Optimizing Electro-Hydraulic Actuator System through Enhanced Meta-heuristic Algorithms

Afaq Shoukat

Registration No: 173-FET/MSEE/F22

Supervisor:

Dr. Khizer Mehmood

Co Supervisor:

Dr. Zeeshan Aslam Khan

Department of Electrical and Computer Engineering

Faculty of Engineering and Technology International Islamic University Islamabad

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DISSERTATION

A dissertation submitted to the Department of Electrical Engineering, International Islamic University Islamabad as a partial fulfillment of the requirements for the award of the degree.

Department of Electrical Engineering

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DEDICATION

I dedicate research work to my beloved parents, respected teachers, siblings and all those who prayed for my success.

“Alhamdulillah for everything, we can never thank Allah enough for the countless bounties He blessed us with”

CERTIFICATE OF APPROVAL

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Name of Student: Afaq Shoukat

Registration No: 173/MSEE/FET/F22

Accepted by the Faculty of Engineering and Technology, International Islamic University Islamabad in partial fulfillment of the requirement of the MS Degree in Electrical Engineering.

Viva voice committee:

Dean FET, IIU Islamabad

Assistant Professor, Chairman DEE, FET, IIUI

External Examiner

Internal Examiner

Supervisor:

Dr. Khizer Mehmood

DECLARATION

I certify that research work titled "Optimizing Electro-Hydraulic Actuator System through Enhanced Meta-heuristic Algorithms" has been completed by me and it has not been done before and presented anywhere for evaluation. Furthermore, I have properly acknowledged the material taken from related sources.

ACKNOWLEDGEMENT

First of all, I would like to thank ALLAH (SWT) for giving me the great family, supportive teachers and co-operative friends. I couldn't finish my Research-work without His help.

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ABSTRACT

The accurate mathematical modeling and identification of Electro Hydraulic Actuator System (EH-AS) is a challenging task due to various non-linearities. Meta-Heuristics have gained significant attention in the literature for solving various optimization tasks occurs in engineering domain. In this work forty new variants of Swarm Intelligence Algorithm based Crayfish Optimization Algorithm (COA) were proposed by integrating ten chaotic maps in the summer resort stage and foraging stage of COA. The proposed methodology is further investigated for the positional control parameter estimation of EH-AS. The fitness function of EH-AS is formulated on the basis of mean square error between the desired and estimated values. Results shows that COA integrated with Sinusoidal map in the temperature stage (M1COA9) out performs COA its chaotic variants as well as Aquila optimizer (AO), coati optimizer (CO), reptile search algorithm (RSA), and whale optimization algorithm (WOA). Statistical complexity and convergence analysis on multiple independent executions verifies the reliability of M1COA9 for EH-AS identification.

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CHAPTER 1

INTRODUCTION

1.1 Introduction

This chapter provides an overview of electrohydraulic actuator systems, highlighting their necessity, significance, and practical applications. It delves into the conventional techniques employed by EHAS systems, along with their benefits and constraints. Additionally, it recognizes the crucial contribution of optimization techniques in developing adaptive, innovative, robust, convergent, and dependable algorithms for rating and ranking prediction within EHAS systems.

1.2 Inspiration and Background

Electro-Hydraulic Actuator System (EH-AS) is an essential drive system in the production sector and engineering fields. EH-AS has many benefits over other electric drives in various applications because of its high-power density, integration with electronics, fast response, smooth operation, load holding, remote operation, precise control, high reliability in harsh environments, energy efficiency at high loads, and cost-effectiveness for high power. Applications of EH-AS are the energy generation sector [1], flight control [2], exoskeleton robots [3], control applications in clutches and transmission [4], robotics [5], and aerospace applications [6]. As shown in Figure.1. If we take a look in the past many optimization approaches has been done regarding position tracking by Appling different meta-heuristic algorithms, fuzzy logics, PID controller optimization. With the passage of time, the complexities in the way of problem solving have increased also with fluctuations in results regarding system's optimization, to overcome this issue meta-heuristic algorithms gained attention. This opened very broad research space also with continuity and combined design. In this process the goal is to find the minimum and maximum value of the function $P(y)$. The parameter $\boldsymbol{y}$ is in the range of search and becomes a solution. Many iterations will be applied on the problem to be optimized, in order to find the best solution. $y_{best} = \{y_1, y_2, y_3, \cdots, y_i\}$, where $\boldsymbol{i}$ refers to the dimension of the solution. Every iteration gives us a new solution $y_{new} = \{y_1, y_2, y_3, \cdots, y_i\}$. If the new solution (y_{new}) is more efficient than the previous one (y_{best}), we can say $y_{best} = y_{new}$. Like this, every iteration will go through the problem until a desired result/goal is achieved. This is the technique of meta-heuristic algorithms.

If we compare with other traditional algorithms, meta-heuristic algorithms are much easier to understand and also easy to implement. Traditional algorithms generally have fixed structures and a fixed problem on which a specific algorithm is applied like linear programming, mixed programming, which in result suffers with computational complexities and convergence. Metaheuristics are used to identify high-quality solutions to an increasing variety of complicated real-world problems, including combinatorial ones, because they can address multiple-objective multiple-solution and nonlinear formulations. In simple words we can say that meta-heuristic algorithms are flexible and can perform under various conditions, also with a lot of applications such as PV cell parameter identification, 2D strip packing, real looped water distribution network, and much more.

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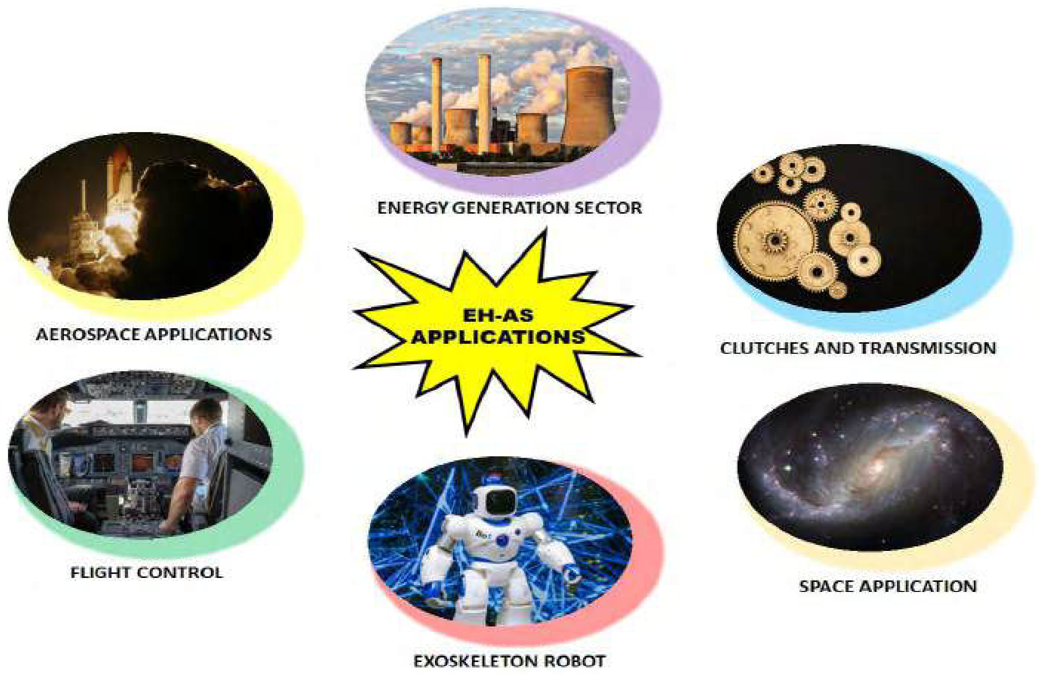


Figure 1: Applications Of EH-AS

1.3 Problem Statement

The complexity involved in Electro hydraulic actuator system's optimization especially in dynamic environments because of components like PID controller, Brushless Direct Current Servo Motor, Fixed Displacement Bi-directional Pump, Non-Return Valves, Pressure Relief Valves, and double actuating cylinders needs to be addressed as a significant engineering challenge. The optimization algorithms including swarm intelligence, evolutionary techniques, human inspired algorithms and physics based are promising for solving problems in a number of areas. But their application to optimize the position control of electrohydraulic actuator system has not been explored yet.

1.4 Goals and Objectives

The major objectives of this research

- Optimize the positional control parameters based in case of accuracy and response time (By investigating position control key parameters).
- Defining and identification of the positioning control parameters that have impact on the systems performance.
- Selecting and applying suitable meta-heuristic algorithm for the optimization process

1.5 Contributions

The primary contributions of the proposed work:

- Swarm intelligence algorithms-based crayfish optimization heuristics combined with chaos theory (CCOA) is recommended for identification of EH-AS.
- Forty chaotic variants of COA were proposed by combining Chebyshev map, circle map, Gauss map, iterative map, logistic map, piecewise map, sine map, singer map, sinusoidal map, and tent map in the temperature stage, summer resort stage and foraging stage of COA.
- Results based on mathematical benchmark functions and EH-AS display that COA integrated with Sinusoidal map in the temperature stage (M1COA9) achieves better results than the COA, its other thirty-nine chaotic variants, AO, CO, RSA, and WOA.
- The reliability of the M1COA9 is validated through the fitness results of multiple executions, complexity analysis and Friedman rank sum test analysis.

1.6 Thesis Organization

The chapter-wise organization of the research work is presented below.

Chapter 1: provides a conceptual overview of the entire thesis, consisting of research gaps, statements, and definitions that clearly define research goals, as well as background and motivations for the determination of problematic issues and research problem definitions.

