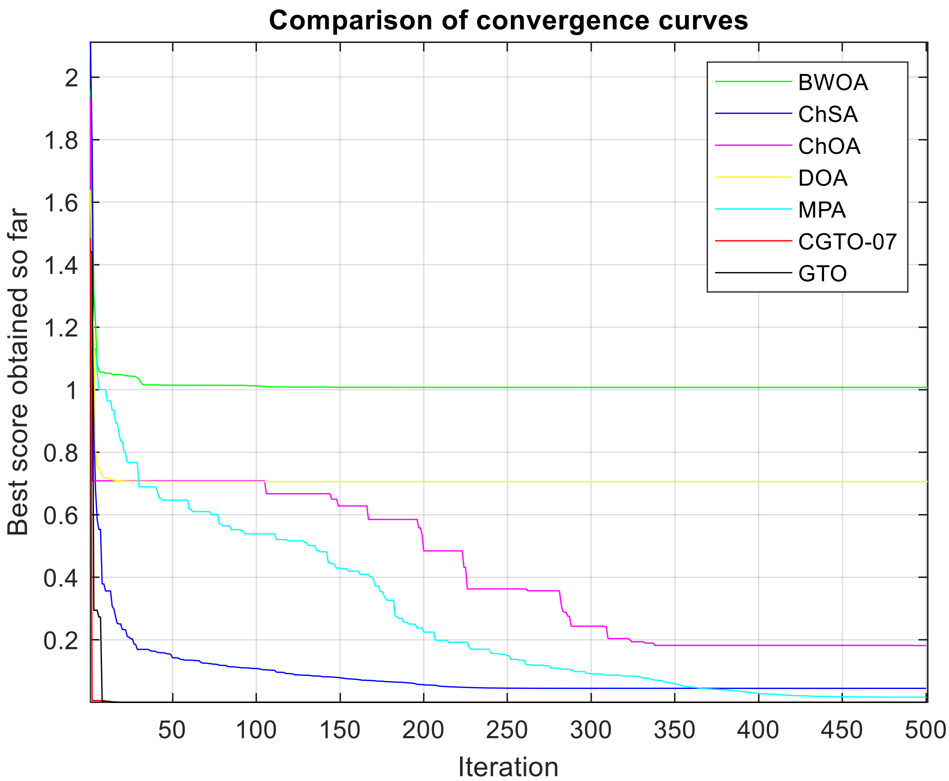

Fig. 4.5. Convergence plots of test function F5

It is clearly indicative from Fig. 4.1-4.5 that the proposed CGTO approaches provide better convergence speed and accuracy than the parent GTO algorithm as well as a host of techniques used for comparison.

Experiment 2: A 50 HP induction motor [44] is also considered for the study. The machine model is 5th order as given below by its transfer function.

$$G_1(s) = \frac{2085s^3 + 511000s^2 + 3.081e07\ s + 4.676e09}{s^5 + 397.9s^4 + 184800s^3 + 4.151e07s^2 + 3.408e09\ s + 4.076e10} \quad (4.1)$$

The corresponding delta transformed model represented in γ-domain with a sampling time of 0.0025 secs is denoted by

$$G_1(\gamma) = \frac{2.131\gamma^4 + 2084.7\gamma^3 + 3.887e05\gamma^2 + 3.179e07\gamma + 2.71e09}{\gamma^5 + 609.98\gamma^4 + 2.17e05\gamma^3 + 3.454e07\gamma^2 + 2.125e9\gamma + 2.362e10} \quad (4.2)$$

It is quite difficult to develop an implementable controller corresponding to this higher order machine model. Thus, this model is reduced to a second order system by using the proposed CGTO-6 method. For this experiment however, 20 search agents and 100 iterations are selected as this involves finding only four decision variables. Several new algorithms like MPA, BWOA, ChOA, ChSA, DOA including GTO are utilized for comparison. The reduced models are provided in Table 4.2. Since only the heuristic technique is used to bring about the reduced model, hence average and standard deviation of the optimized error value viz. ITAE in this case is provided in this Table. The best error values are also bolded in this Table for the convenience of the readers.

Table 4.2. Reduced models of the 50 hp induction motor in the unified delta domain, average and standard deviation of error function

Algorithms	Reduced transfer functions in the delta domain	Avg. error	Std. error
CGTO-06	$\frac{1.284\gamma + 20.37}{\gamma^2 + 23.83\gamma + 161.62}$	**0.0103297**	1.8977e-09

GTO	$\frac{1.33\gamma + 5.874}{\gamma^2 + 14.02\,\gamma + 50}$	0.010337	8.87e-07
BWOA	$\frac{1.398\gamma + 6.298}{\gamma^2 + 15.17\,\gamma + 49.41}$	0.010341	1.29e-06
ChOA	$\frac{1.404\,\gamma + 0.5254}{\gamma^2 + 11.26\,\gamma + 4.287}$	0.010343	1.66e-06
ChSA	$\frac{1.329\,\gamma + 5.744}{\gamma^2 + 13.93\,\gamma + 49.04}$	0.010337	1.86e-06
DOA	$\frac{1.33\,\gamma + 5.874}{\gamma^2 + 14.02\,\gamma + 50}$	0.010337	1.24e-06
MPA	$\frac{1.33\,\gamma + 5.874}{\gamma^2 + 14.02\,\gamma + 50}$	0.010337	**1.03e-10**

It is found from Table 4.2 that the proposed CGTO-6 technique outperforms other methods in terms of average ITAE error optimized. The standard deviation of the ITAE error is however least in the MPA method indicating that the algorithm is more stable in terms of the other techniques used for comparison. Further, the convergence characteristics are drawn as given by Fig. 4.6.

Even an intelligent PID controller is also developed for this motor using the proposed technique. The sum of square error (SSE) is optimized to evaluate the controller parameters. The controller parameters are determined using approximate model matching method in the delta domain. A fixed reference model is taken up for the study. A handful of new algorithms are used for comparison.

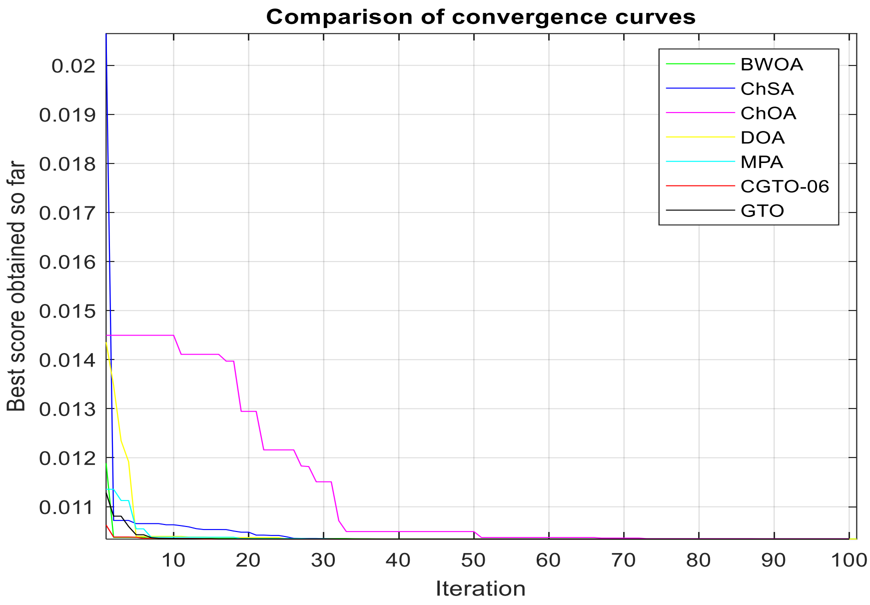

Fig. 4.6. Convergence plots of reduced 50 HP induction motor

There are only three decision variables involved in the controller tuning process. Hence, the population size and the maximum number of iterations are taken up as 20 and 100 respectively for this optimization problem. The tuned controller parameters are provided in Table 4.3. The least optimized value of the fitness function is bolded.

Table 4.3. Tuned controller parameters of 50 hp induction motor in the unified domain

Algorithms	K_p	K_i	K_d	SSE
CGTO-06	42.5827	0.0450849	4.1988	0.025139
GTO	42.5827	0.04508	4.19880	0.02513
BWOA	38.5511	0.14823	7.33556	0.10407
ChOA	42.5222	0.04504	4.19780	**0.02508**
ChSA	42.6455	0.04558	4.20314	0.02548
DOA	50	0.14792	5.10177	0.04164
MPA	42.5825	0.04507	4.19877	0.02513

From the results of Table 4.3 it is clear that the ChOA method gives the least square error. The results of GTO, MPA and the proposed CGTO-6 are also close by. Moreover, the convergence plot of this controller tuning problem is shown in Fig. 4.7.

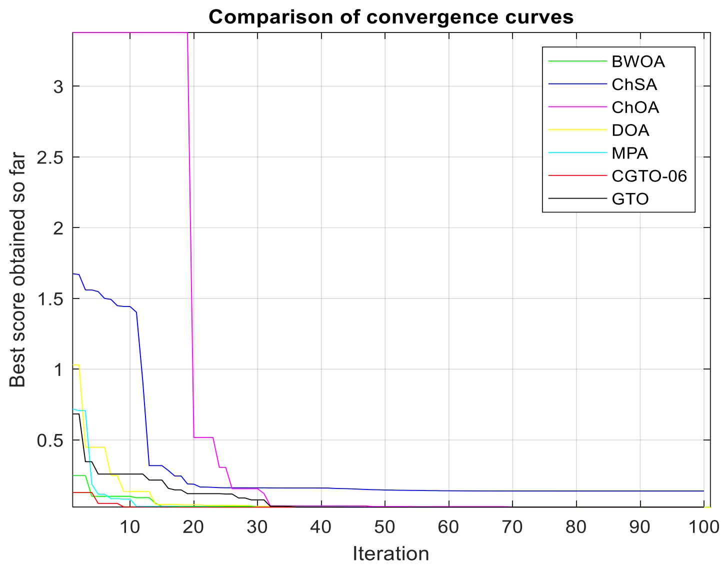

Fig. 4.7. Convergence plots of controller tuning problem for the 50 hp induction motor

From the convergence plot of Fig. 4.7, it is evident that the proposed CGTO-06 shows an appreciable good convergence when compared with a host of the latest techniques reported in the literature.

Experiment 3: The next test system chosen for the study is an induction motor drive model [45]. The transfer function of the drive model is denoted by

$$G_2(s) = \frac{13.381s + 40.54}{8.58e{-}07s^3 + 0.003517s^2 + 4.802s + 40.69} \tag{4.3}$$

The drive system is modelled in the delta domain as

$$G_2(\gamma) = \frac{1.128e03\gamma^2 + 4.643e05\gamma + 1.395e06}{\gamma^3 + 8.23e03\gamma^2 + 1.728e05\gamma + 1.402e06} \tag{4.4}$$

The model corresponds to a sampling period of 0.0025 seconds. Once again, the experimentation is performed to reduce this model to a lower order second order system choosing four unknown parameters. Hence the choice of 20 search agents and 100 iterations can be considered appropriate. The reduced model in the unified domain of the proposed method and their optimized fitness function values (mean and standard deviation) are depicted in Table 4.4. A handful number of methods are also applied for comparison purpose. The least error values are marked with the help of bold letters.

Table 4.4. Reduced models of the induction motor drive in the unified delta domain, average and standard deviation of error function

Methods	Reduced transfer functions in the delta domain	Avg. error	Std. error
CGTO-06	$\frac{1128.4616\gamma + 3416.3041}{\gamma^2 + 414.73204\gamma + 3428.5995}$	**0.0000184**	**1.8273e-10**
GTO	$\frac{2784.7\gamma + 3325.1}{\gamma^2 + 1536.4\gamma + 3031.7}$	**0.0000184**	0.000073
BWOA	$\frac{1998.54\gamma + 1994.01}{\gamma^2 + 706.3\,\gamma + 1994.386}$	0.017274	0.024938

ChOA	$\dfrac{13000\,\gamma + 13000}{\gamma^2 + 4634.68\,\gamma + 13000}$	0.035431	0.035431
ChSA	$\dfrac{4416.35\,\gamma + 4222.24}{\gamma^2 + 1647.04\,\gamma + 4430.1}$	0.015290	0.018626
DOA	$\dfrac{649.92\,\gamma + 1266.36}{\gamma^2 + 240.2\,\gamma + 1367.97}$	0.047036	0.108978
MPA	$\dfrac{4341.04\,\gamma + 6758.52}{\gamma^2 + 1586.87\,\gamma + 6971.5}$	0.000165	0.000057

From Table 4.4, it is clear that the proposed method provides least error values in terms of both average as well as standard deviation. Only GTO method provides same average error. The standard deviation is significantly low proving that the proposed algorithm is quite stable. The convergence diagram is also plotted in Fig. 4.8 to validate the proposed technique.

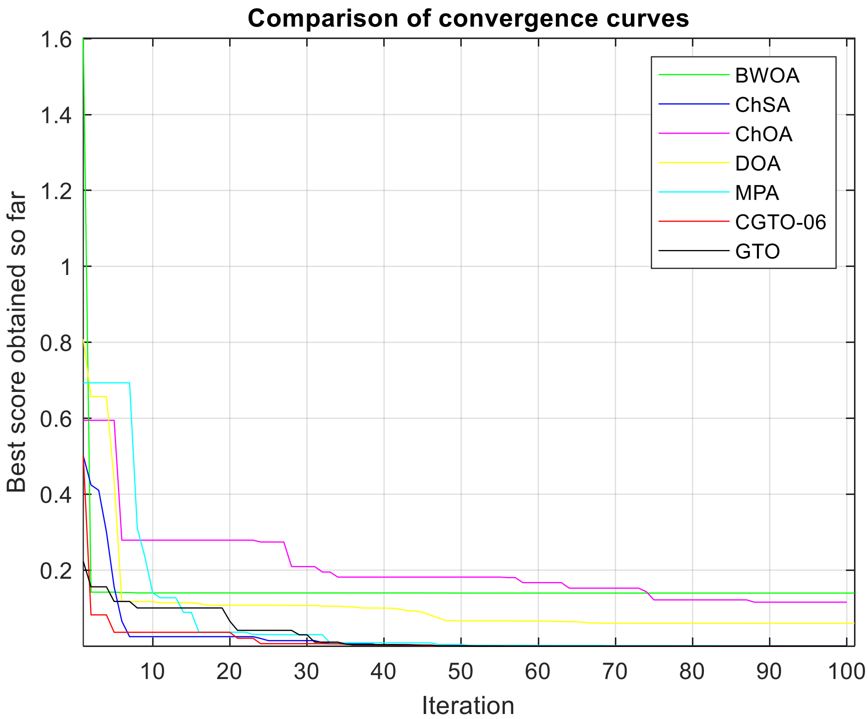

Fig. 4.8. Convergence plots of reduced induction motor drive in the combined domain

The proposed technique provides quite good convergence in terms of the algorithms being compared. Using the proposed technique, an intelligent PI controller is also constructed for this drive application. To evaluate the controller parameters, the sum of square errors (SSE) is optimised. The controller parameters are calculated in the delta domain using the approximate model matching method. The study employs a fixed reference model. For comparison, a number of latest algorithms are applied. The controller parameters optimized as well as their error values are presented in Table 4.5.