Chapter 2: provides detail of the work done so far by discussing the advantages and disadvantages of already suggested methods in the literature.

Chapter 3: describes the research methodology that has been employed in this research work highlighting the algorithms that are been exploited for optimization and parameter estimation.

Chapter 4: includes the detailed analyses and simulation results.

Chapter 5: holds the conclusions drawn from the research work along with future research directions for the possible extension of a current study.

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

This chapter includes the survey of the literature that has been carried out during the course of this research work.

2.2. Literature Review

Nowadays, many researchers have proposed several types of meta-heuristic algorithms based on different categories. These categories can be divided in to four of them. Swarm-Intelligence algorithm, Evolutionary algorithm, Physics-based algorithm and Human-inspired algorithms, as shown in the Figure.2.

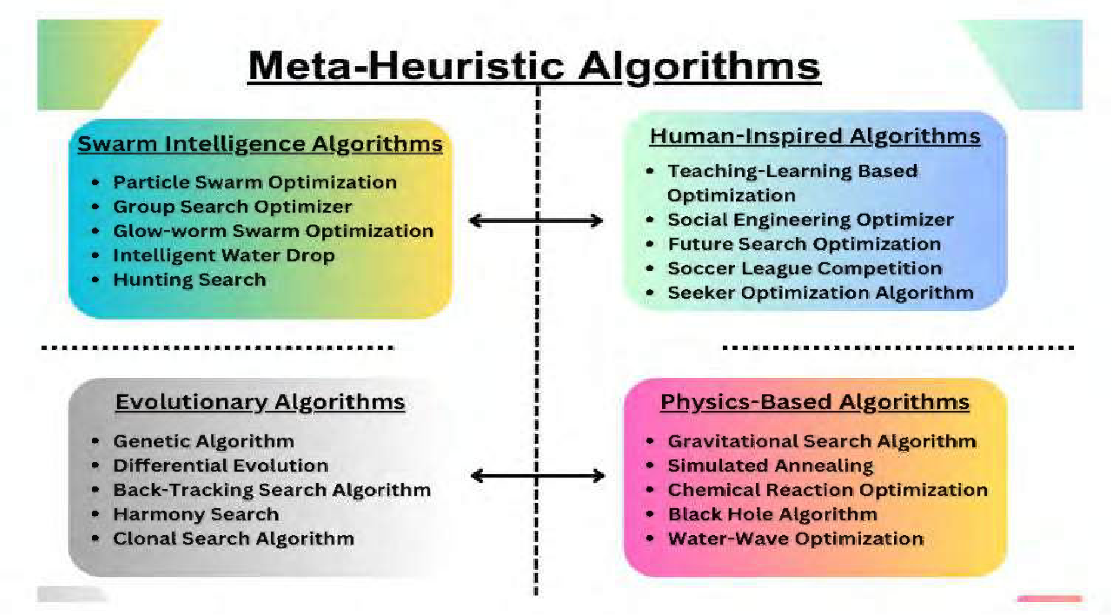


Figure 2: Classification of Meta-Heuristic Algorithms

Swarm-Intelligence Algorithms are basically inspired by the behavior of animals and was first proposed by Kennedy and Eberhard and they named as Particle Swarm

Optimization Algorithm [7], PSO is inspired by collective foraging behavior of birds in which a population solution (known as particles) adjust their position while in search of the optimal solution, each of the particle is guided through local optimum and global optimum while searching for the best solution. In Group Search Optimizer [8], this specific optimization algorithm is inspired by the searching behavior of different animals, "group" is the term for addressing the population of GS optimizer and of them is known as a member. GS optimizer also deals with the searching process like animals do in order to find food etc. Glow-worm swarm optimization is another meta-heuristic algorithm which mimics the glowing behavior of glowworm [9], in which the agent moves towards the brighter neighbor. The next one that falls in the same category is the Intelligent Water-Drop Algorithm [10], a natural river makes or we can say find its path from the source to the destination. This algorithm is inspired by the water drops that flow in the river. Hunting Search Optimization Algorithm is basically inspired by the group hunting of animals after doing the search process such as marine animals and predators [11]. Their hunting behaviors are different by the techniques are the same.

Types of meta-heuristic algorithms that are inspired by human behavior are known as Human-Inspired Algorithms. This first algorithm that comes under this list is named as Teaching Learning Based Optimization Algorithm [12], TLBO is also called population-based algorithm which deals with the learning and teaching process in a class, the algorithm contains two phases teaching phase and learner phase and from teacher phase we have best solution then we find mean of the solutions which is then sent to the learner phase where greedy selection is applied. The next Human-Inspired Algorithm that falls in the same category is named as Social Engineering Optimizer [13], which is inspired by attacking and defending techniques. How an attacker attacks and what type of strategy is attained by the defender. Future Search Algorithm [14] is that type of human-inspired meta-heuristic algorithm, mimics a person's life that how people always stay in search of batter life. When someone finds that he/she is not living a perfect life then they start to follow the footsteps of that person who is living his best life. Soccer League Competition [15] is another type, water distribution system is a very essential system in urban area. Optimization of water distribution system is considered as nonlinear optimization problem, for this SLC has been proposed. The algorithm that refers to the experience, memory and reasoning ability of human. When a starting point, search direction and search radius etc. is given to a seeker which then moves towards the new position according to the social learnings etc.

The next category of meta-heuristic algorithm is Evolutionary Based Algorithms. The first one that comes in our list is the Genetic Algorithm (GA) [16], its main operators are selection, cross-over and mutation. GA aims to optimize solution for consecutive generations. The next evolutionary algorithm is Differential Evolution [17], this algorithm is or global optimization over continuous space. Some chosen numerical values are kept fixed for an optimization process. Each solution is called "chromosome or genome", its main operations are mutation and cross-over. Back-Tracking Search Algorithm (BTS) [18] is another type of evolutional algorithm that is used for the solution of nonlinear, nondifferential and complex numerical optimization problem. BTS has the ability to control the most sensitive parameters. Harmony Search Algorithm [19] is next after BTS, HS mimics the role play of a music player, this algorithm employs a method of creating new solution vector that boost accuracy and convergence rate and is best applicable on standard engineering problems. Human's natural immune system uses the Clonal Selection Algorithm [20], that defines the basic features of the immune response to the stimulus.

The next category of meta-heuristic algorithm is named as Physics-Based Algorithms, this first algorithm that comes in the list is Gravitational Search Algorithm (GSA) [21]. GSA is based on the laws of gravitation and also with the interaction of mass, collection of masses is called as agents which interact with other agents under the Newtons law of gravitation and Newtons law of motion. GSA has been used for solving non-linear problems. Simulated Annealing [22] is based on the changes when a solid is heated in a chamber to highest temperature, the solid changes its state to liquid and then on cooling some changes occurs again. The arrangement of molecules changes when heated or cooled. The next one is the Chemical Reaction Optimization Algorithm (CRO) [23], they occur naturally for bring a substance from unstable state to a stable one. Before chemical reaction some substances contain molecules with excess energy and are in excited state but after the reaction, they are converted to those with minimum energies to support their existence. Black Hole Algorithm [24] is inspired by black hole, best candidates are selected at every iteration and is called “black hole” and other candidate are then pulled by the black hole around and they are named as “stars”. If stars get to close to the black hole if will be gone forever. Water-wave Optimization Algorithm (WWO) [25] is another type of algorithm that falls in the category of Physics-based Algorithm which is inspired by the waves that forms in shallow water. It mimics the propagation, refraction and breaking properties of water waves. WWO is used for global optimization problems.

Recently, a new meta-heuristic algorithm named as Crayfish Optimization Algorithm (COA) [26] is introduced. It is applied in various applications such as battery energy storage systems. Krit Wichitkrailat, has presented location and optimal sizing of different Battery Energy Storage System (BESSs), which is used in distributed systems which are then connected with the Distribution Generators (DGs). They have incorporated multiple Battery Storage Systems. To solve the problem that only a single BESS might be inadequate for the Distribution System (DS), which is connected with several Distributed Generators (DGs), the researchers have utilized the potential of Crayfish Optimization Algorithm to address the problem[27].

Sadiq M. Sait has proposed an article in which the researchers explored various application regarding recently introduced meta-heuristic algorithm known as Crayfish Optimization Algorithm (COA). They have also incorporated Artificial Neural Network (ANN) with COA in order to optimize various engineering designs. ANN is utilized only to boost the performance and accuracy of COA. The applications they have included are diaphragm spring, suspension system of different vehicles and hydrostatic thrust bearing etc.[28].

Diaa Salama Abdelminaam, carried out the parameter estimation in Photovoltaic (PV) system design. The estimated parameters have been approached by using hybrid, numerical and analytical techniques. In the proposed work they have incorporated COA along with various other algorithms which includes SOA, STOA, Hunger Game Search, Synergistic Mimic Algorithm (SMA), Lightning Attachment Procedure Optimization (LAPOP) and TURBULAS Swarm Algorithm (TSA). However, from the results the COA performs the best in comparison with the other algorithms mentioned[29].

Burcin Ozkaya used Enhanced Crayfish Optimization Algorithm (ECOA) integrated with Opposition Based Learning (OBL) strategies for the parameter estimation of three different Photovoltaic (PV) modules. They have utilized six variants of ECOA and three OBL strategies. From the result it can be concluded that ECOA has showed higher performance to carry out the task of parameter estimation [30].

Lakhdar Chaib has presented a unique and different method which combines Crayfish Optimization Algorithm with fractional order chaos maps (FC-Maps). The purpose of utilizing FC maps is to adjust COA adaptability. However, the crayfish optimization algorithm is enhanced by utilizing dimension learning settings. This has been done for the parameter estimation of photovoltaic. This improved COA is combined with the Newton-Raphson numerical method. Results shows that ICOA contributed significantly in terms of convergence, precision and consistency [31].

Abdelghani Draoui, Crayfish Optimization Algorithm is utilized to track the Global Maximum Power Point (GMPP) by reading the output power of photovoltaic system under partial shading conditions. Their research work is entirely based on simulations by using MATLAB/Simulink platforms and shows good results in tracking and also proved the system's robustness in order to predict rapidly varying solar irradiance level[32].

Ying Cheng has proposed an automatic assessment method which is based on deep confidence network with the utilization of Crayfish Optimization Algorithm (COA), in order to address the current automatic assessment methods which includes poor generalization and poor real time performance etc. They have constructed multi-dimensional listening strategy and then they have used COA for the construction of automatic evaluation model. The results shows the significant improvement in robustness, accuracy and real time performance [33].

Nabila H. Shikoun has proposed a new variant of Crayfish Optimization Algorithm called Binary Crayfish Optimization Algorithm with two primary enhancements for the purpose of gaining increase in performance. They have added the crisscross strategy to the original COA which increases the convergence accuracy of COA. They have also evaluated the proposed BinCOA with comparison of seven contemporary wrapper feature selection methods. They have tested their strategy on set of 30 benchmark datasets. Results shows the performance of BinCOA with the existing algorithm in case of average fitness value, classification accuracy and the number of selected features [34].

Nebojsa Bacanin, introduced a hybrid deep learning model incorporated with Gated Recurrent Unit (GRU) neural network which is optimized by Crayfish Optimization Algorithm (COA) along with firefly algorithm. For the comparison purpose they have used the other high performance optimization algorithms. They have proposed this model in order to diagnose the Parkinson's disease which is based on the disturbance in the patient's gait. Their proposed model shows improvement in the performance and attain the accuracy of 87.08% [35].

Sahaya Stalin Jose. G, to overcome the challenges of security and privacy in Cloud Computing (CC), they have proposed Self-Attention Condition Generative Adverbial Network which is optimized by Crayfish Optimization Algorithm for the improvement of cyber security in cloud computing (CybS_CC_SACGAN_COA). The results shows higher lower computational time, higher detection accuracy, higher AUC, lower detection error and higher scalability [36].

Marko Stankovic has done the innovative approach using CNN and signal processing for the purpose of violating speed detection which is crucial for traffic management. For the tuning purpose of CNN, they have utilized the potential of an altered variant of COA. This work contributed in both traffic safety and management along with provides a framework for signal processing and artificial intelligence technique [37].

Vinit Kumar has devised a technique for the detection of kidney diseases like kidney tumor etc. Because the kidney tumor comes in various forms in which majority of them are cancerous also, they are difficult to detect by using renal Computerized Tomography (CT) images. To tackle this problem, they have proposed a classification model for kidney tumor segmentation in order to recognize the tumor at early stages. Their model includes a deep learning model called Adaptive & Attentive Residual DenseNet along with GRU (AA_RD_GRU) and the parameters are optimized with Modified Crayfish Optimization Algorithm (MCOA). Results shows the improved classification and segmentation of kidney tumor [38].

Heming Jia has introduced a Modified Crayfish Optimization Algorithm (MCOA) which lies on the life style of crayfish. Their proposed mechanism includes water quality factor which help the crayfish for finding better environment. They have tested the performance of MCOA by using IEEE CEC2020 standard benchmark functions. By the results it has been concluded that MCOA shows better results than the original variant of COA. This contributes a lot for the development in the field of optimization [39].

Sumika Chauhan has proposed an advance technique to address the friction force and lubricating condition of Ti-64AI-4V alloy. Their framework includes parallel structure of COA and arithmetic optimization algorithm (PSCOAAOA) for addressing the issue of slow convergence etc. For parameter estimation they incorporated Support Vector Machine (SVM). They have carried out the analysis on CEC2014 standard benchmark functions and achieved a high accuracy of 95.85% [40].

Yi Zhang has presented an enhanced variant of Crayfish Optimization Algorithm (ECOA) , they have also imposed Halton sequence to improve the initialization of population of the crayfish optimization algorithm. However, to increase the COA searching ability quasi opposition-based learning base strategy is applied. To avoid blindness the elite factor guides are applied to the predation stage. They have tested their model IEEE CEC2019 benchmark functions are utilized. Results shows the significant increase in faster convergence speed and great performance ability etc[41].

Bingsong Xiao has proposed a simplified version of crayfish optimization algorithm in order to address the low efficiency and complexities of basic optimization algorithm. At first, they have analyzed the position update method of foraging behavior. They have tested their algorithm on 23 universal benchmark functions and the proposed algorithm has to go under 30 operations and they have also compared standard deviation, average and running time. The results shows a significant increase in robustness, accuracy and convergence speed and the running time is reduced by 7.63% which has also improved the running efficiency [42].

Himani Daulat has proposed a control approach regarding Crayfish Optimization Algorithm (COA) fitness and population diversity in order to tackle the limitation of less robust exploration capabilities. Furthermore, they have also utilized the Gaussian Distribution (GD) parameters. They called their newly proposed algorithm GD_COA also they have tested their proposed strategy by using 27 uni-model and multi-model benchmark functions. The results shows that the proposed GD_COA has higher efficiency and effectiveness other than the original COA [43].

Ruitong Wang proposed improved multi strategy crayfish optimization algorithm in order to solve numerical optimization problems and to tackle the problem of sensitivity and slow convergence speed. They have evaluated the performance of IMCOA by the use of CEC2017 and CEC2022 standard benchmark datasets and they have also compared eight different algorithms. They have also carried out statistical analysis of IMCOA and results shows that the proposed algorithm showed significant improvement in optimization accuracy, convergence speed and ability to converge [44].

Debashis Dutta has presented an optimization technique called fuzzy bluefin trevally optimizer (BTO), inspired by the corporative nature of bluefin. They have carried out the effectiveness with benchmark functions and also used other metaheuristic algorithms for the purpose of comparison also they have carried out statistical significance by using Kruskal Wallis Test (KWT) [45].

Taimoor Ali Khan has proposed a population based gazella optimization algorithm which has gained the inspiration from evolutionary characteristics of gazelle. They have further extended the GOA through the stiff parameters estimations of electrically stimulated muscle model (ESMM). They have carried out the efficiency by using Wilcoxon signed rank statistical test. They have also compared the proposed GOA with other nature inspired meta-heuristic algorithms which includes Whale Optimization Algorithm, Harris Hawks Optimization Algorithm and Runge Kutta Optimization Algorithm [46].

Roland has proposed a Convolutional Neural Network (CNN) model which is designed and optimized by the selected genetic algorithm in order to use computer vision for the purpose of recognition and to differentiate between batik patterns. They have used the potential of VGG-19 model, which has gained an accuracy of 0.7596 [47]. Various methods were used for the optimization of autoregressive model-based systems such as PSO, which has the inspiration from the social lifestyle of birds which is then used for the optimization purpose. PSO is used widely in machine learning and engineering tasks to solve multi-dimension and complex problems[48], dwarf mongoose optimization gets inspiration from the food searching ability of dwarf mongooses. The algorithm has various phases under consideration, which majorly includes exploration and exploitation due to which they converge on the promising areas. DMO shows great performance in the field of data science, machine learning and engineering[49] and fractional calculus, uses the principles of fractional calculus. This technique has the ability to capture the memory of dynamic systems more effectively. This technique has the found the applications in field of signal processing, machine learning and control theory[50]. Various methods were used for the identification of EH-AS such as adaptive neuro-fuzzy approach by developing a scheme for the controlling purpose of EH-AS by incorporating compound controller with Intelligent Feed Forward Compensator (IFFC), also with the integration of off-line self-tuning mechanism[51], Kalman filter by developing hybrid formulation of Fault Detection and Identification (FDI). The key physical parameters of EH-AS are utilized with FDI for monitoring purpose, the incorporated parameters includes effective bulk modulus and torque motor equivalent resistance which showed promising results[52], and chaotic atom search optimization utilizes chaotic maps with a meta-heuristic algorithm named as atomic search optimization algorithm. In CASO the search agents get involved with each other and experiences attractive and repulsive forces in order to search the solution space. The chaotic variant of the algorithm has shown effectiveness for solving complex problems related to optimization feasible in those fields which require precision and adaptability[53].

In this work, ten chaotic maps were integrated in the temperature, summer resort and foraging stages of COA for the identification of the EH-AS model. The analysis was performed at various iterations, population, and noise levels. It is proved that the chaotic COA has better exploration and exploitation than COA. Statistical analysis shows that the chaotic variants of COA has better performance than COA, Aquila optimizer (AO) is inspired by the hunting ability of an eagle (aquila) which incorporated four different strategies which includes exploration, exploitation, intensification and diversification, this optimization technique shows best performance in exploration and exploitation phase, which in result boost up its ability of global optimization[54], coati optimizer (CO) gets its inspiration form coatis which shows the social behavior as it keep the search under consideration both strategies locally and globally. CO shows its effectiveness while handing high dimension optimization problems such as gradient based methods face limitations[55], reptile search algorithm (RSA) is based on the hunting behavior of reptiles. The ability of reptiles while they are in search of prey incorporates movement, exploration and exploitation patterns. RSA has been utilized in various field to carry out multiple tasks related to optimization[56], and whale optimization algorithm (WOA), this meta-heuristic algorithm stimulates the hunting behavior of hump back whales. WOA utilizes a strategy called bubble net hunting in which whales create movement of spiral shape in order to trap its pray. WOA is used widely in the field of economics, engineering and machine learning because of its efficiency, flexibility and simplicity while handling complex optimization problems [57].