Table 4.5. Tuned controller parameters of induction motor drive in the unified domain

Methods	**K_p**	**K_i**	**SSE**
CGTO-06	0.20908	3.3422	**0.11039**
GTO	0.20908	3.3422	**0.11039**
BWOA	0.17846	2.8542	0.28102
ChOA	0.26104	3.2569	0.19027
ChSA	0.18612	2.9712	0.27689
DOA	0.21803	3.6775	0.25561
MPA	0.20173	3.3341	0.26197

The time and frequency domain responses of the controlled plant are compared with the reference model whose graphs are shown in Fig. 4.9 and 4.10 respectively.

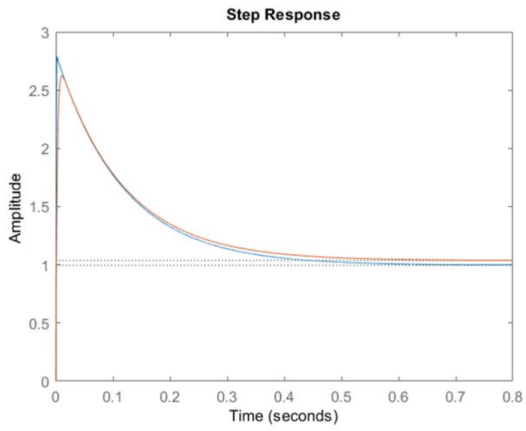

Fig. 4.9. Step responses of controlled induction motor drive and reference model

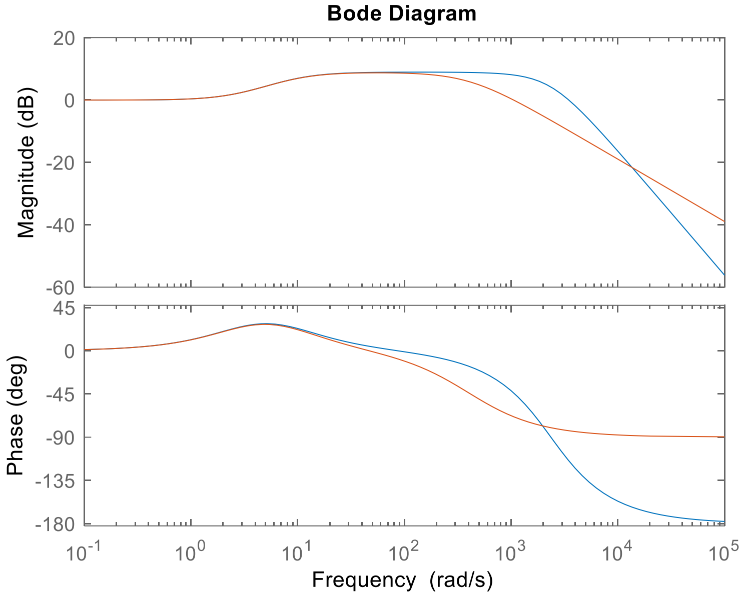

Fig. 4.10. Bode response of controlled induction motor drive and reference model

From the frequency domain plot in Figure 6, it is evident that the controlled induction motor drive and reference model in the delta domain show close resemblance at lower frequency but there is some mismatch at relatively higher frequency levels. Further, the convergence curve is also plotted in Fig. 4.11 for the proposed CGTO-06 technique and is compared with some of the popular heuristic techniques available in the literature.

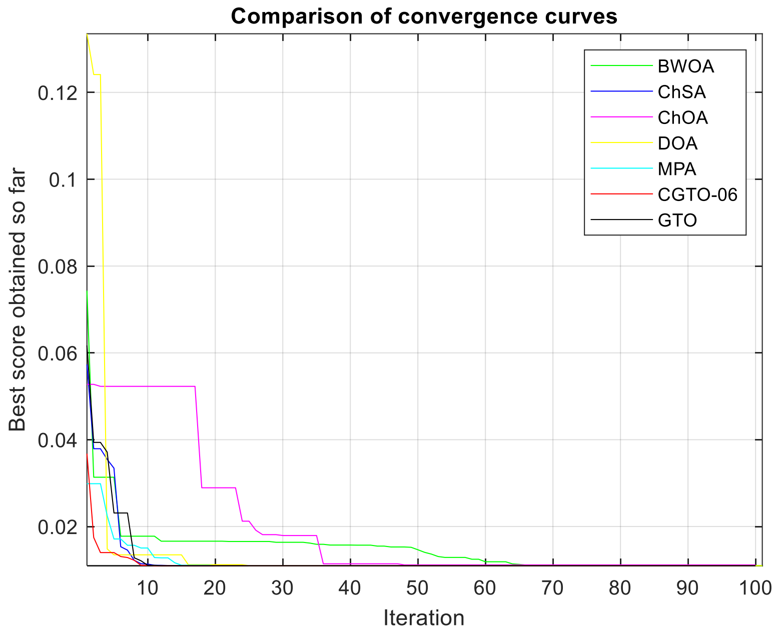

Fig. 4.11. Convergence diagram of controller tuning problem for the induction motor drive

The Fig. 4.11 depicts good convergence behaviour of the proposed technique over the existing standard heuristic methods. Thus the proposed CGTO approaches prove successful for modelling and control in the combined domain of analysis. There are several ways by virtue of which new chaotic versions of GTO can be developed. There are two controlling parameters in the GTO algorithm which can also be chaotically varied. This chaos inspired algorithm is considered in the next section. Further, there are some random parameters used in this GTO method which can be replaced by one-dimensional chaotic maps which can be taken up in future.

4.3 Simulation results for proposed method-2

Test-1: It is proposed to experiment with two unimodal test functions first to see if the proposed methods are effective. The mathematical descriptions, search domain and ideal optimum values of these test functions are found in Table 4.1. In this test, the two functions are labeled F1 and F2. 100 decision variables are optimized in each of these test functions. These test cases have a population size of 30 and a maximum number of iterations of 500. This means that the number of function evaluations (NFE) is $30 \times 500 = 15{,}000$, which can produce a stiff competition in terms of the number of decision variables considered in the study.

With the help of the proposed methods, the test functions have been verified. Among the various algorithms used for comparison are the Artificial Gorilla Troop Optimizer (AGTO), Marine Predator Algorithm (MPA), Black Widow Optimization Algorithm (BWOA), Chimp Optimization Algorithm (ChOA), Chameleon Swarm Algorithm (ChSA), Dingo Optimization Algorithm (DOA), Slime Mould Algorithm, Wild Horse Optimizer (WHO), and War Strategy Optimizer (WSO). Figs. 4.12-4.13 show the convergence plots of the test functions (F1-F2).

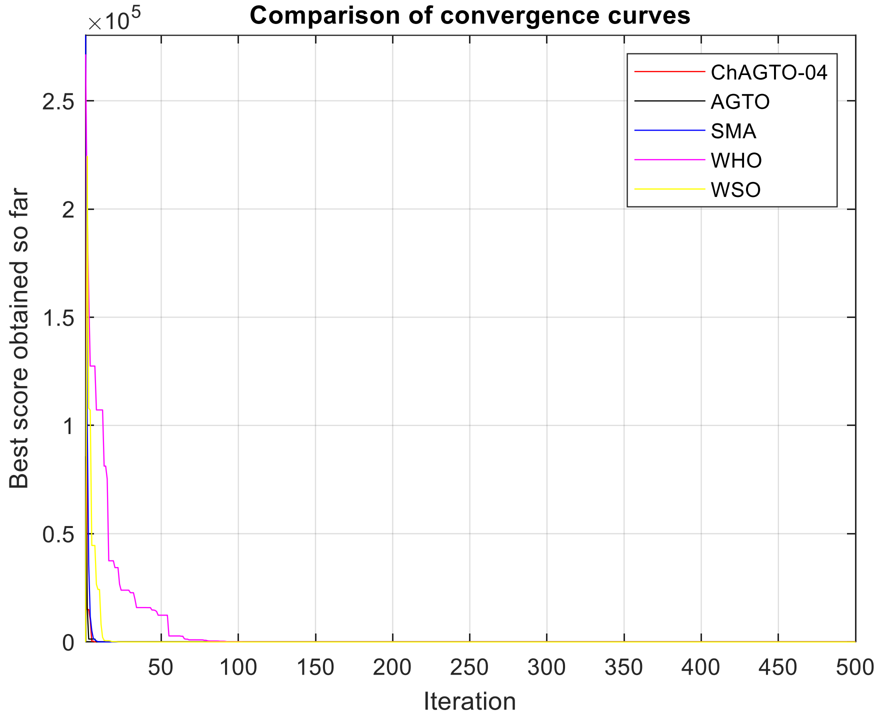

Fig. 4.12. Convergence plots of benchmark function F1

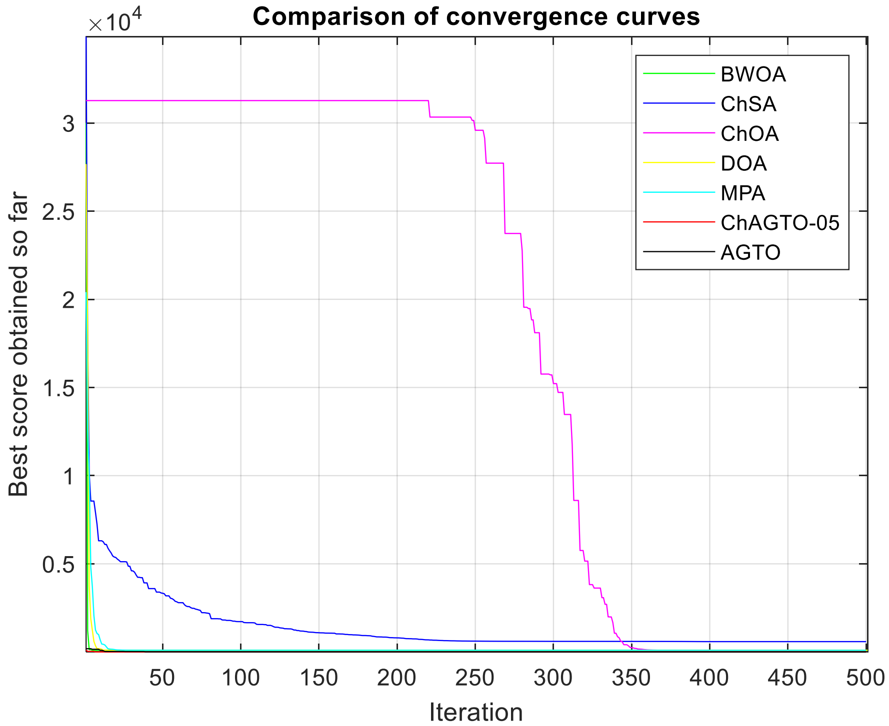

Fig. 4.13. Convergence plots of benchmark function F2

With respect to convergence speed and accuracy, the proposed ChAGTO approaches outperform a wide range of existing methods, which is evident from Figs. 4.12-4.13.

Test-2: Similar experiments are also performed with three standard benchmark functions which are multi-modal in nature. These functions are referred in this work by F3, F4 and F5. The detailed description of these functions is provided in Table 4.1. These functions are also tested with 100 decision variables considering same population size and total iterations as in Test-1. A handful of algorithms are applied for the purpose of comparison. Their convergence diagrams are provided in Figs. 4.14-4.16. Selected results of these test functions are presented in these Figures.

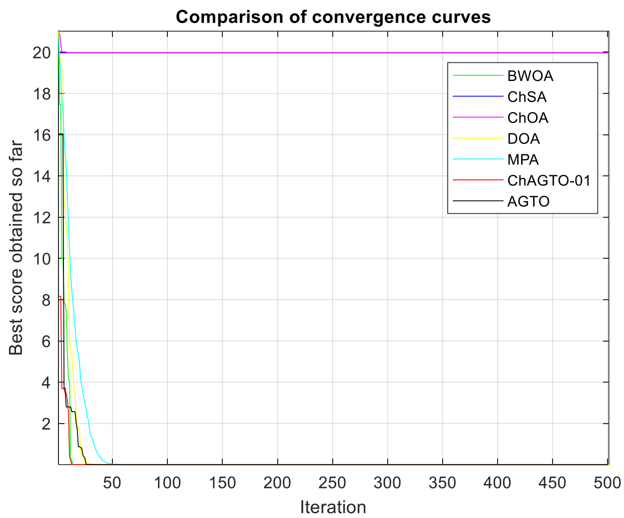

Fig. 4.14. Convergence characteristics of the multi-modal test function F3

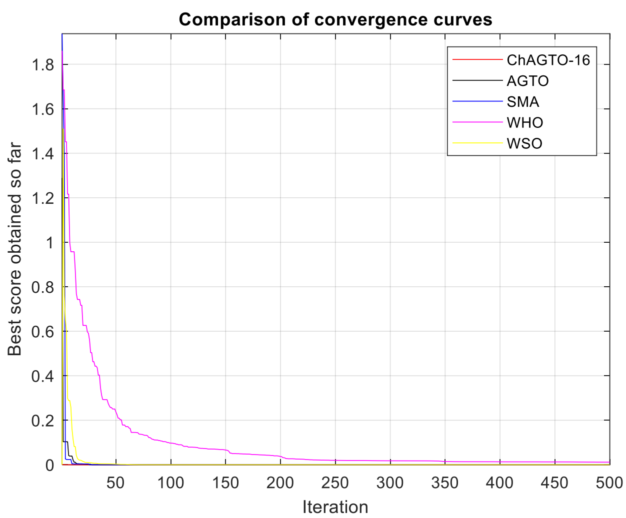

Fig. 4.15. Convergence characteristics of the multi-modal test function F4

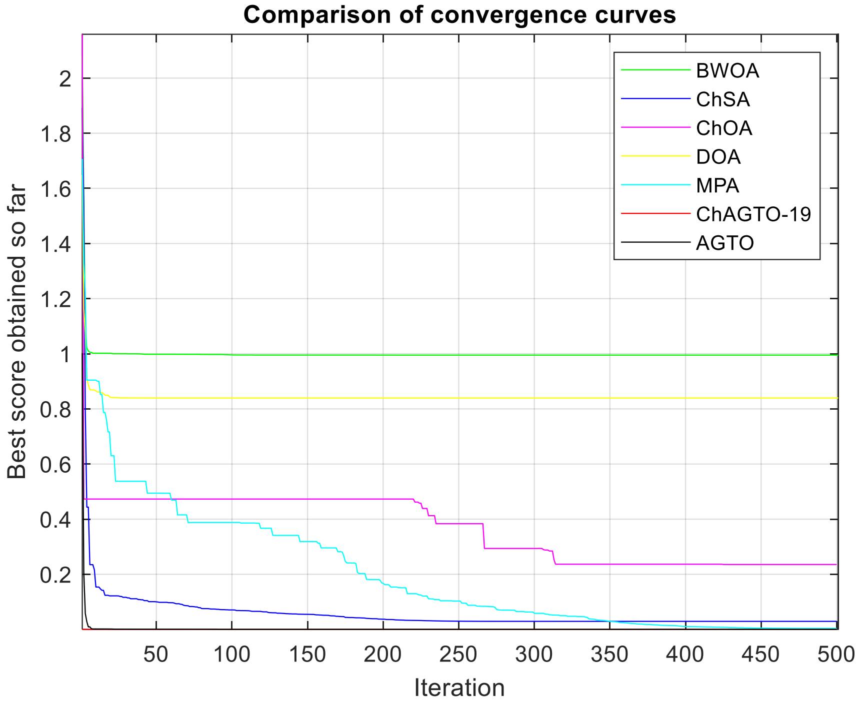

Fig. 4.16. Convergence characteristics of the multi-modal test function F5

It is clear from the above diagrams that the proposed ChAGTO methods supersede the existing algorithms both in terms of convergence speed and accuracy.