CHAPTER 3

PROPOSED METHODOLOGY

In this section the mathematical model of EH-AS, COA and Chaotic variants of COA are presented along with their Pseudo codes.

3.1 Electrohydraulic Actuator Systems

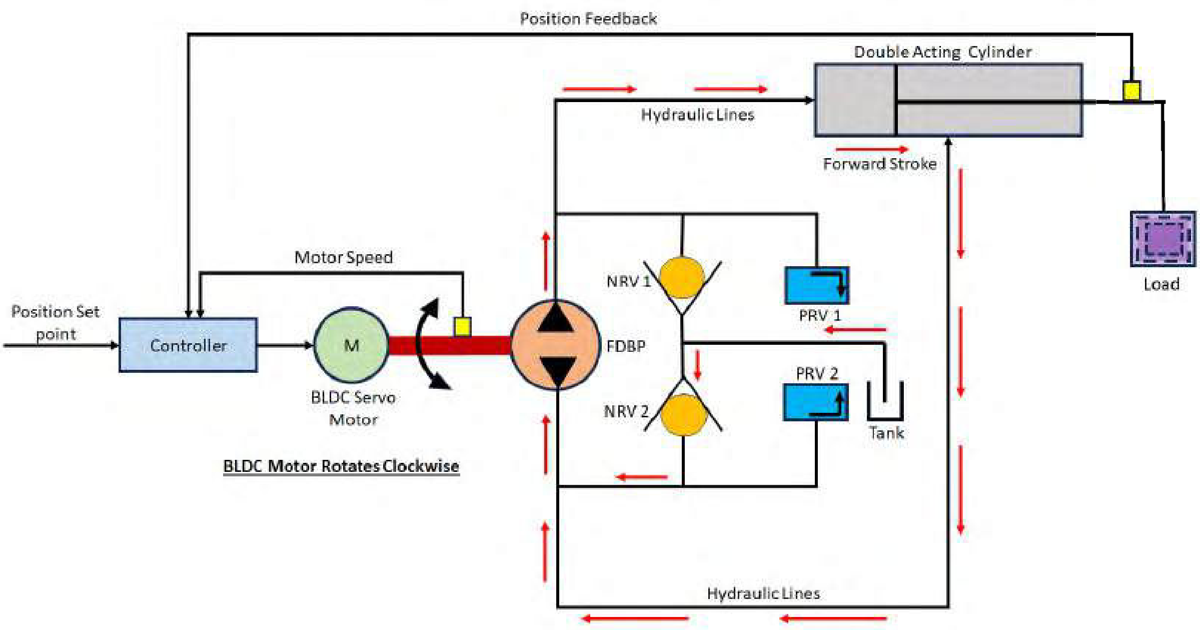


Figure 3: Operation Of EH-AS

In Figure.3 we have presented a pictorial representation of Electro-Hydraulic Actuator System. The system consists of a controller (i.e., PID controller, Lab view etc.) connected with a Brushless Direct Current Servo Motor which is then connected with a Fixed Displacement Bi-directional Pump, we have two Non-Return Valves for controlling flow of liquid named NRV-1 and NRV-2, PRV-1 and PRV-2 are called Pressure Relief Valves. A double actuating cylinder is connected which can only attain to and fro motion only which is connected with an inertial load for support while returning back. First a position set point is given to the controller. A tank is used as reservoir for oil. When the BLDC servo motor rotates clockwise the oil will flow from NRV-2 and will pass through the FDBP and heads straight to the front of piston as shown in the figure. The oil will create a pressure and force the piston to moves backward and the oil will flow through the hydraulic lines and collected in the FDBP. The FDBP will not let the oil to take path to the reservoir but guide the fluid to back of the piston. Position feedback is given to the controller for assuming the piston's next position. Same as when the BLDC servo motor rotated anti-clockwise, the oil will flow through the NRV-1 and pass through the FDBP and heads straight to the back of the piston and push the piston in the forward direction and from hydraulic lines it comes back and collected in FDBP. The position once again is provided to the controller.

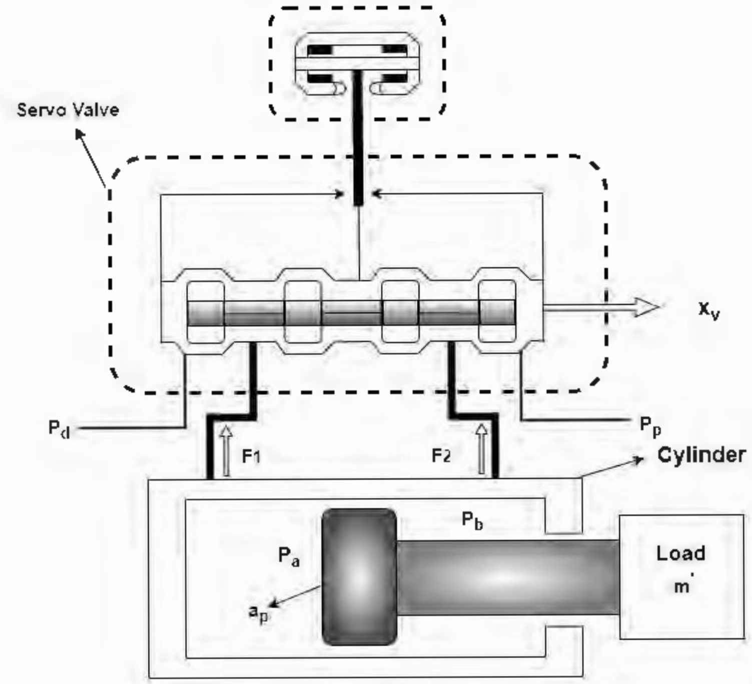


Figure 4: Electro-Hydraulic Actuator System

Figure#4 shows Electro-Hydraulic Actuator System consist of a piston with a load m attached, fluid flow indicated as F1 and F2, servo valves, P_a and P_b are the fluid pressure in upper and lower chambers of the cylinder while a_p shows the acceleration of the piston [34].

Newton's second law of motion is applied then we can extract

$$m'a_p = F_1 - F_2 - f_3 \tag{1}$$

(Where m', F_1, F_2 and f_3 are the total mass, actuating mass of hydraulics, hydraulic force of friction, non-linearity due to disturbance that exist externally respectively).

After going through some mathematics, we get

$$m = f\left(\bar{u}, p_a, p_b, V_a, V_b\right) \tag{2}$$

(Where $\bar{u}$ is the input signal, V_a and V_b both are directly proportional to a_P ,the above relation can be rewritten as,

$$m = f\left(\bar{u}, p_a, p_b, m\right) \tag{3}$$

From this relation it has been shown that, while obtaining the position of the piston in the system a_p, the input signal $\bar{u}$, pressure P_a and P_b, also the position of the piston a_p is needed. The new piston position is obtained with the help of the previous position. Thus, the equation (3) can be re-written as,

$$m\left(d\right) = f\left(\bar{u}(d), p_a(d-1), p_b(d-1), m(d-1)\right) \tag{4}$$

3.2 Autoregressive Exogenous (ARX) Model

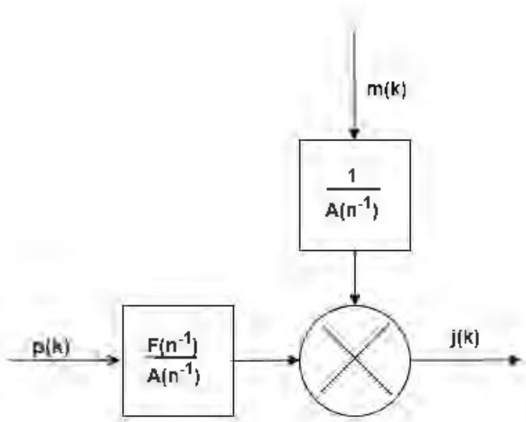


Figure 5: ARX Model

Figure#5 shows a block diagram of ARX model, that we have a certain input, we say p(k) with a random noise m(k) and the output j(k). Two polynomials $A\left(n^{-1}\right)$ (with a degree of b_x) and $F\left(n^{-1}\right)$ (with a degree of b_i).

$$A\left(n^{-1}\right) = 1 + a_1 n^{-1} + a_2 n^{-2} + - - - + a_{n_a} n^{-n_a} \tag{5}$$

$$F\left(n^{-1}\right) = f_1 n^{-1} + f_2 n^{-2} + - - - + f_{nf} n^{-n_f} \tag{6}$$

The ARX Model shown in the figure gives the output,

$$j(k) = \frac{F(n^{-1})}{A(n^{-1})} p(k) + \frac{1}{A(n^{-1})} m(k) \tag{7}$$

After multiplying equation (7) by $A(n^{-1})$, the new equation will become,

$$A\left(n^{-1}\right) j(k) = F\left(n^{-1}\right) p(k) + m(k) \tag{8}$$

The information vector can be extracted as,

$$l_m(k) = \left[-j(k-1), -j(k-2), ---, -j(k-n_a)\right] \tag{9}$$

Similarly, parameter vectors can be estimated as

$$l_o(k) = \left[-p(k-1), -p(k-2), ---, -p(k-n_f)\right] \tag{10}$$

$$a = [a_1, a_2, ..., a_{n_a}] \tag{11}$$

$$f = [f_1, f_2, ..., f_{n_f}] \tag{12}$$

The ARX system identification model according to the information and parameter can be withdrawn as,

$$j(k) = l^T(k)\alpha + m(k) \tag{13}$$

$$l(k) = \left[l_m(k) \quad l_i(k)\right] \tag{14}$$

$$\alpha = \left[m \quad i\right] \tag{15}$$

3.3 Crayfish Optimization Algorithm

Crayfish optimization algorithm is a nature inspired swarm based meta heuristic algorithm inspired by the life style of Crayfish. Whose behavior changes with the variation in temperature.