Test-3: This study also considers a 500 HP induction motor [44]. According to its transfer function, the machine model is 5th order. The input-output relationship of this model is thus given by

$$G(s) = \frac{1930s^3 + 267900s^2 + 8.065e06\ s + 2.566e08}{s^5 + 142s^4 + 149200s^3 + 8.549e06\ s^2 + 4.026e08\ \ s + 7.645e09} \quad (4.5)$$

The delta transformed model in the γ-domain with a sampling time of 0.0025 seconds is represented as

$$G(\gamma) = \frac{2.214\gamma^4 + 2065.32\gamma^3 + 2.3476e05\gamma^2 + 7.308e06\gamma + 2.0052e08}{\gamma^5 + 430.25\gamma^4 + 1.442e05\gamma^3 + 8.336e06\gamma^2 + 3.519e08\gamma + 5.974e09} \quad (4.6)$$

Developing an implementable controller for this higher-order machine model is extremely difficult. As a result, the proposed ChAGTO-06, ChAGTO-13 and ChAGTO-20 methods are employed to reduce this model to their respective second-order systems. Only four decision variables are involved in this experiment, so only 20 search agents and 100 iterations are used. Many new algorithms, including MPA, BWOA, ChOA, ChSA, DOA, and AGTO, are put to the test in this study. Table 4.6 shows the developed lower-order models. This Table also provides the average and standard deviation of the optimised error value, i.e. ITAE in this case, because only heuristic techniques were used to reduce the model. For the sake of clarity, the best error values are marked with bold letters.

Table 4.6. Lower-order models of the 500 hp induction motor in the combined domain of analysis, mean and standard deviation of error function

Methods	Lower-order transfer functions in the delta domain	Mean error	Std. error
ChAGTO-06	$\frac{3.533\gamma + 13.997}{\gamma^2 + 119.965\gamma + 143.398}$	0.009986	5.01e-09
ChAGTO-13	$\frac{3.523\gamma + 13.996}{\gamma^2 + 119.966\gamma + 143.398}$	**0.009945**	1.06e-10
ChAGTO-20	$\frac{3.523\gamma + 14.044}{\gamma^2 + 119.966\,\gamma + 144.01}$	0.009986	6.26e-10
AGTO	$\frac{3.857\gamma + 3.52}{\gamma^2 + 137\gamma + 2000}$	0.012519	**3.14e-11**
BWOA	$\frac{0.9346\,\gamma + 2.905}{\gamma^2 + 20\gamma + 200}$	0.012217	2.64e-04
ChOA	$\frac{4.233\gamma + 20.84}{\gamma^2 + 150\gamma + 262.7}$	0.009949	1.84e-05
ChSA	$\frac{3.372\gamma + 34.77}{\gamma^2 + 100\gamma + 1500}$	0.010214	2.80e-05

DOA	$\frac{2.029\gamma + 3.393}{\gamma^2 + 50\gamma + 150}$	0.011065	8.35e-05
MPA	$\frac{4.167\gamma + 16.6}{\gamma^2 + 141.8\gamma + 170}$	**0.009945**	3.99e-11

From Table 4.6 it is observed that the suggested ChAGTO-13 method surpasses other methods in terms of mean ITAE error minimized. Only same average value is provided by MPA method. The parent AGTO method as well as MPA technique provides less standard deviation of the error. Therefore these algorithms are more stable than the proposed method. Further, the convergence plots are drawn as found in Fig. 4.17-4.19.

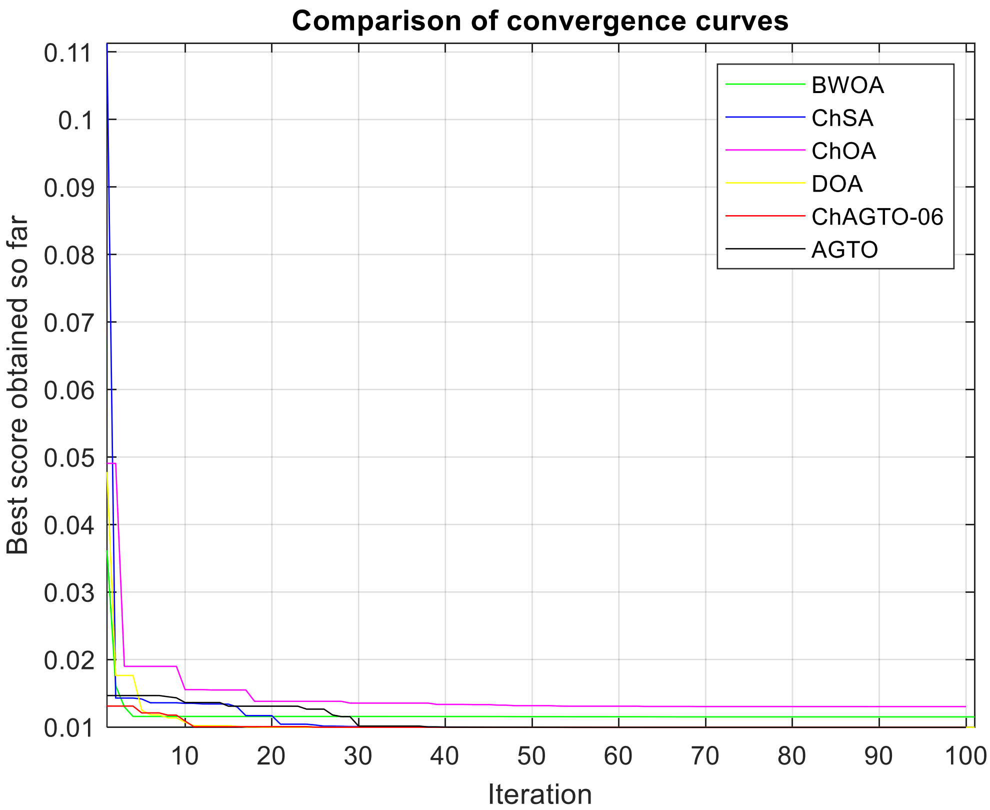

Fig. 4.17. Convergence characteristics of the reduced 500 hp induction motor

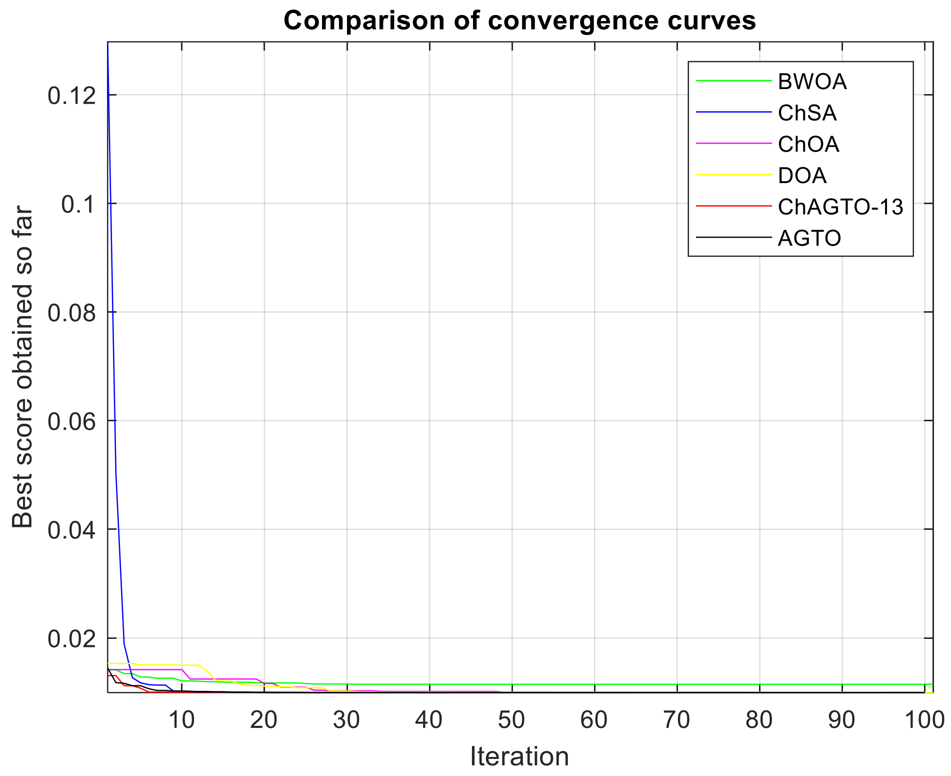

Fig. 4.18. Convergence behaviour of the reduced 500 hp induction motor

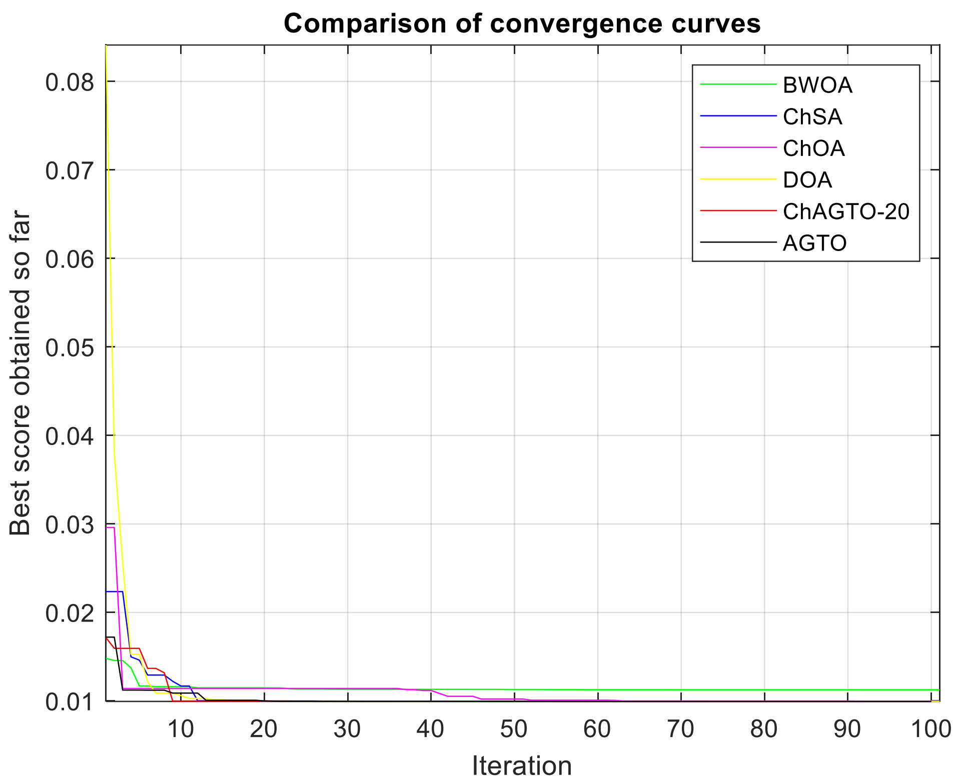

Fig. 4.19. Convergence plots of the reduced 500 hp induction motor

From the convergence plots of Fig. 4.17-4.19, it is observed that the showcased techniques viz. the ChAGTO-06, ChAGTO-13 and ChAGTO-20 are outperforming with respect to a number of algorithms used for comparing. A PID controller for this motor is also developed using the proposed methodology. In order to evaluate controller parameters, the sum of square errors (SSE) is optimised. The approximate model matching method in the delta domain is used to determine the controller parameters. It is decided to use a specific model as a basis for the investigation. For the sake of comparison, a host of brand-new algorithms is employed.

In the controller tuning process, there are only three decision variables. As a result, the population size and maximum number of iterations for this optimization problem are set to 20 and 100, respectively. Table 4.7 lists the fine-tuned controller parameters. The least fitness function value is bolded for the understanding of the readers.

Table 4.7. Tuned controller parameters of 500 hp induction motor in the combined domain.

Algorithms	K_p	K_i	K_d	Square error
ChAGTO-06	13.637	100.85	0.10413	0.043044
ChAGTO-13	13.637	100.85	0.10413	0.043044
ChAGTO-20	13.637	100.85	0.10413	0.043044
AGTO	150	1828.2193	5.7472001	0.52619
BWOA	28.59511	285.9511	1.134043	0.31905
ChOA	13.64164	100.852	0.1042414	0.043081
ChSA	13.49304	211.8456	0.09777029	**0.037472**
DOA	11.69444	168.7538	0.3056345	0.14654

MPA	13.64164	100.852	0.1042414	0.043081

It is clear from Table 4.7 that the ChSA method produces the minimum square error. The results of the proposed ChAGTO techniques as well as the MPA, ChOA methods are both nearby. In addition, Figs. 4.20-4.21 depict the convergence plot for this controller tuning problem.

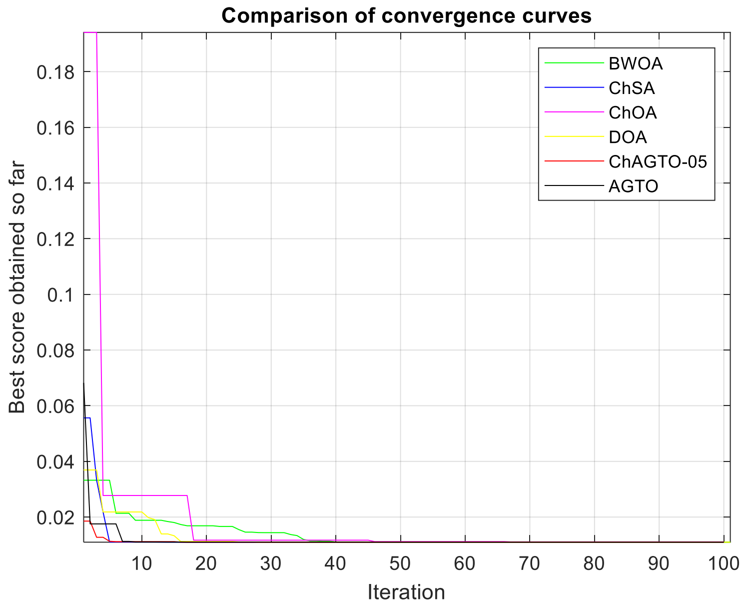

Fig. 4.20. Convergence diagrams of the controller with ChAGTO-05 method

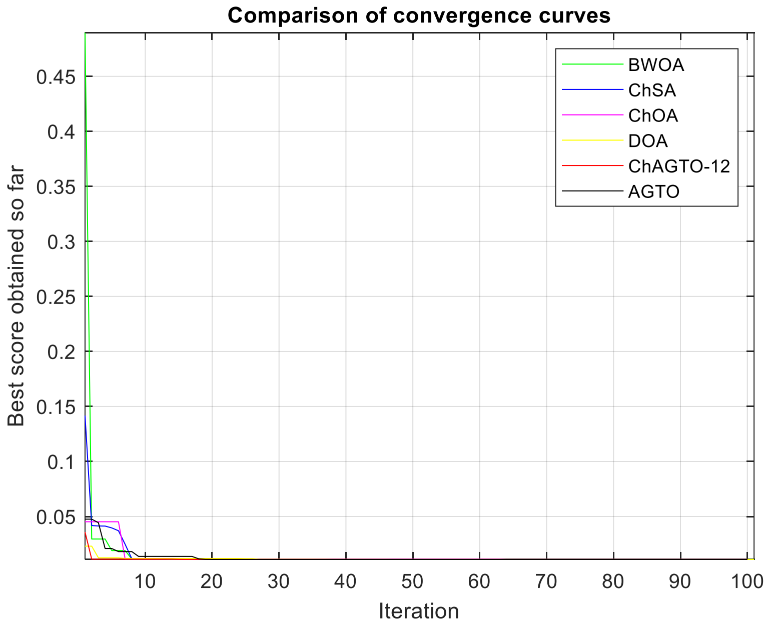

Fig. 4.21. Convergence plots of the controller with ChAGTO-12 method

From Figs. 4.20-4.21, we can see that proposed ChAGTO techniques show an appreciable good convergence in comparison to numerous recent techniques reported in the literature. For modelling and control in the combined analysis domain, the proposed ChAGTO approaches are thus successful. It is also possible to create new chaotic AGTOs in a variety of ways. Furthermore, both the controlling parameters of the AGTO method can be varied in a chaotic manner together. This is attempted in the next section. Moreover, two-dimensional chaotic maps can be substituted against these parameters in the AGTO method to develop even more new chaotic AGTO methods.