3.3.1. Defining Temperature

Crayfish shows different behavior according to the environmental temperature, if temperature is high enough to make the crayfish unstable, it will show the summer resort behavior. Temperature variation will be followed by the following equation.

$$T = rand \times 10 + 25 \tag{16}$$

Where T refers to the temperature in the crayfish is located.

3.3.2. Population Initializing

In a specific dimensional optimization problem of Crayfish Optimization Algorithm, in which each crayfish is in $1 \times \dim$ matrix which represents the solution. There are set of variables $A = \lfloor A_1, A_2, \cdots, A_Z \rfloor$, in the search space each individual crayfish is between the upper boundary $u(b)$ and the lower boundary $l(b)$. The population of crayfish can be calculated the using the following equation.

$$A_{l,m} = pq_m + \left(xq_m - pq_m\right) \times rand \tag{17}$$

Where $A_{l,m}$ shows the crayfish position in l^{th} crayfish in m^{th} dimension.

3.3.3. Competition Stage (Exploitation Stage)

In summers when the temperature gets higher than 30°C, crayfish will be unstable and begins to look for a cave in according to tackle the problems caused high temperature. The summer resort behavior can be defined as,

$$A_{hide} = \frac{\left(A_p + A_h\right)}{2} \tag{18}$$

Where A_{hide} represents shade or cave, A_p and A_h represents position optimal by number of iterations and position optimal of population.

If we take the value of rand less than 0.5, this means that crayfish will not fight each other but instead gets straight into the cave.

$$A_{l,m}^{c+1} = A_{l,m}^{c} + Q_2 \times rand \times \left(A_{hide} - A_{l,m}^{c}\right) \tag{19}$$

$$Q_2 = 2 - \left(\frac{c}{N}\right) \tag{20}$$

Where, c is the number of iterations, $c+1$ indicates the next iteration, Q_2 represents the decreasing curve(mentioned below) and N is the total number of iterations.

When crayfish approaches the cave of low temperature, which in result brings the individual close to the solution. If the rand value is greater than 0.5 and the temperature exceeds than 30°C, the crayfish will fight each other for the cave. While in state of competition, the crayfish individual A_l adjust position with the position A_x which is the position of another crayfish. This will expand the search range of Crayfish Optimization Algorithm.

$$A_{l,m}^{c+1} = A_{l,m}^{c} - A_{x,m}^{c} + A_{hide} \tag{21}$$

Here x is a random crayfish individual.

3.3.4. Foraging Stage (Exploitation Stage)

While in state of competition, the crayfish individual A_l adjust position with the position A_x which is the position of another crayfish. This will expand the search range of Crayfish Optimization Algorithm.

$$A_o = A_p \tag{22}$$

A_o indicated the location of food.

Crayfish has strong foraging behavior where the temperature lies between 20°C to 30°C. According to the proposed crayfish optimization algorithm[41] the foraging temperature of crayfish is defined from 20°C to 35°C.

$$k = Q_1\left(\frac{1}{\sqrt{2\pi}\times\beta}\times\exp\left(-\frac{(T-\alpha)^2}{2\beta^2}\right)\right) \tag{23}$$

Where α represents the suitable temperature, Q_1 and β both are the food intake control parameters.

When the temperature is less than 30°C, in this temperature the crayfish will be in search of food. Once, the food is found the crayfish will inspect the food for its size. If the size is too large the crayfish will tear the food for intake.

$$M = Q_3 \times rand \times \left(\frac{R_l}{S_o} \right) \tag{24}$$

Q_3 represents the largest food/food parameter and its value is 3 which is kept constant, R_l indicated the fitness value of l^{th} crayfish and S_o indicated the value of fitness of food location.

If the food is too large and need to be torn apart than,

$$M > \frac{(Q_3 + 1)}{2} \tag{25}$$

$$A_o = \exp\left(\frac{-1}{M} \right) \times A_o \tag{26}$$

$$A_{l,m}^{c+1} = A_{l,m}^{c} + A_o \times e \times \cos(2\pi \times rand) - \sin(2\pi \times rand) \tag{27}$$

When the food is small then the crayfish will simple starts to eat without doing the tearing process of food.

$$A_{l,m}^{c+1} = \left(A_{l,m}^{c} - A_o \right) \times e + e \times rand \times A_{l,m}^{c} \tag{28}$$

The pseudo code of COA is shown below:

COA Pseudo-Code

Initialize

Iteration (N), population (Z), dimension (dem)

Calculate fitness value to get A_p, A_h

When C<N

Temperature defined by $T = rand \times 10 + 25$

If T>30°C

Define shaded place A_{hide} by $A_{hide} = \frac{(A_p + A_h)}{2}$

If rand < 0.5

Crayfish will go for summer vacations by $A_{l,m}^{c+1} = A_{l,m}^{c} + Q_2 \times rand \times \left(A_{hide} - A_{l,m}^{c}\right)$

Else

Crayfish will fight for cave by $A_{l,m}^{c+1} = A_{l,m}^{c} - A_{x,m}^{c} + A_{hide}$

End

Else

The crayfish feed intake (e) and size of food (M) are by

$$k = Q_1\left(\frac{1}{\sqrt{2\pi} \times \beta} \times \exp\left(-\frac{(T-\alpha)^2}{2\beta^2}\right)\right) \; \& \; M = Q_3 \times rand \times \left(\frac{R_l}{S_o}\right)$$

If M>2

The crayfish tears the food by $A_o = \exp\left(\frac{-1}{M}\right) \times A_o$

The crayfish foraging behavior will be according to

$$A_{l,m}^{c+1} = A_{l,m}^{c} + A_o \times e \times \cos(2\pi \times rand) - \sin(2\pi \times rand)$$

Else

The crayfish foraging behavior will be according to

$$A_{l,m}^{c+1} = \left(A_{l,m}^{c} - A_o\right) \times e + e \times rand \times A_{l,m}^{c}$$

End

End

Update the fitness value A_p, A_h

c=c+1

End

3.4. Chaotic Crayfish Algorithm

We use chaotic maps (C_{maps}) for the enhancement of the exploration and exploitation capabilities of optimization algorithms. Here are the ten chaotic maps that was incorporated in three different ways for the improvement of exploration and exploitation of Crayfish Optimization Algorithm. Table.1 shows the ten chaotic maps.

Table 1: Chaotic Maps

Map Number	Map Name	Map Equation
CCOA1	Chebyshev map [58]	$a_{x+1} = \cos(x\cos^{-1}(a_x))$
CCOA 2	Circle map [59]	$a_{x+1} = \mathrm{mod}\left(a_x + 0.2 - \left(\frac{0.5}{2\pi}\right)\sin(2\pi a_x), 1\right)$
CCOA3	Gauss/mouse map [60]	$a_{x+1} = \begin{cases} 1, a_x = 0 \\ \frac{1}{\mathrm{mod}(a_x, 1)} & \text{otherwise} \end{cases}$
CCOA4	Iterative map [61]	$a_{x+1} = \sin\left(\frac{0.7\pi}{a_x}\right)$
CCOA5	Logistic map [62]	$a_{x+1} = 4a_x(1 - a_x)$
CCOA6	Piecewise map [63]	$a_{x+1} = \begin{cases} \frac{a_x}{0.4}, 0 \le a_x < 0.4 \\ \frac{a_x - 0.4}{0.1}, 0.4 \le a_x < 0.5 \\ \frac{0.6 - a_x}{0.1}, 0.5 \le a_x < 0.6 \\ \frac{1 - a_x}{0.4}, 0.6 \le a_x < 1 \end{cases}$
CCOA7	Sine map [64]	$a_{x+1} = \sin(\pi a_x)$
CCOA8	Singer map [65]	$a_{x+1} = 1.07(7.86a_x - 23.31a_x^2 + 28.75a_x^3 - 13.30a_x^4)$
CCOA9	Sinusoidal map [66]	$a_{x+1} = 2.3a_x^2\sin(\pi a_x)$
CCOA10	Tent map [67]	$a_{x+1} = \begin{cases} \frac{a_x}{0.7}, a_x < 0.7 \\ \frac{10}{3}(1 - a_x), a_x \ge 0.7 \end{cases}$

In this work these C_{maps} were incorporated by using four different ways in COA. These modifications are presented below:

3.4.1. Modification 1 M1COA:

In this modification the chaotic maps were incorporated in Eq 16 as given in Eq (17)

$$T = C_{maps} \times 10 + 25 \tag{29}$$

The pseudo code of M1COA is shown below:

M1COA Pseudo code
Initialize Iteration (N), population (Z), dimension (dem) Calculate fitness value to get A_p, A_h When C<N Temperature defined by $T = C_{maps} \times 10 + 25$ If T>30°C Define shaded place A_{hide} by $A_{hide} = \frac{(A_p + A_h)}{2}$ If rand < 0.5 Crayfish will go for summer vacations by $A_{l,m}^{c+1} = A_{l,m}^{c} + Q_2 \times rand \times (A_{hide} - A_{l,m}^{c})$ Else Crayfish will fight for cave by $A_{l,m}^{c+1} = A_{l,m}^{c} - A_{x,m}^{c} + A_{hide}$ End Else The crayfish feed intake (e) and size of food (M) are by $k = Q_1 \left(\frac{1}{\sqrt{2\pi} \times \beta} \times \exp\left(-\frac{(T-\alpha)^2}{2\beta^2} \right) \right)$ & $M = Q_3 \times rand \times \left(\frac{R_l}{S_o} \right)$ If M>2 The crayfish tears the food by $A_o = \exp\left(\frac{-1}{M} \right) \times A_o$ The crayfish foraging behavior will be according to $A_{l,m}^{c+1} = A_{l,m}^{c} + A_o \times e \times \cos(2\pi \times rand) - \sin(2\pi \times rand)$ Else The crayfish foraging behavior will be according to $A_{l,m}^{c+1} = (A_{l,m}^{c} - A_o) \times e + e \times rand \times A_{l,m}^{c}$ End End

Update the fitness value A_p, A_h

c=c+1

End

3.4.2. Modification 2 M2COA:

In this modification the chaotic maps were incorporated in summer resort stage as indicated in pseudo code.

$$C_{map} < 0.5 \tag{30}$$

The pseudo code of M2COA is shown below

M1COA Pseudo code
Initialize Iteration (N), population (Z), dimension (dem) Calculate fitness value to get A_p, A_h When C<N Temperature defined by $T = rand \times 10 + 25$ If T>30°C Define shaded place A_{hide} by $A_{hide} = \frac{(A_p + A_h)}{2}$ If $C_{map} < 0.5$ Crayfish will go for summer vacations by $A_{l,m}^{c+1} = A_{l,m}^{c} + Q_2 \times R \times (A_{hide} - A_{l,m}^{c})$ Else Crayfish will fight for cave by $A_{l,m}^{c+1} = A_{l,m}^{c} - A_{x,m}^{c} + A_{hide}$ End Else The crayfish feed intake (e) and size of food (M) are by $k = Q_1\left(\frac{1}{\sqrt{2\pi} \times \beta} \times \exp\left(-\frac{(T-\alpha)^2}{2\beta^2}\right)\right)$ & $M = Q_3 \times rand \times \left(\frac{R_l}{S_o}\right)$ If M>2 The crayfish tears the food by $A_o = \exp\left(\frac{-1}{M}\right) \times A_o$

The crayfish foraging behavior will be according to $A_{l,m}^{c+1} = A_{l,m}^{c} + A_o \times e \times \cos(2\pi \times rand) - \sin(2\pi \times rand)$ Else The crayfish foraging behavior will be according to $A_{l,m}^{c+1} = \left(A_{l,m}^{c} - A_o\right) \times e + e \times rand \times A_{l,m}^{c}$ End End Update the fitness value A_p, A_h c=c+1 End

3.4.3. Modification 3 M3COA:

In this modification the chaotic maps were incorporated in Eq 37 as given in Eq 38

$$M = Q_3 \times C_{maps} \times \left(\frac{R_l}{S_o}\right) \tag{31}$$

The pseudo code of M3COA is shown below:

M3COA Pseudo code
Initialize Iteration (N), population (Z), dimension (dem) Calculate fitness value to get A_p, A_h When C<N Temperature defined by $T = rand \times 10 + 25$ If T>30°C Define shaded place A_{hide} by $A_{hide} = \frac{(A_p + A_h)}{2}$ If rand < 0.5 Crayfish will go for summer vacations by $A_{l,m}^{c+1} = A_{l,m}^{c} + Q_2 \times rand \times \left(A_{hide} - A_{l,m}^{c}\right)$ Else Crayfish will fight for cave by $A_{l,m}^{c+1} = A_{l,m}^{c} - A_{x,m}^{c} + A_{hide}$ End Else

The crayfish feed intake (e) and size of food (M) are by

$$k = Q_1\left(\frac{1}{\sqrt{2\pi}\times\beta}\times\exp\left(-\frac{(T-\alpha)^2}{2\beta^2}\right)\right) \; \& \; M = Q_3 \times C_{maps} \times \left(\frac{R_l}{S_o}\right)$$

If M>2

The crayfish tears the food by $A_o = \exp\left(\frac{-1}{M}\right)\times A_o$

The crayfish foraging behavior will be according to

$$A_{l,m}^{c+1} = A_{l,m}^{c} + A_o \times e \times \cos(2\pi\times rand) - \sin(2\pi\times rand)$$

Else

The crayfish foraging behavior will be according to

$$A_{l,m}^{c+1} = \left(A_{l,m}^{c} - A_o\right)\times e + e \times rand \times A_{l,m}^{c}$$

End

End

Update the fitness value A_p, A_h

c=c+1

End

3.4.4. Modification 4 M4COA:

In this modification, M1COA, M2COA and M3COA are combined as indicated in the pseudo code.

The pseudo code of M4COA is shown below:

M4COA Pseudo code
Initialize Iteration (N), population (Z), dimension (dem) Calculate fitness value to get A_p, A_h When C<N Temperature defined by $T = C_{maps}\times 10 + 25$ If T>30°C

Define shaded place A_{hide} by $A_{hide} = \frac{\left(A_p + A_h\right)}{2}$

If $C_{maps} < 0.5$

Crayfish will go for summer vacations by $A_{l,m}^{c+1} = A_{l,m}^{c} + Q_2 \times R \times \left(A_{hide} - A_{l,m}^{c}\right)$

Else

Crayfish will fight for cave by $A_{l,m}^{c+1} = A_{l,m}^{c} - A_{x,m}^{c} + A_{hide}$

End

Else

The crayfish feed intake (e) and size of food (M) are by

$$k = Q_1\left(\frac{1}{\sqrt{2\pi} \times \beta} \times \exp\left(-\frac{\left(T-\alpha\right)^2}{2\beta^2}\right)\right) \ \& \ M = Q_3 \times C_{maps} \times \left(\frac{R_l}{S_o}\right)$$

If M>2

The crayfish tears the food by $A_o = \exp\left(\frac{-1}{M}\right) \times A_o$

The crayfish foraging behavior will be according to

$$A_{l,m}^{c+1} = A_{l,m}^{c} + A_o \times e \times \cos\left(2\pi \times rand\right) - \sin\left(2\pi \times rand\right)$$

Else

The crayfish foraging behavior will be according to

$$A_{l,m}^{c+1} = \left(A_{l,m}^{c} - A_o\right) \times e + e \times rand \times A_{l,m}^{c}$$

End

End

Update the fitness value A_p, A_h

c=c+1

End

CHAPTER 4

SIMULATIONS AND ANALYSES

This chapter presents the details of experimentation and results obtained in a simulated environment.

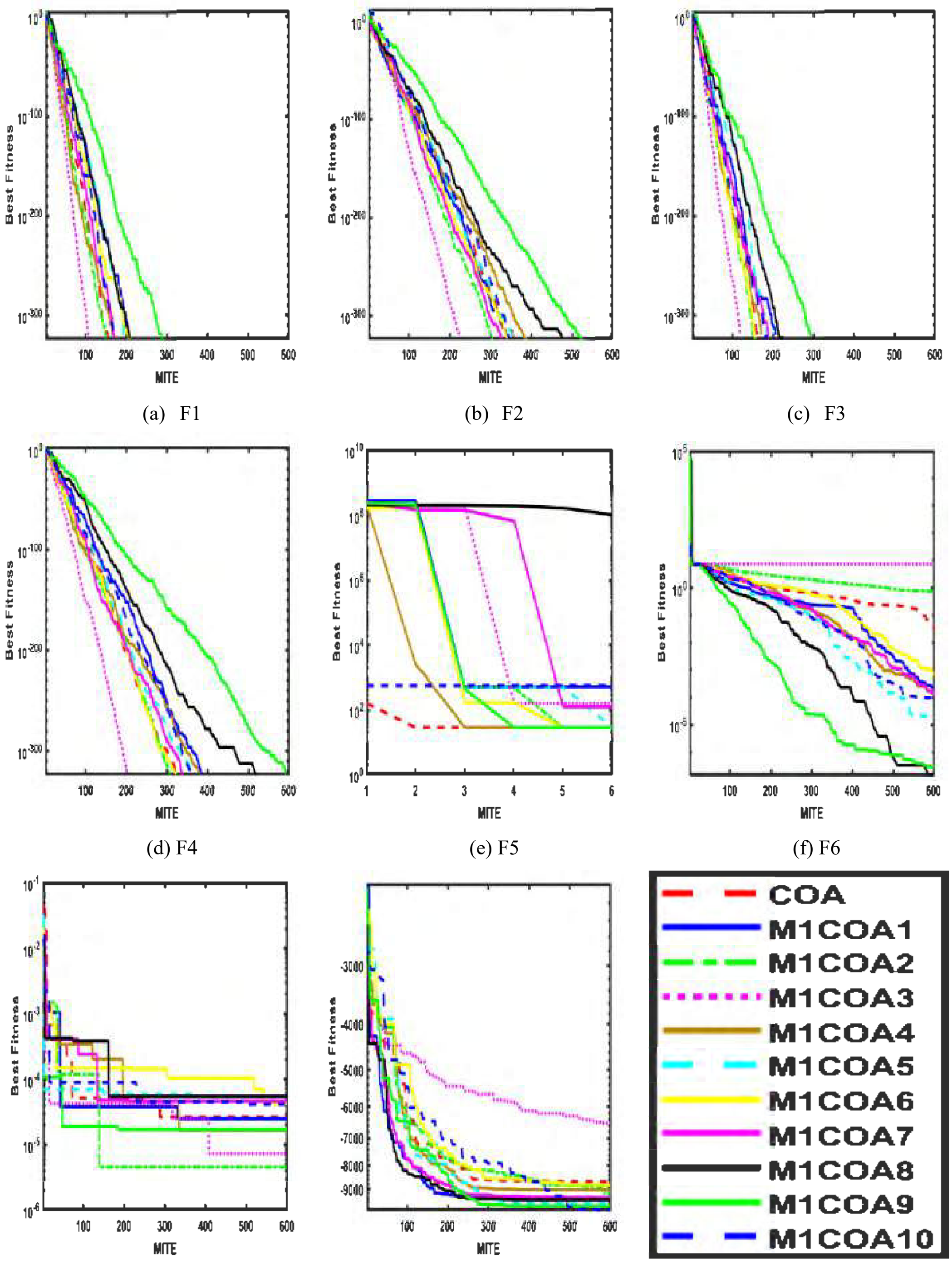
4.1 Simulations and Results

In this section, M1COA1, M1COA2, M1COA3, M1COA4, M1COA5, M1COA6, M1COA7, M1COA8, M1COA9, M1COA10, M2COA1, M2COA2, M2COA3, M2COA4, M2COA5, M2COA6, M2COA7, M2COA8, M2COA9, M2COA10, M3COA1, M3COA2, M3COA3, M3COA4, M3COA5, M3COA6, M3COA7, M3COA8, M3COA9, M3COA10, M4COA1, M4COA2, M4COA3, M4COA4, M4COA5, M4COA6, M4COA7, M4COA8, M4COA9, M4COA10, AO, COA, CO, WOA, and RSA are assessed for mathematical benchmark functions and EH-AS.