4.4 Simulation results for proposed method-3

Test System-1: There are two types of test functions under consideration for experimentation to test the efficacy of the proposed methods: unimodal and multi-modal. There are two unimodal tests and three multi-modal benchmarks used in the study. In Table 4.1 the mathematical definitions for these test functions are provided. In addition, their search area and ideal optimum values are specified as well. Unimodal functions F1 and F2 are being considered, whereas multimodal test functions are represented by F3, F4, and F5. There are hundreds of optimization variables in each of these test functions. This problem's sample size and maximum iterations are 30 and 500, respectively. There are 15,000 number of function evaluations (NFE) in this study, which is very competitive when it comes to the number of decision variables that are being considered.

The proposed techniques are used to improve the performance of the test functions. Among the various algorithms used for comparison are the Artificial Gorilla Troop Optimizer (AGTO), Marine Predator Algorithm (MPA), Black Widow Optimization Algorithm (BWOA), Chimp Optimization Algorithm (ChOA), Chameleon Swarm Algorithm (ChSA), Dingo Optimization Algorithm (DOA), Slime Mould Algorithm (SMA) and War Strategy Optimizer (WSO). Figs. 4.22-4.26 give the convergence plots of these benchmark functions (F1-F5).

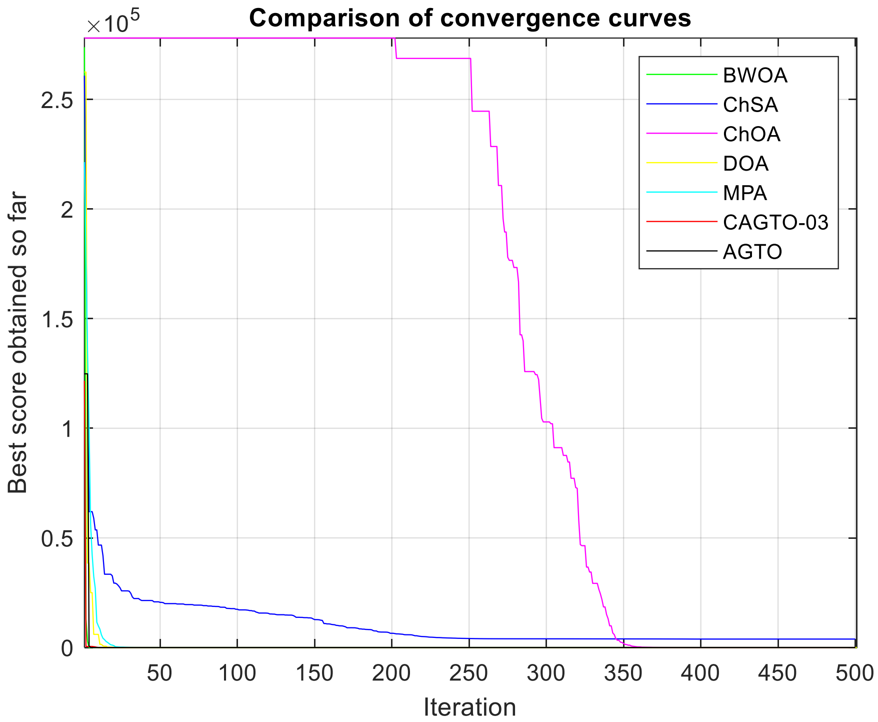

Fig. 4.22. Convergence plots of test function F1 with CAGTO-03 technique

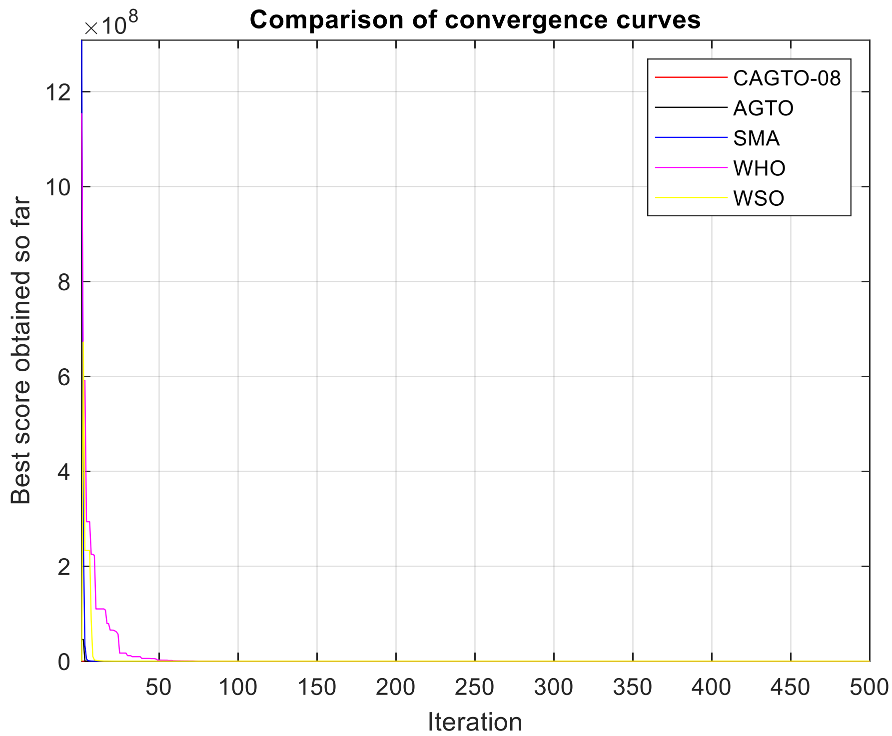

Fig. 4.23. Convergence plots of test function F2 with CAGTO-08 technique

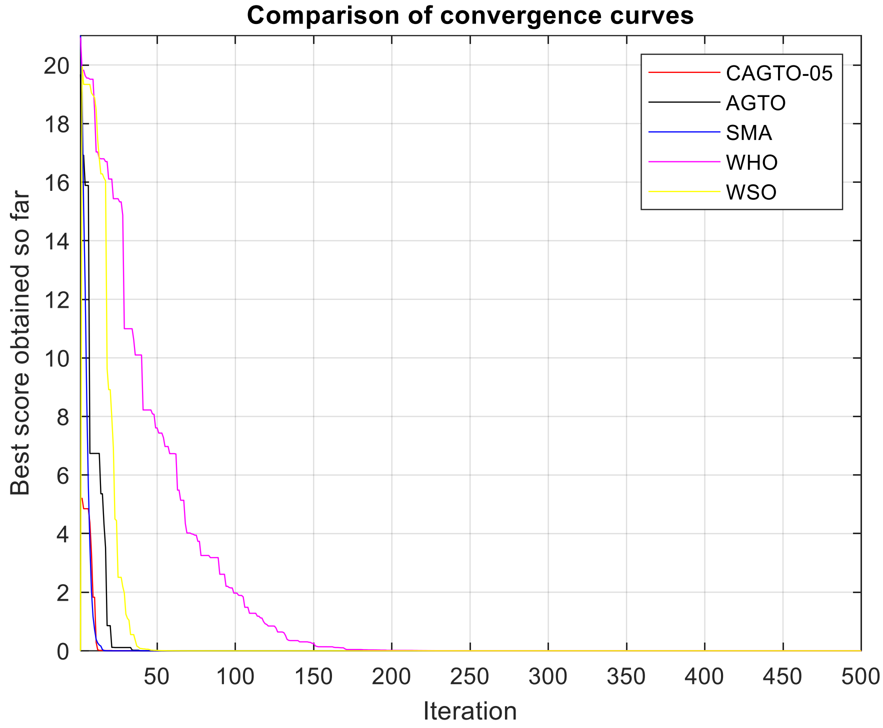

Fig. 4.24. Convergence plots of test function F3 with CAGTO-06 technique

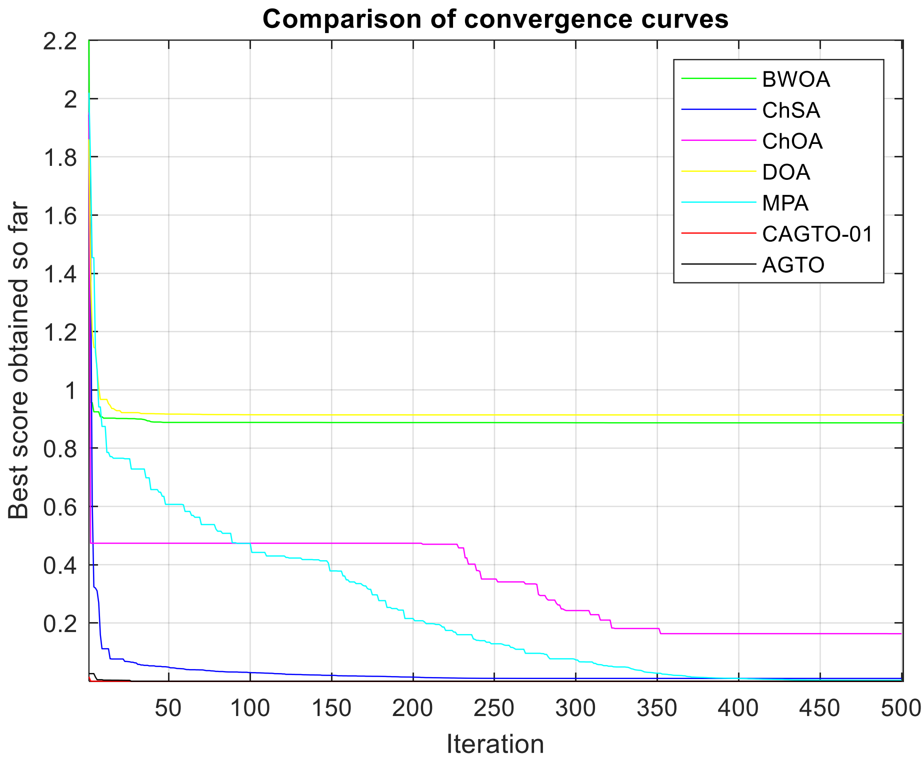

Fig. 4.25. Convergence plots of test function F4 with CAGTO-01 technique

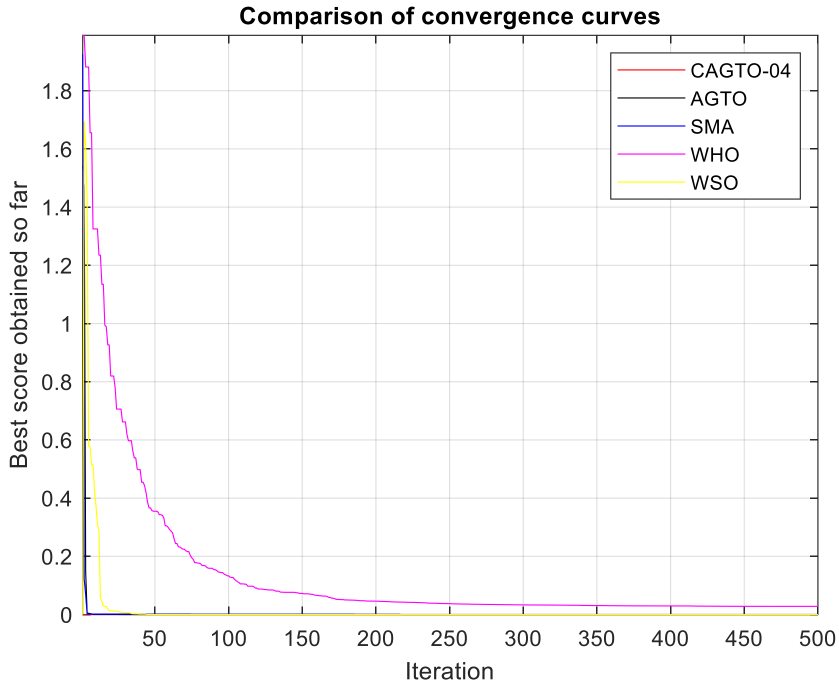

Fig. 4.26. Convergence plots of test function F5 with CAGTO-04 technique

With respect to convergence speed and accuracy, the proposed CAGTO approaches outperform a wide range of existing methods, which is evident from Figs. 4.22-4.26.

Test system-2: A 50 HP induction motor [44] is taken up for the study as well. The machine model is of 5th order as seen from its input-output relation.

$$G_1(s) = \frac{2085s^3 + 511000s^2 + 3.081e07\ s + 4.676e09}{s^5 + 397.9s^4 + 184800s^3 + 4.151e07s^2 + 3.408e09\ s + 4.076e10} \quad (4.7)$$

The model in the δ-domain with a sampling time of 0.0025 seconds is represented by

$$G_1(\gamma) = \frac{2.131\gamma^4 + 2084.7\gamma^3 + 3.887e05\gamma^2 + 3.179e07\gamma + 2.71e09}{\gamma^5 + 609.98\gamma^4 + 2.17e05\gamma^3 + 3.454e07\gamma^2 + 2.125e9\gamma + 2.362e10} \quad (4.8)$$

The development of an implementable controller for this higher-order machine model is extremely difficult. As a result, the proposed CAGTO-01 and CAGTO-09 methods reduce this model to a second-order system. Only four decision variables are involved in this experiment, so only 20 search agents and 100 iterations are used. AGTO is used as a comparison tool along with new algorithms like BWOA as well as ChOA, ChSA and DOA. Eqn. (4.9) shows the condensed versions of the model using the CAGTO-01 method.

$$G_{r1}(\gamma) = \frac{1.284\gamma + 18.795}{\gamma^2 + 22.705\gamma + 149.632} \quad (4.9)$$

The average and standard deviation of the optimised error value (ITAE in this case) are also calculated since only the heuristic technique is used to reduce the model. This proposed method produces a mean error value of 0.0103297 with least standard deviation of 4.0868e-08 amongst the methods compared. A low standard deviation implies more stable algorithm. Fig. 4.27 depicts the convergence characteristics for more detailed analysis.