4.1.1. Mathematical Benchmark Functions Analysis

The fitness curves of M1COA1-10, M2COA1-10, M3COA1-10, M4COA1-10 and COA for mathematical benchmark functions are shown in figures (6-17). Figure 6 (a-h), 7 (a-h), 8 (a-g) shows the plots of all mathematical benchmark functions for COA and M1COA1-10. Similarly Figure 9 (a-h), 10 (a-h), 11 (a-g) shows the plots of all mathematical benchmark functions for COA and M2COA1-10. Similarly Figure 12 (a-h), 13 (a-h), 14 (a-g) shows the plots of all mathematical benchmark functions for COA and M3COA1-10. Similarly Figure 15 (a-h), 16 (a-h), 17 (a-g) shows the plots of all mathematical benchmark functions for COA and M4COA1-10. It is observed form the figures (6-17) that M1COA1-10, M2COA1-10, M3COA1-10, M4COA1-10 gives us better convergence curves for the mathematical benchmark function other than COA.

Table 2-24 represents the analysis of mathematical standard benchmark function for the population size of (P) = 56, No of iterations 600 for 40 independent runs which incorporates Average Fitness (AvG_{FT}) and Standard Deviation (STD_{FT}). It has been observed from the tabular data from Table 1-23 that the chaotic variant that was proposed, gives improved performance then COA for the functions F5, F6, F8, F12, F13, F14, F15, F16, F17, F18, F19, F20, F21, F22, and F23. In functions F1, F2, F3, F4, F7, F10, F11 all methods have comparable performance.

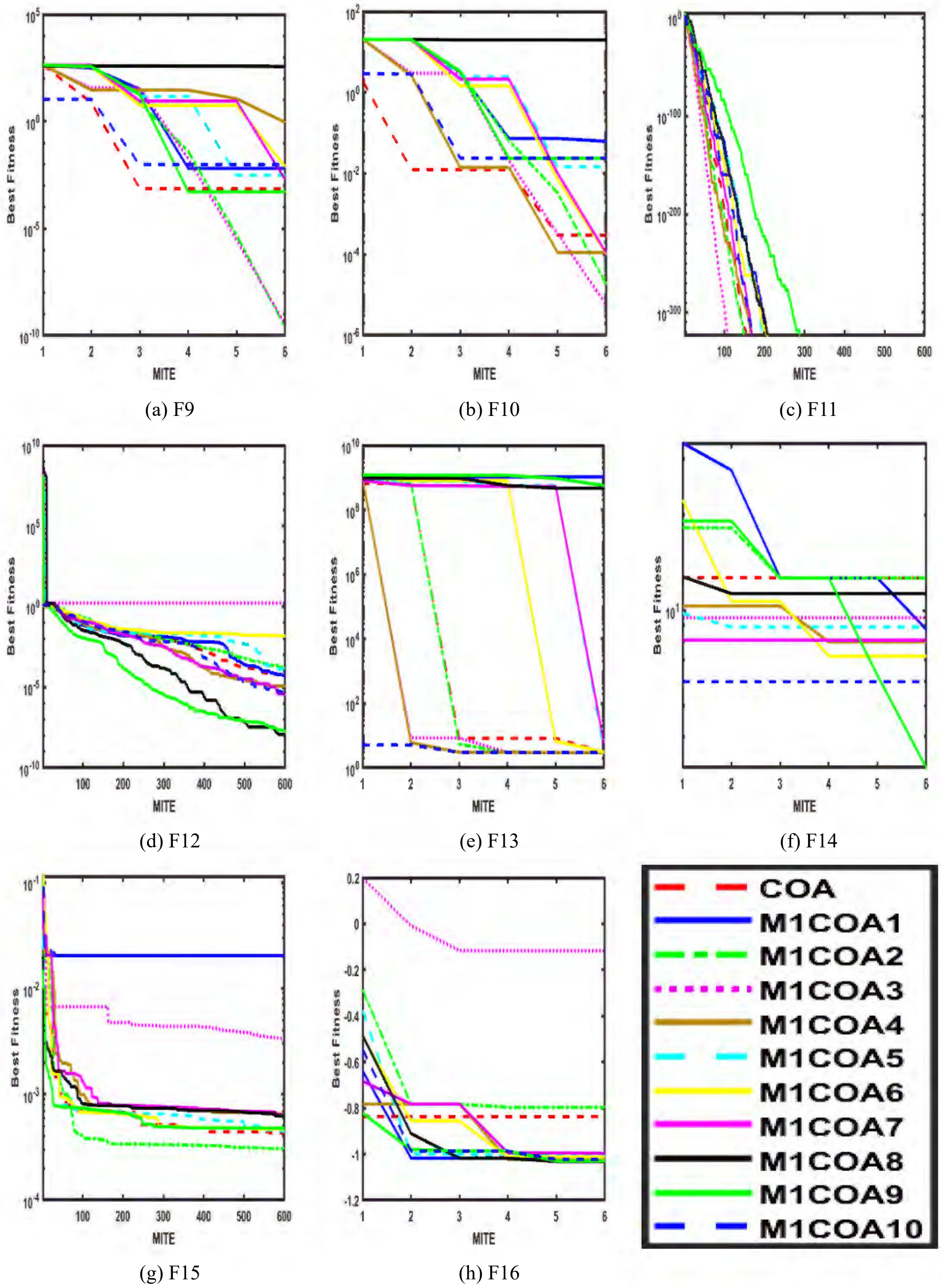


(a) F1 (b) F2 (c) F3

(d) F4 (e) F5 (f) F6

(g) F7 (h) F8

Figure 6: Analysis of F1-F8 for COA and M1COA1-M1COA10

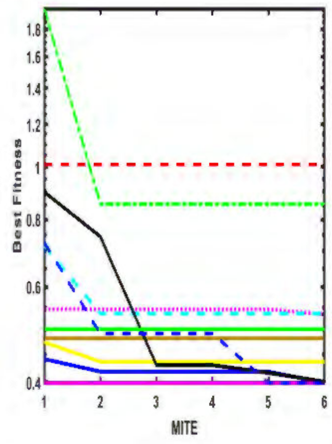


(a) F9 (b) F10 (c) F11

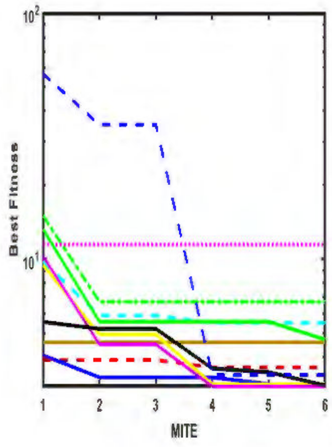
(d) F12 (e) F13 (f) F14

(g) F15 (h) F16

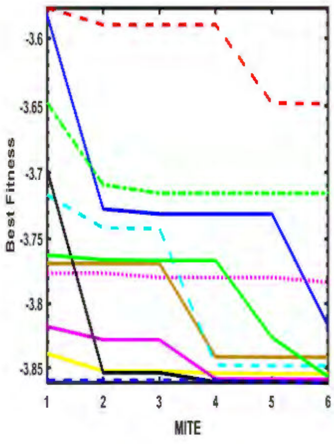
Figure 7: Analysis of F9-F16 for COA and M1COA1-M1COA10