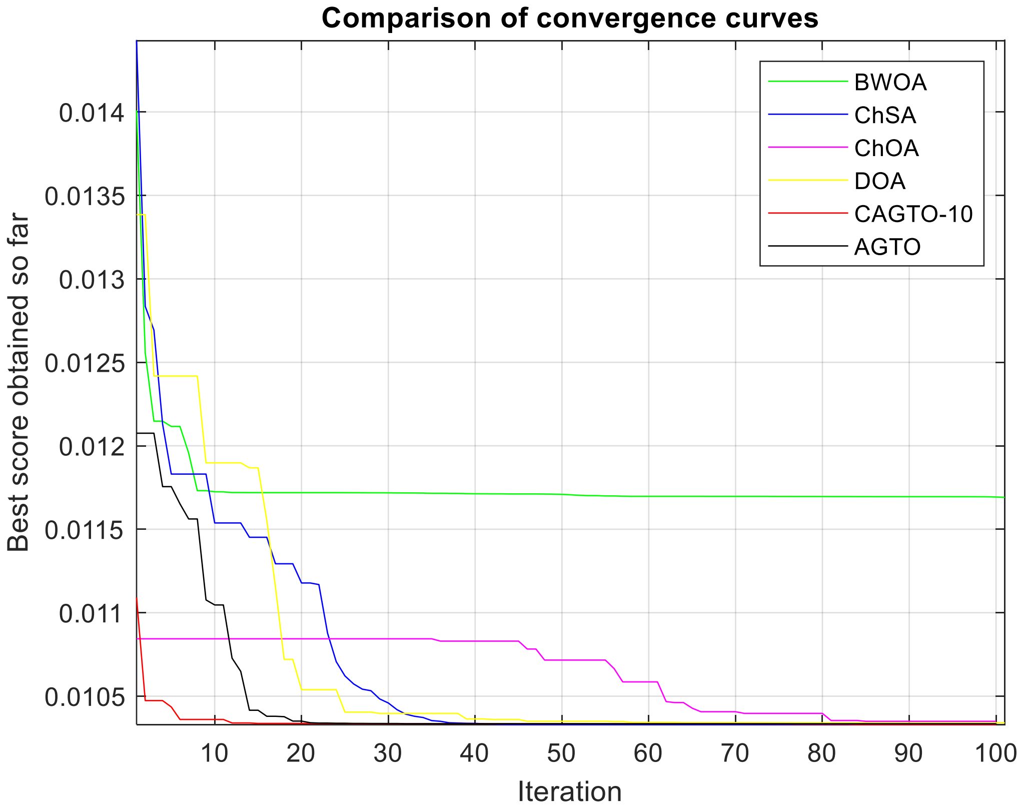

Fig. 4.27. Convergence characteristics of second-order 50 hp induction motor

The Wilcoxon signed rank [12] is conducted to affirm the fact that the results obtained are significantly different from the existing methods. Since equal sample size is considered for the non-parametric assessment, hence Wilcoxon's signed rank test was taken up for the evaluation of the p-values. The results of the p-values are obtained with a default setting of 0.05. This means that a p-value of less than 0.05 is considered significant. The outcomes of this test are presented in Table 4.8. The insignificant p-values are underlined. Out of the 10 proposed methods only 5 selected methods are displayed in this Table.

Table 4.8. Non-parametric assessments with Wilcoxon' signed rank test

Algorithms	BWOA	ChOA	ChSA	DOA	AGTO
CAGTO-01	0.000074	0.000061	0.000079	0.03125	0.000065
CAGTO-03	0.000074	0.000061	0.000079	0.03125	0.000065
CAGTO-05	0.000074	0.000061	0.000079	0.03125	0.000065
CAGTO-07	0.0137152	0.000078	0.4678072	0.00337	0.3041365
CAGTO-10	0.0079956	0.000078	0.0625000	0.000074	0.1025390

From Table 4.8, it is observed that nearly 84% of the presented outcomes are significant. To cross validate, another non-parametric test namely Kruskal-Wallis method [13] is adopted. Since multiple datasets are involved, it is useful to conduct this test to verify whether the mean ranks of the proposed methods are significantly from the compared methods. The diagrams corresponding to Kruskal-Wallis test are presented in Figs. 4.28-4.30. Only selected outcomes of this test are presented.

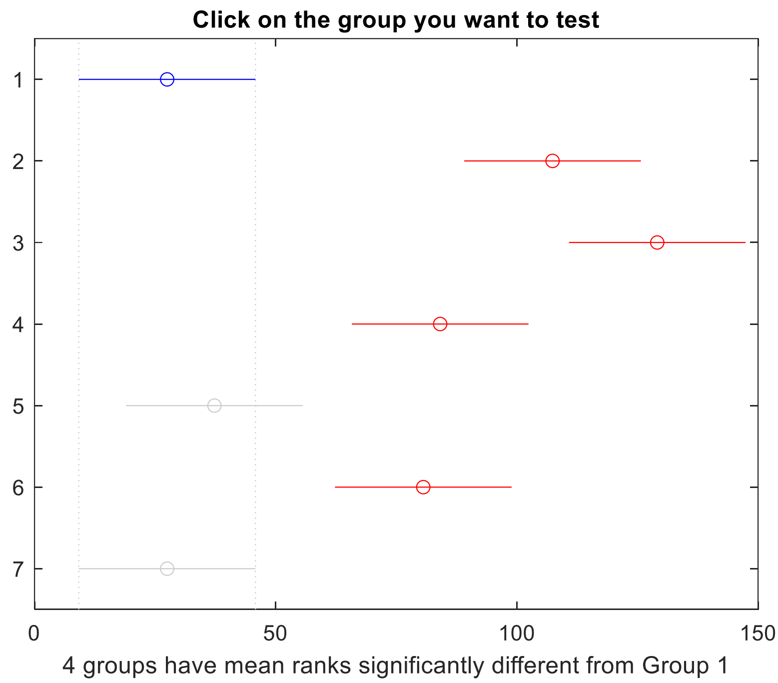

Fig. 4.28. Kruskal-Wallis test diagram for non-parametric assessment of CAGTO-03

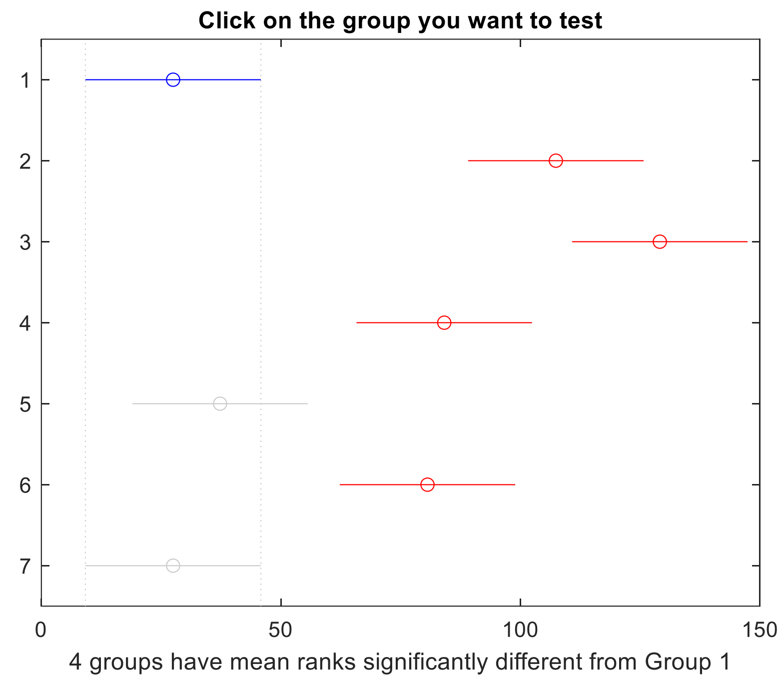

Fig. 4.29. Kruskal-Wallis test diagram for non-parametric assessment of CAGTO-05

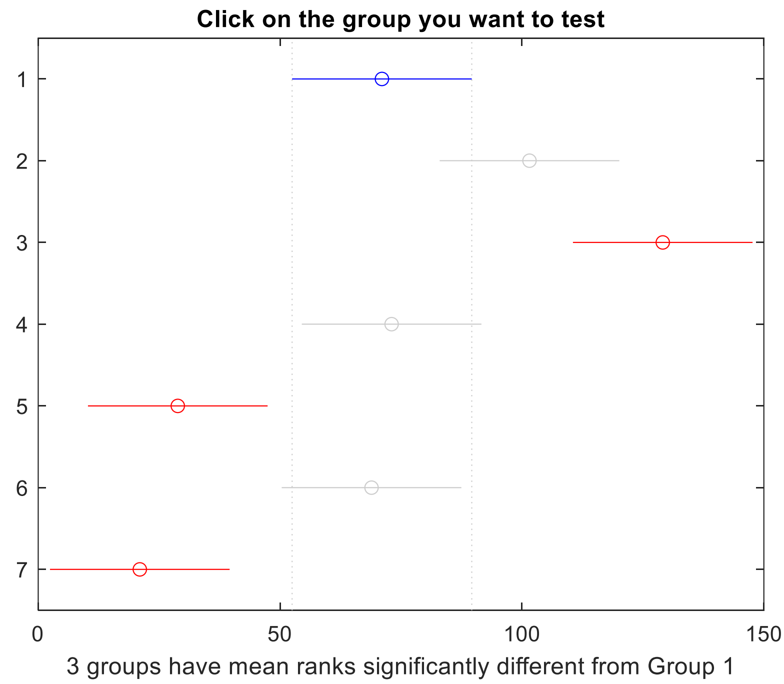

Fig. 4.30. Kruskal-Wallis test diagram for non-parametric assessment of CAGTO-07

From Figs. 4.28-4.30, it is evident that nearly 60-80% of the outcomes of this experiment is significant. It can be inferred that the proposed algorithms perform quite well as compared to some of the latest methods reported in the literature. Using the technique described here, an intelligent PID controller can be designed for this motor. The controller parameters are best evaluated using the sum of square errors (SSE). Using an approximation of model matching in the delta domain, the controller's control parameters are derived. The study is based on a predetermined model that is used as a guide. For comparison, a few new algorithms are employed. The proposed CAGTO-04 method produces a controller in the delta domain given by

$$G_{c1}(\gamma) = 1939.8413 + \frac{6.5207025}{\gamma} + 168.91911\gamma \tag{4.10}$$

This PID controller model also produces least error functional value. Another of the proposed method viz. CAGTO-04 also shows greater convergence speed and accuracy too as compared to the other approaches as is evident from Fig. 4.31.

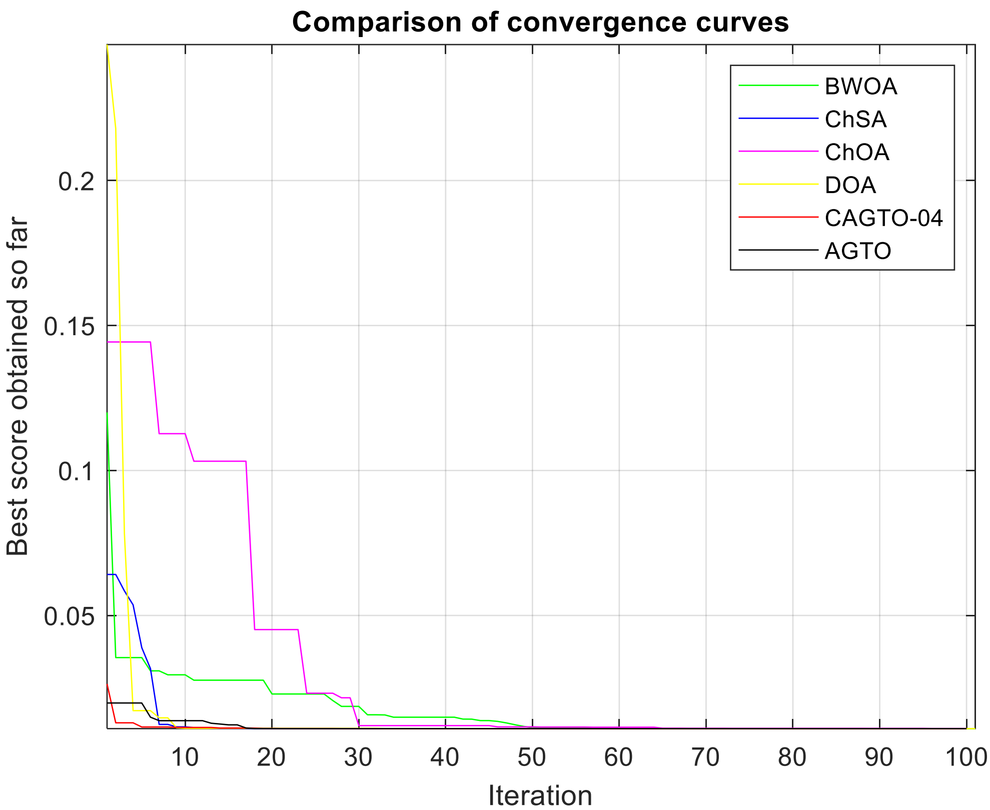

Fig. 4.31. Convergence plot of controller corresponding to 50 hp induction motor

Similar assessments are also carried out for a 500 hp induction motor model in Test system-3.

Test system-3: A 500 HP induction motor is also taken into account in this study [44]. The machine model has a transfer function of fifth order. The model's input-output relationship is thus written as

$$G_2(s) = \frac{1930s^3 + 267900s^2 + 8.065e06\ s + 2.566e08}{s^5 + 142s^4 + 149200s^3 + 8.549e06\ s^2 + 4.026e08\ \ s + 7.645e09} \quad (4.11)$$

Using a sampling time of 0.0025 seconds, the delta transformed model in the γ-domain is given by

$$G_2(\gamma) = \frac{2.214\gamma^4 + 2065.32\gamma^3 + 2.3476e05\gamma^2 + 7.308e06\gamma + 2.0052e08}{\gamma^5 + 430.25\gamma^4 + 1.442e05\gamma^3 + 8.336e06\gamma^2 + 3.519e08\gamma + 5.974e09} \quad (4.12)$$

The proposed lower order model developed by the CAGTO-07 method is obtained as

$$G_{r2}(\gamma) = \frac{3.53\gamma + 13.99}{\gamma^2 + 119.96\gamma + 143.39} \quad (4.13)$$

This model produces the least average and standard deviation of the error values amongst the different methods compared. This is evident from the convergence plot shown in Fig. 4.32.

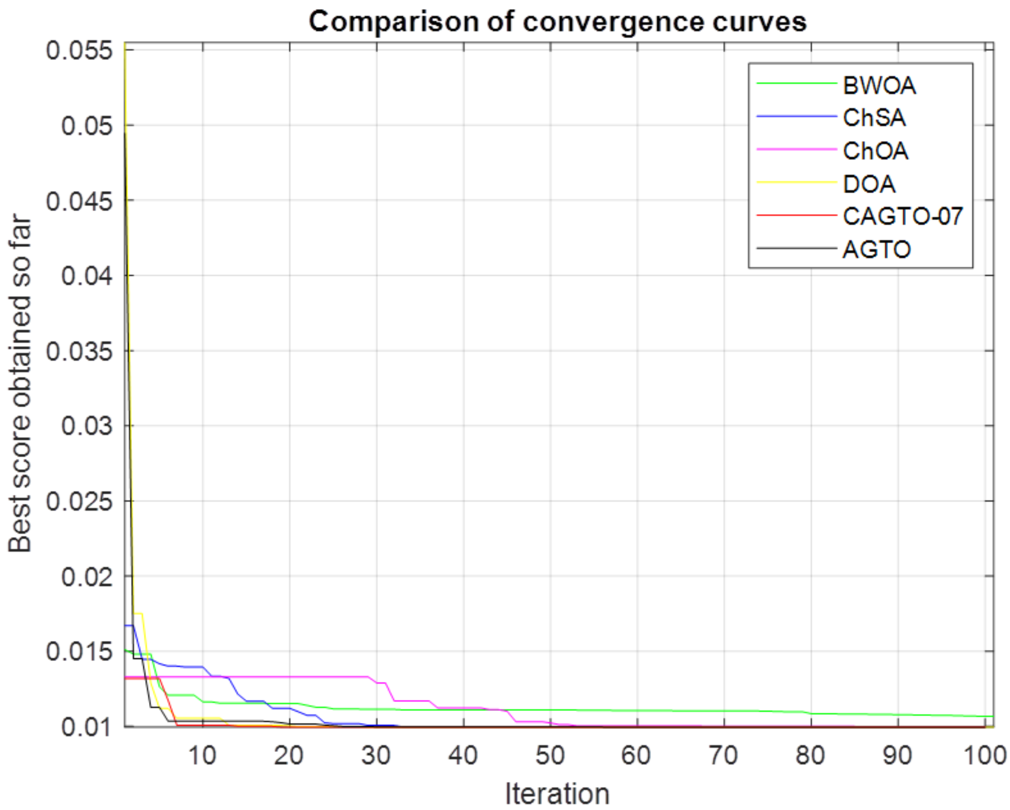

Fig. 4.32. Convergence comparison of CAGTO-07 with different methods

The Wilcoxon's signed rank test is carried out to validate the significance of the outcomes obtained by the proposed methods. Selected results have been presented in Table 4.9 where the p-values are mainly showcased. Once again, the p-values reported in the Table with greater than 0.05 are underlined. This gives a measure of the insignificant results.

Table 4.9. Non-parametric measures with Wilcoxon' signed rank test.

Algorithms	BWOA	ChOA	ChSA	DOA	AGTO
CAGTO-01	0.0001291	0.00008857	1	1	1
CAGTO-03	0.0001291	0.00008857	1	1	1
CAGTO-05	0.0001291	0.00008857	1	1	1
CAGTO-07	0.0001291	0.00008857	1	1	1
CAGTO-10	0.0069843	0.04380372	0.0004882	0.0004882	0.0004882

It is found from Table 4.9 that almost 52% of the results are significant. The outcomes '1' in the result Table denote similar data set with respect to 500 hp induction motor. Moreover, it is noteworthy; the outcomes of the proposed techniques are quite similar to ChSA, DOA as well as the parent AGTO methods. Thus it implies that the proposed method is not so successful in bringing about much significant results. To confirm further, Kruskal-Wallis test is also taken up for the same test system. The test diagram is shown in Fig. 4.34-4.34 for the understanding of the readers.

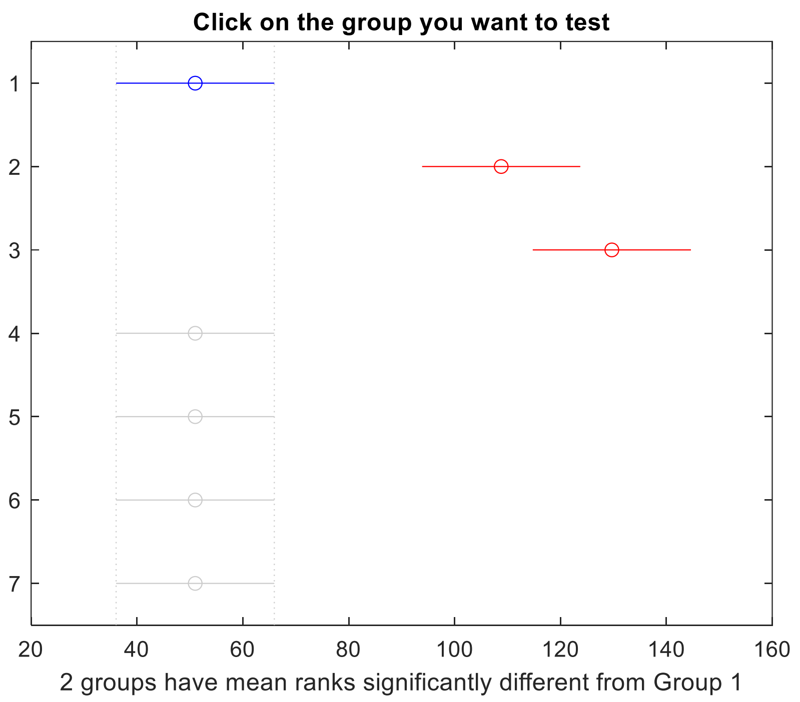

Fig. 4.33. Kruskal-Wallis test for non-parametric analysis with CAGTO-08

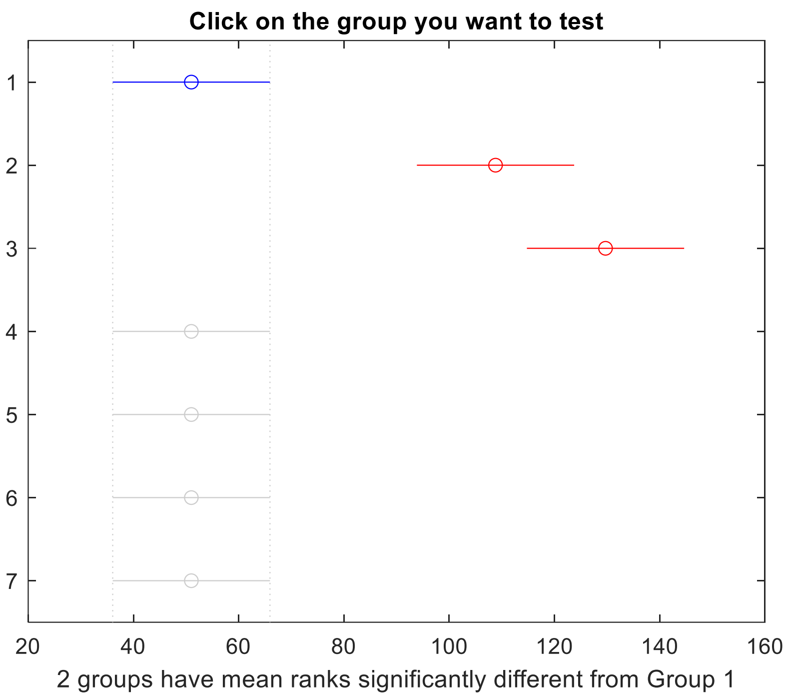

Fig. 4.34. Kruskal-Wallis test for non-parametric analysis with CAGTO-05

As seen earlier in Wilcoxon test, the Kruskal-Wallis test too has only produced 40% significant outcomes. Hence further improvement in the proposed technique may be required. Chaotically updating the exploitation phase of the parent AGTO method along with variation of 'P' and 'ω' may yield significant enhancement. A PID controller is also developed where three decision variables are evaluated using various metaheuristic algorithms including the proposed methods. An approximate model matching method with a chosen reference model is adopted to determine the controller parameters. The proposed CAGTO-05 method yields a controller given by

$$G_{c2}(\gamma) = 1939.8413 + \frac{6.5207025}{\gamma} + 168.91911\gamma \tag{4.14}$$

The convergence curve is also drawn in Fig. 4.35 to prove that this method gives better convergence speed as well as accuracy as compared to some of the well-established techniques taken from the literature.

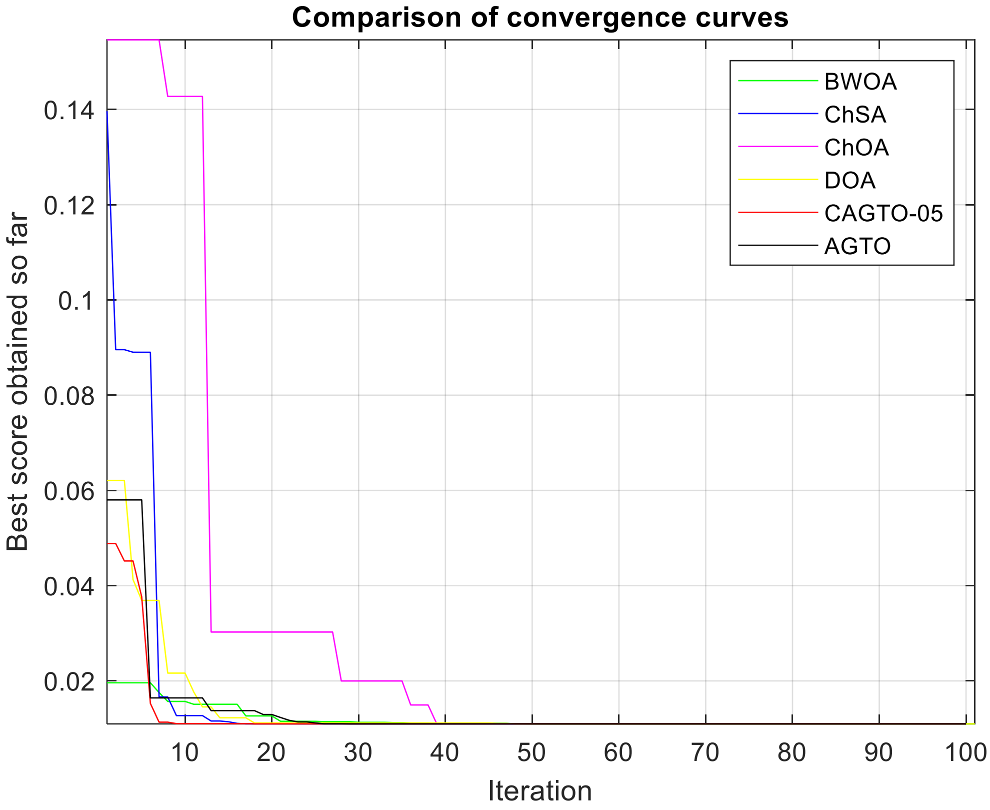

Fig. 4.35. Convergence curves of CAGTO-05 vis-à-vis other methods

The convergence curve proves clearly that the suggested method yields better convergence when compared with other existing algorithms. The method can also be applied for other engineering applications like modelling and control of electric drives.

4.5 Simulation results for proposed method-4

Expt.-1: With the proposed methods coined as ChGTO in this section, five standard test functions are evaluated and compared with a handful number of algorithms. The number of search agents is chosen as 30 while the maximum number of iterations is selected as 500. The number of decision variables optimized in each of these problems is taken as 100. The convergence curves are plotted in Figs. 4.36-4.40 to check the efficacy of the suggested techniques.

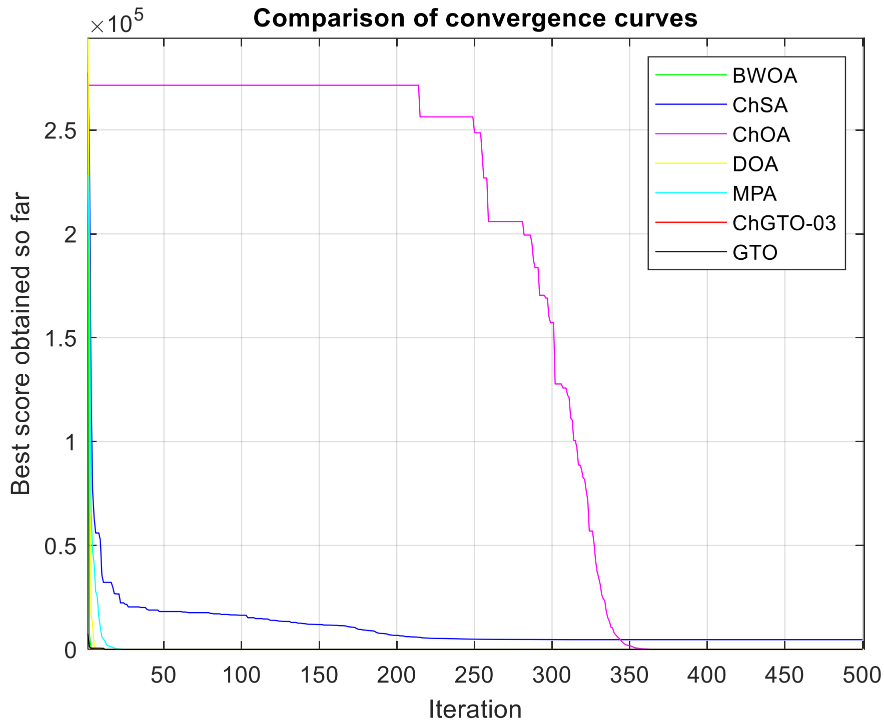

Fig. 4.36. Convergence curve of the unimodal test function F1

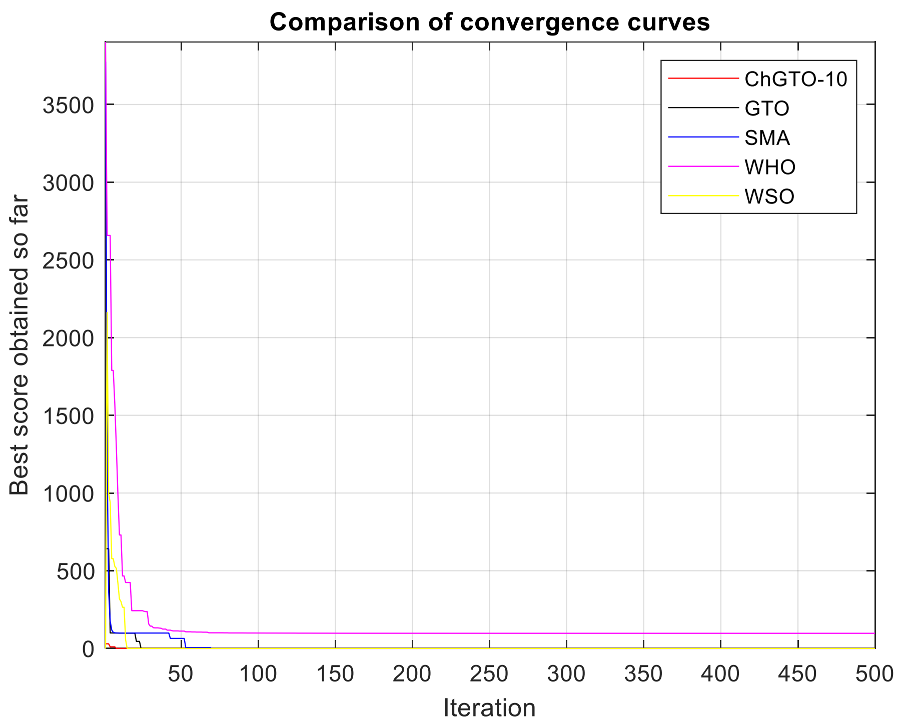

Fig. 4.37. Convergence curve of the unimodal test function F2

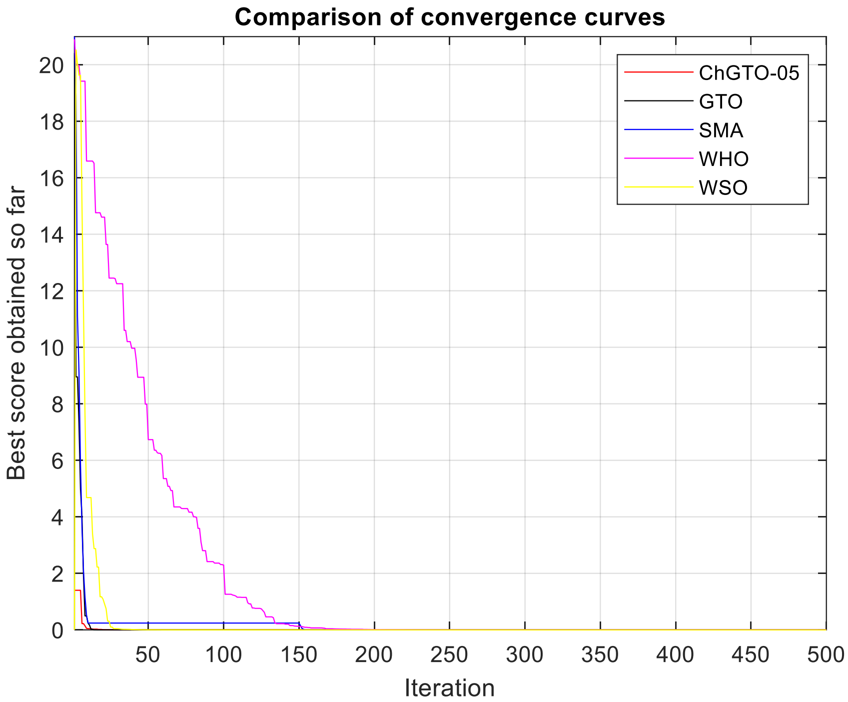

Fig. 4.38. Convergence curve of the multi-modal test function F3

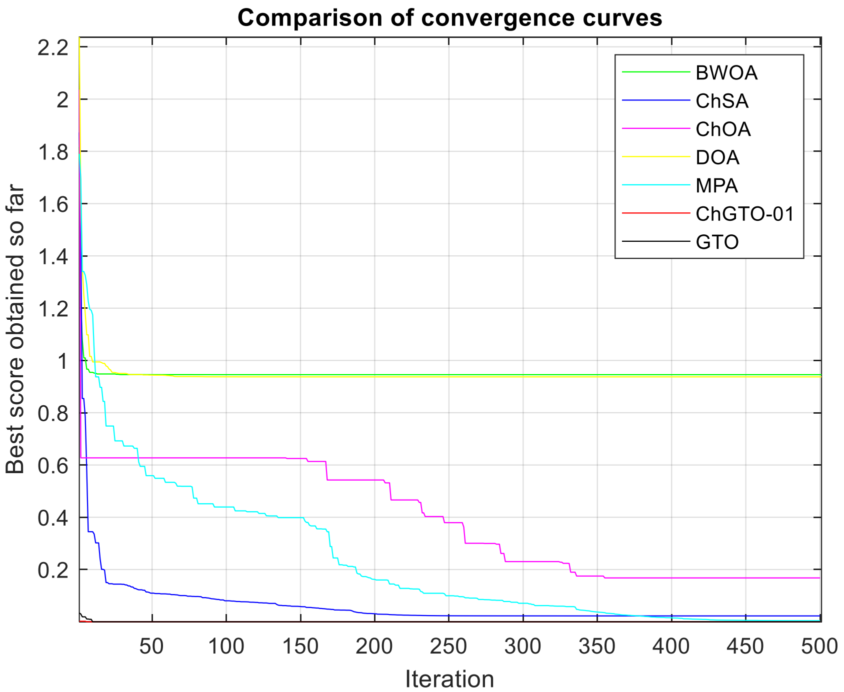

Fig. 4.39. Convergence curve of the multi-modal test function F4

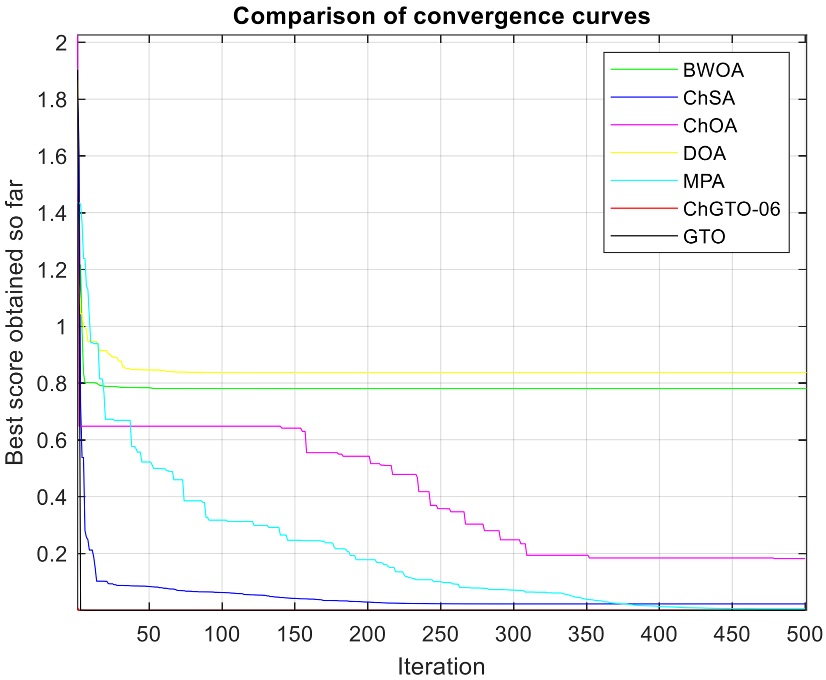

Fig. 4.40. Convergence curve of the multi-modal test function F5

From the above convergence plots it is quite clear that the proposed ChGTO methods prove successful in bringing about greater convergence speed and accuracy. Some practical test systems are also used to validate the efficiency of the proposed approaches.

Expt.-2: A 50 hp induction motor is considered. The 5th order machine model is given by

$$G_1(s) = \frac{2085s^3 + 511000s^2 + 3.081e07\ s + 4.676e09}{s^5 + 397.9s^4 + 184800s^3 + 4.151e07s^2 + 3.408e09\ s + 4.076e10} \tag{4.15}$$

The model using the delta operator framework is thus represented by

$$G_1(\gamma) = \frac{2.131\gamma^4 + 2084.7\gamma^3 + 3.887e05\gamma^2 + 3.179e07\gamma + 2.71e09}{\gamma^5 + 609.98\gamma^4 + 2.17e05\gamma^3 + 3.454e07\gamma^2 + 2.125e9\gamma + 2.362e10} \tag{4.16}$$

A sampling time of 0.0025 seconds is chosen for the above test system. The reduced models in the delta domain obtained by the proposed techniques as well as a host of other methods with which comparison is carried out are provided in Table 4.10. The average value as well as the standard deviation of the error value is narrated in this Table. The best values in columns 3 and 4 of the Table are marked with bold letters.

Table 4.10. Reduced models with selected ChGTO methods and their comparison

Methods	Reduced transfer functions	Mean err	Std. err
ChGTO-03	$\frac{1.284\gamma + 18.76}{\gamma^2 + 22.706\gamma + 149.622}$	**0.0103297**	**3.1868e-08**
ChGTO-10	$\frac{1.283\gamma + 18.801}{\gamma^2 + 22.703\gamma + 149.996}$	0.0103362	1.2053e-07
GTO	$\frac{1.33\gamma + 5.874}{\gamma^2 + 14.02\,\gamma + 50}$	0.010337	8.87e-07
BWOA	$\frac{1.398\gamma + 6.298}{\gamma^2 + 15.17\,\gamma + 49.41}$	0.010341	1.29e-06
ChOA	$\frac{1.404\,\gamma + 0.5254}{\gamma^2 + 11.26\,\gamma + 4.287}$	0.010343	1.66e-06
ChSA	$\frac{1.329\,\gamma + 5.744}{\gamma^2 + 13.93\,\gamma + 49.04}$	0.010337	1.86e-06
DOA	$\frac{1.33\,\gamma + 5.874}{\gamma^2 + 14.02\,\gamma + 50}$	0.010337	1.24e-06

Amongst the selected results presented, the ChGTO-03 marks the least mean error value. Further, this method also yields the minimum standard deviation. Thus this algorithm is most stable amongst the showcased outcomes. The convergence plot of this method is also carried out in Fig. 4.41 to test its accuracy and speed.

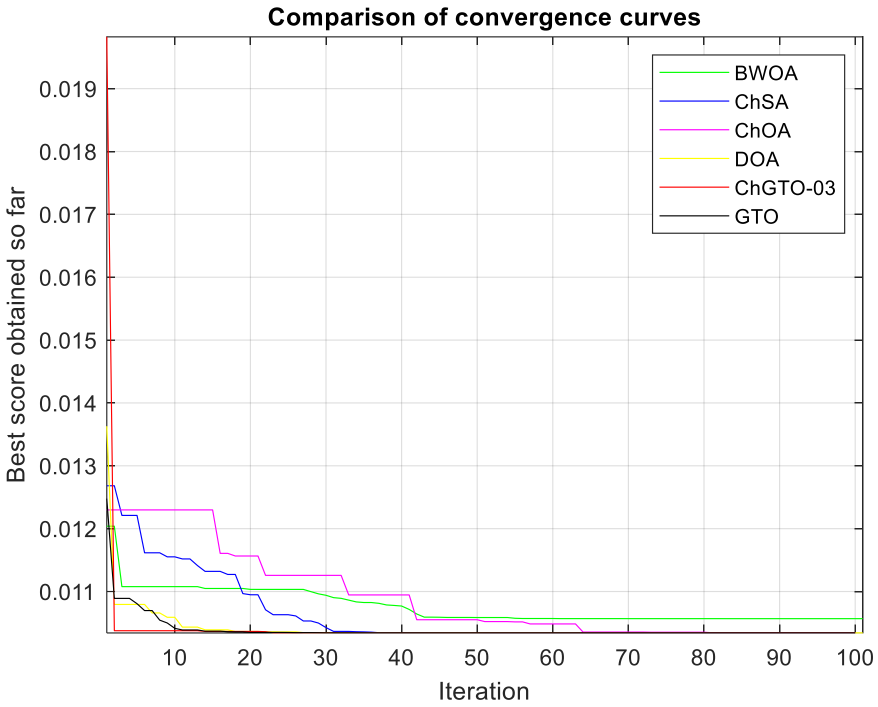

Fig. 4.41. Convergence comparison of ChGTO-03 with other techniques

From the above Fig. it is found that the suggested ChGTO method proves better in comparison to the parent method as well as a host of new algorithms. The Wilcoxon's signed rank test is conducted to verify that the outcomes obtained by the ChGTO methods did not come by fluke. The selected results showing the p-values are presented in Table 4.11.

Table 4.11. Non-parametric test results of Wilcoxon's signed rank test

Algorithms	BWOA	ChOA	ChSA	DOA	GTO
ChGTO-01	6.3587e-09	4.9994e-09	6.9830e-09	0.00948	5.3999e-09
ChGTO-03	6.3587e-09	4.9994e-09	6.9830e-09	0.00948	5.3999e-09
ChGTO-05	6.3587e-09	4.9994e-09	6.9830e-09	0.00948	5.3999e-09
ChGTO-08	6.3587e-09	4.9994e-09	6.9830e-09	0.03190	5.3999e-09
ChGTO-10	6.3587e-09	4.9994e-09	6.9830e-09	0.00948	5.3999e-09

Seeing the p-values in Table 4.11, it can be inferred that the outcomes obtained by the suggested ChGTO techniques are significant. Further, any non-parametric test, viz. Kruskal Wallis test is performed on the test results to validate the outcomes graphically. Few selected results are presented in Figs. 4.42 and 4.4.43 respectively.

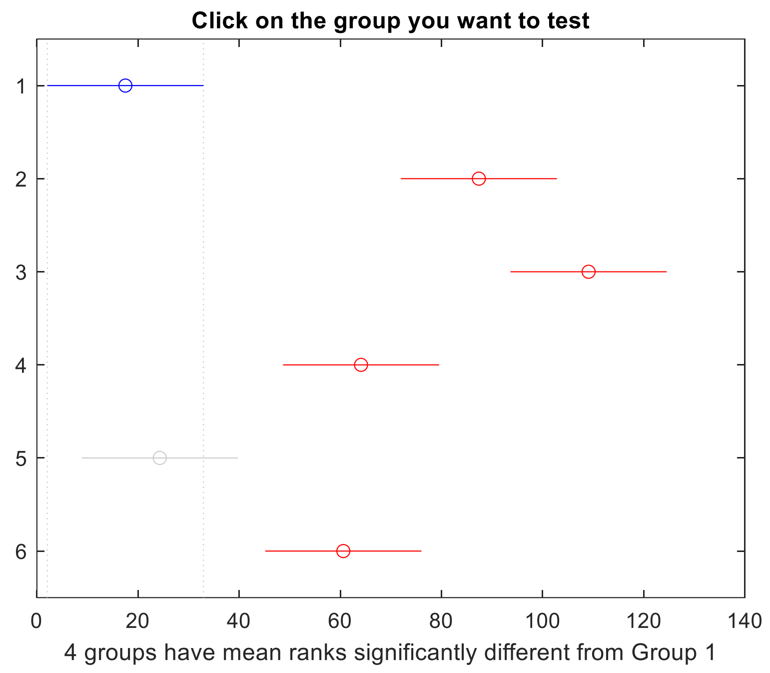

Fig. 4.42. Kruskal-Wallis test for non-parametric analysis with CAGTO-05

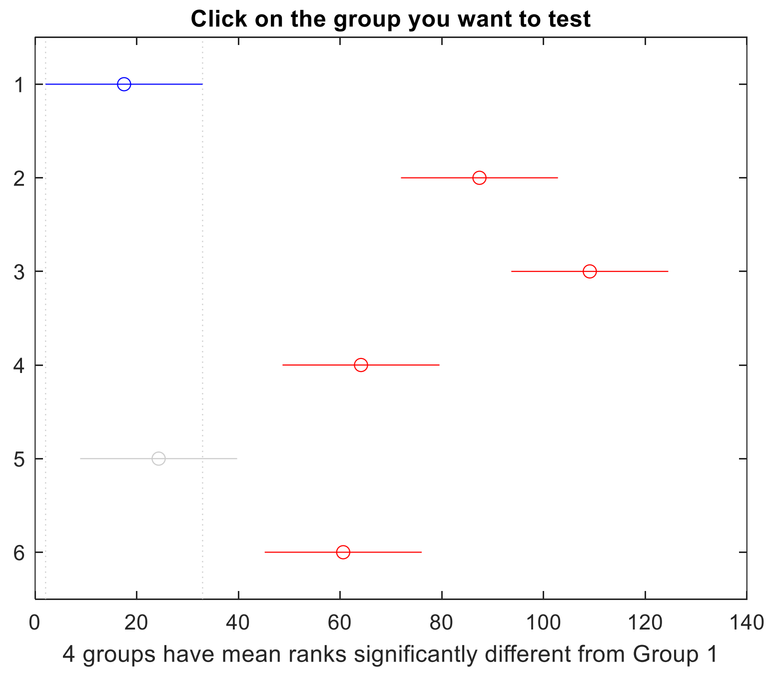

Fig. 4.43. Kruskal-Wallis test for non-parametric analysis with CAGTO-08

From the above Figs. it is evident that nearly 80% of the test outcomes obtained by the proposed methods are significant. A PID controller is realized for the reduced system in model matching framework. The proposed PID controller obtained by ChGTO-10 method is thus denoted by

$$G_{c1}(\gamma) = 42.5827 + \frac{0.0450849}{\gamma} + 4.1988\gamma \tag{4.17}$$

The convergence characteristic is shown in Fig. 4.43 to verify that this approach gives better convergence as compared to some of the well-known methods quoted in the literature.

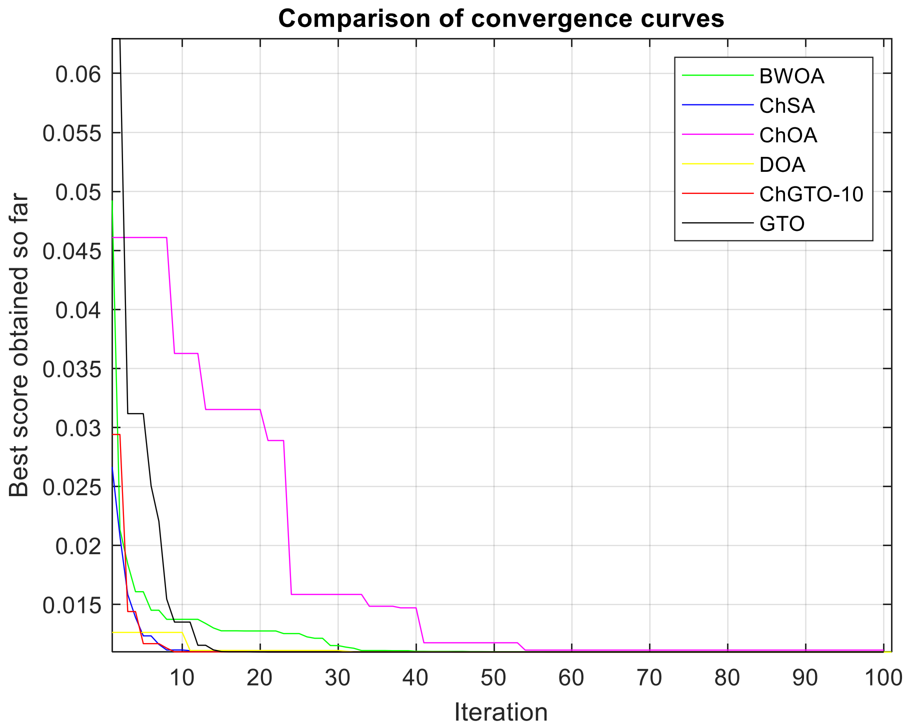

Fig. 4.44. Convergence plot of the controller for 50 hp induction motor

Expt.-3: An induction motor drive is now considered. Its model is represented by

$$G_2(s) = \frac{13.381s + 40.54}{8.58\text{e}{-}07s^3 + 0.003517s^2 + 4.802s + 40.69} \tag{4.18}$$

With a sampling time of 0.0025 seconds, the 5th order model in the γ-domain is written as

$$G_2(\gamma) = \frac{1.128\text{e}03\gamma^2 + 4.643\text{e}05\gamma + 1.395\text{e}06}{\gamma^3 + 8.23e03\gamma^2 + 1.728\text{e}05\gamma + 1.402\text{e}06} \tag{4.19}$$

The reduced system developed by the suggested ChGTO-05 method is denoted by

$$G_{r2}(\gamma) = \frac{1128.4638\gamma + 3549.3035}{\gamma^2 + 414.84203\,\gamma + 3486.5993} \tag{4.20}$$

This method produces an average error value of 0.0000184 with a standard deviation of 1.0901e-6, least amongst the methods compared. The convergence curve of this reduced model is given in Fig. 4.44.

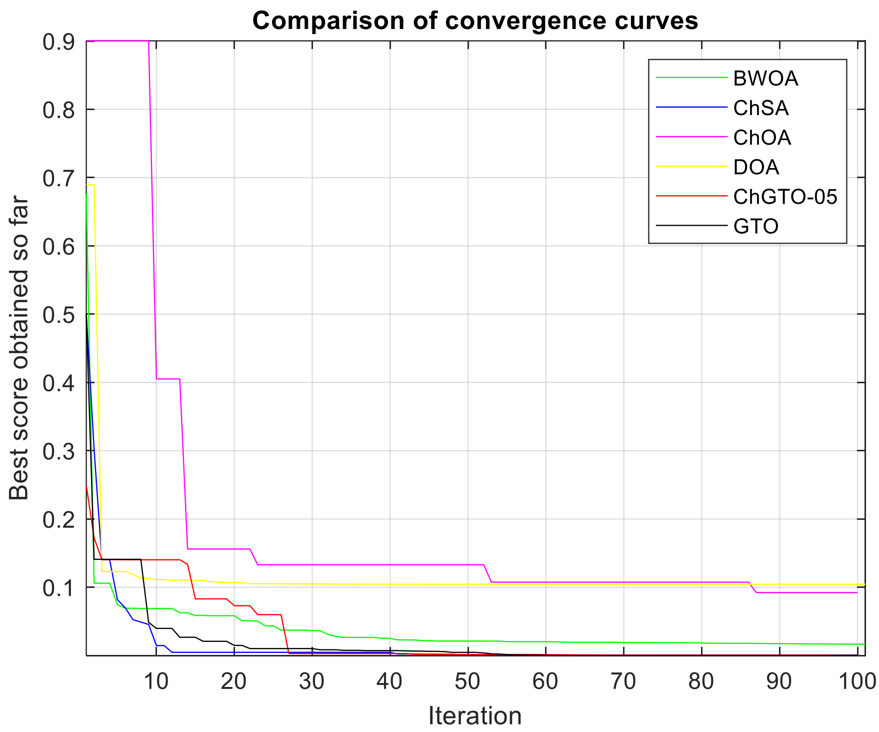

Fig. 4.45. Convergence comparison of ChGTO-05 with other approaches

The convergence is appreciably good with respect to the other methods. The non-parametric assessment of the test data is carried out for the induction motor drive as well. The p-values are presented in Table 4.12.

Table 4.12. Non-parametric test results with selected ChGTO methods

Algorithms	BWOA	ChOA	ChSA	DOA	GTO
ChGTO-01	6.2413e-08	6.2413e-08	<u>0.05243</u>	<u>0.52459</u>	2.3652e-08
ChGTO-03	6.2413e-08	6.2413e-08	0.00248	0.00121	2.3652e-08
ChGTO-05	5.8267e-08	5.8267e-08	5.8267e-08	1.912e-06	2.1883e-08
ChGTO-08	5.2496e-08	5.2496e-08	1.3528e-05	<u>0.26609</u>	<u>0.266094</u>
ChGTO-10	6.2413e-08	6.2413e-08	0.00248	0.01323	2.36528e-08

More than 80% of the results are found to be significant as being observed from the p-values of Table 4.12. Moreover, the Kruskal-Wallis test is also performed to visualize the significant test data from the multiple methods compared. The test diagrams are presented in Figs. 4.45-4.46.

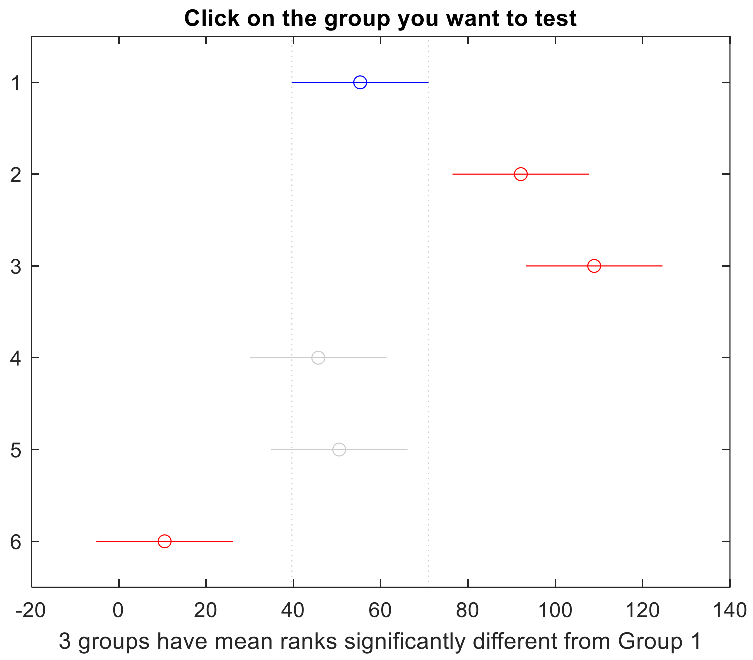

Fig. 4.46. Kruskal-Wallis test diagram with ChGTO-01 as compared with other methods

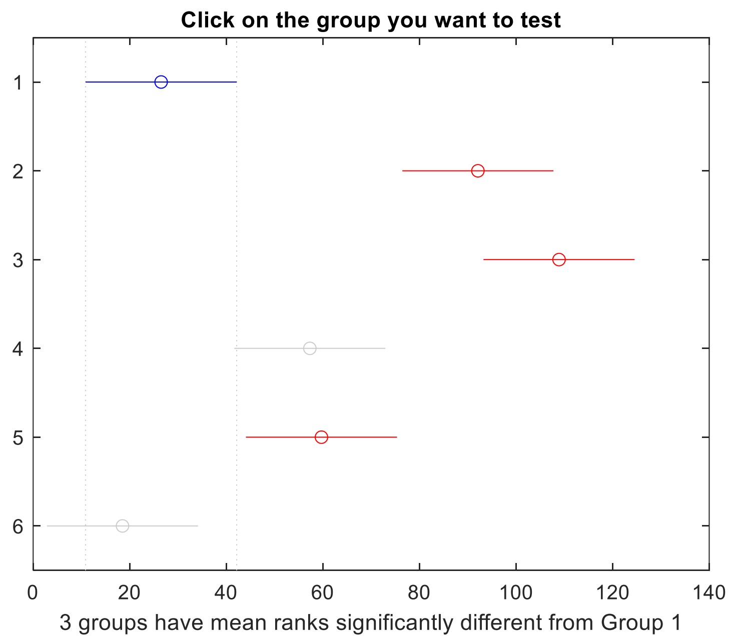

Fig. 4.47. Kruskal-Wallis test diagram with ChGTO-08 as compared with other methods

From the Kruskal-Wallis test it is found that nearly 60% of the outcomes obtained by the proposed ChGTO methods are significantly different from the existing methods. A conventional PI controller is synthesized corresponding to the reduced models via approximate model matching technique. One such proposed controller (ChGTO-05) is represented by the following equation as

$$G_{c2}(\gamma) = 0.20908 + \frac{3.3422}{\gamma} \tag{4.21}$$

This method also produced the least optimized value of SSE as 0.11039, minimum amongst the methods compared. This is also validated by the convergence plot shown in Fig. 4.47.

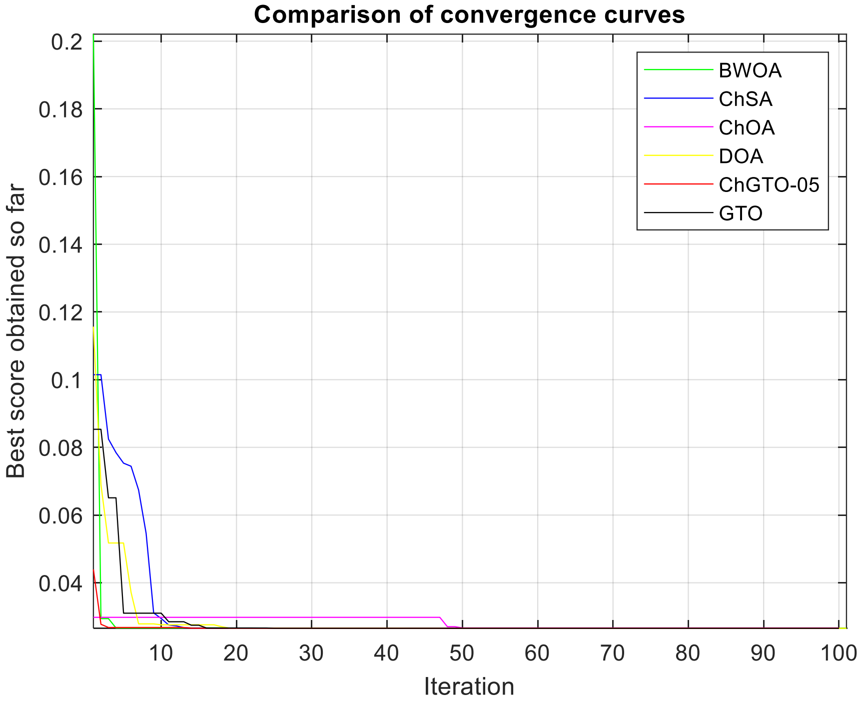

Fig. 4.48. Convergence comparison of controller model with ChGTO-05

4.6 Conclusions and future scope of work

Four sets of chaotic development in gorilla troop optimizer is put forth in this dissertation work. The position update equation is varied chaotically in the first case. In the second case, two controlling parameters are modified separately. In the third case, both these parameters are varied chaotically to get even better yield. In the fourth case, the position update rule as well as the controlling parameters is varied with chaos maps to get maximum benefit out of it in terms of better output. For the creation of new chaotic algorithms, ten well-known and widely cited chaotic maps are being considered. The proposed methods are tested using both unimodal and multimodal test functions. With the help of the delta transform theory, induction motor models with a power rating of 50 and 500 hp are also reduced in size. Even an induction motor drive model is also considered for the test. The controller is implemented through the use of an approximation model-matching framework. The proposed methods outperform the most recent and standard methods in terms of speed and accuracy. Non-parametric tests are also conducted to verify the significance of the outcomes obtained.

The proposed method can also be used to solve various complicated design problems in engineering. Further, varying the random parameters chaotically in the algorithm may also yield improvement from the basic GTO technique. A multi-objective approach could also be developed for the reduced order modelling problem as well. Other metaheuristic algorithms can be combined with GTO to develop new hybrid propositions. Even chaotic versions of the new nature-inspired methods can be thought of in future. New delta operator formulations can be developed to provide better closeness with the continuous-time counterpart.

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LIST OF PUBLICATIONS

[1] Chaudhary, R., and Ganguli, S. Modeling and control of induction machine and drive in the combined domain with new chaotic gorilla troop optimizer. Accepted for publication in *ICICNIS 2022 (Springer)*, to be held in Reva University, Bangalore on 1-2 July, 2022.

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