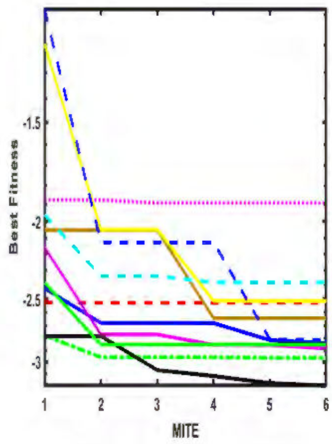
(a) F17



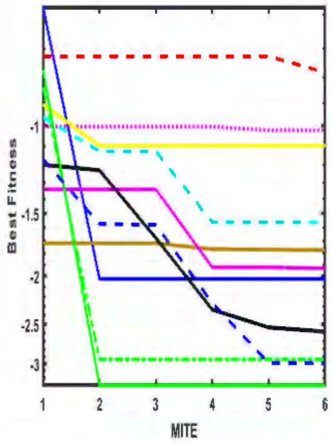
(b) F18



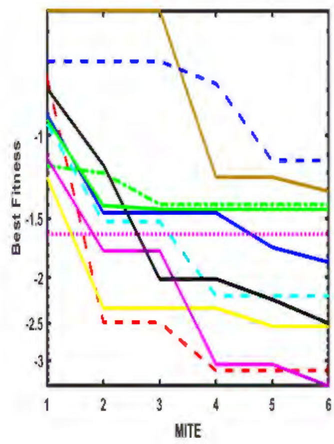
(c) F19



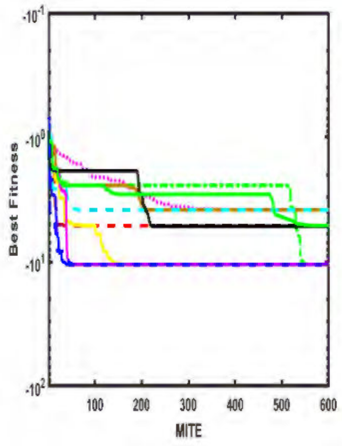
(d) F20



(e) F21



(f) F22



(g) F23

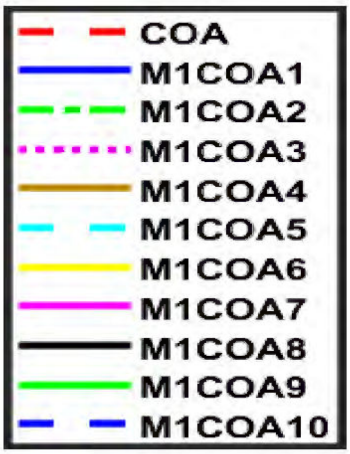
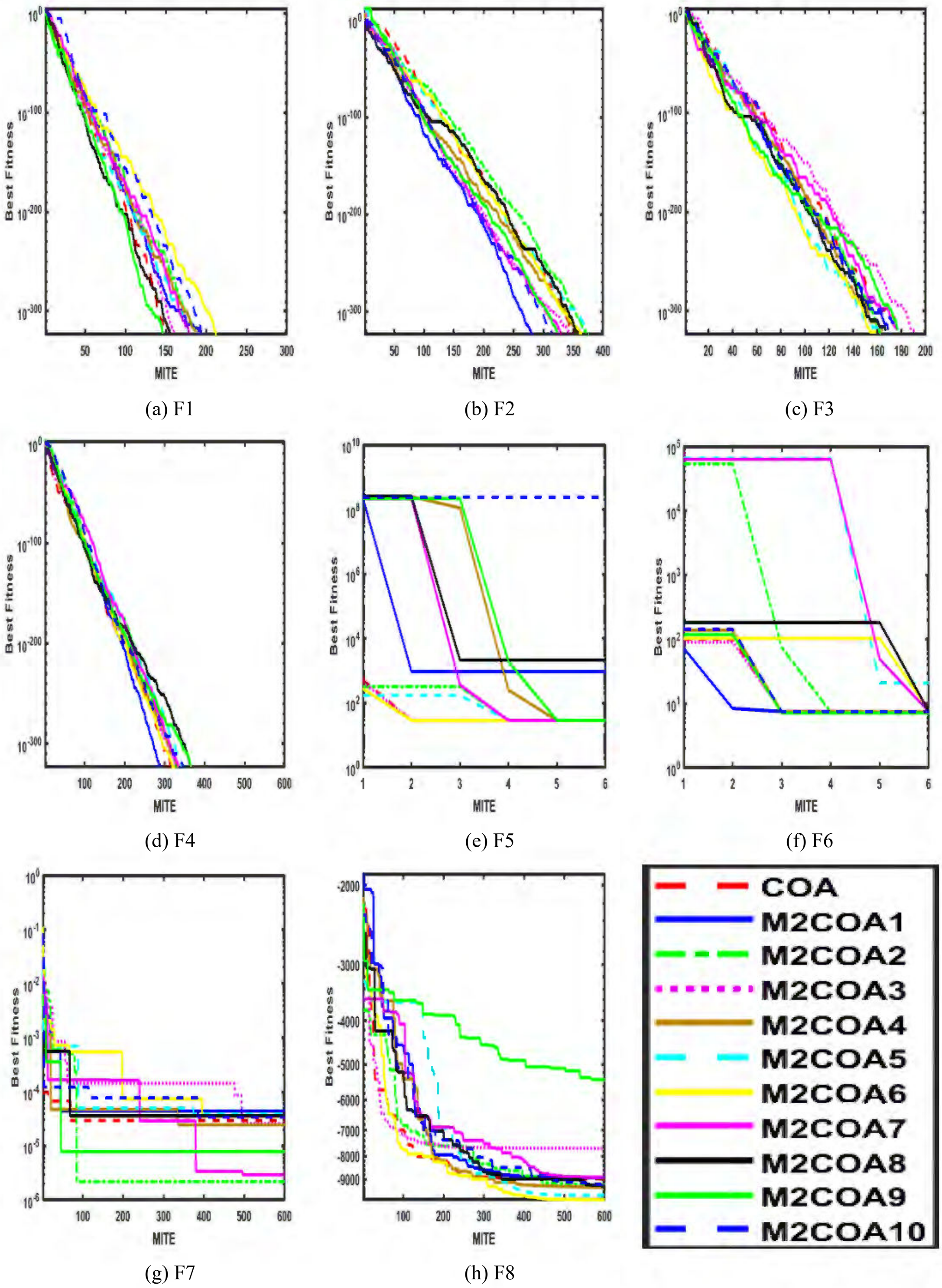


Figure 8: Analysis of F17-F23 for COA and M1COA1-M1COA10

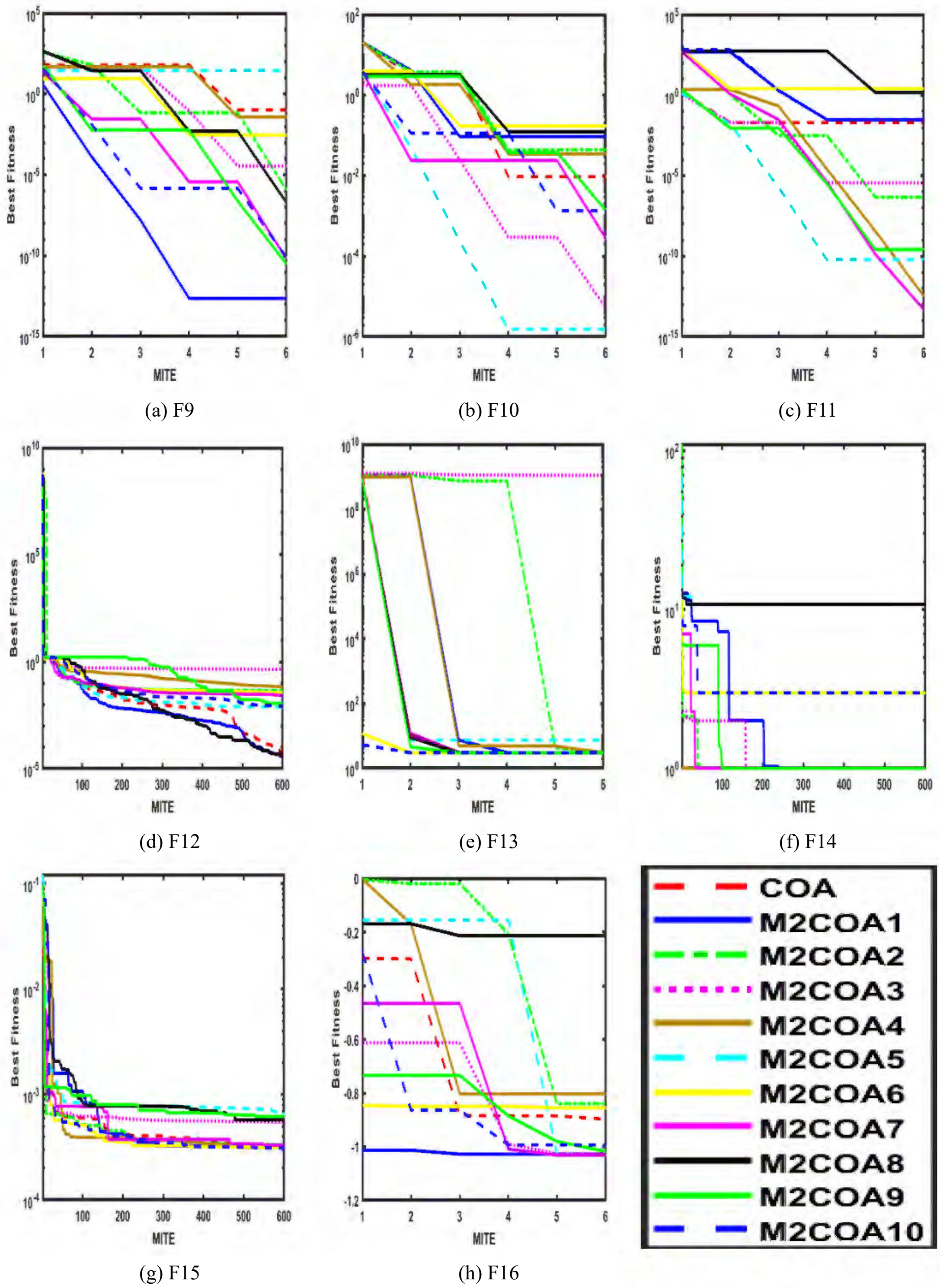


(a) F1 (b) F2 (c) F3

(d) F4 (e) F5 (f) F6

(g) F7 (h) F8

Figure 9: Analysis of F1-F8 for COA and M2COA1-M2COA10

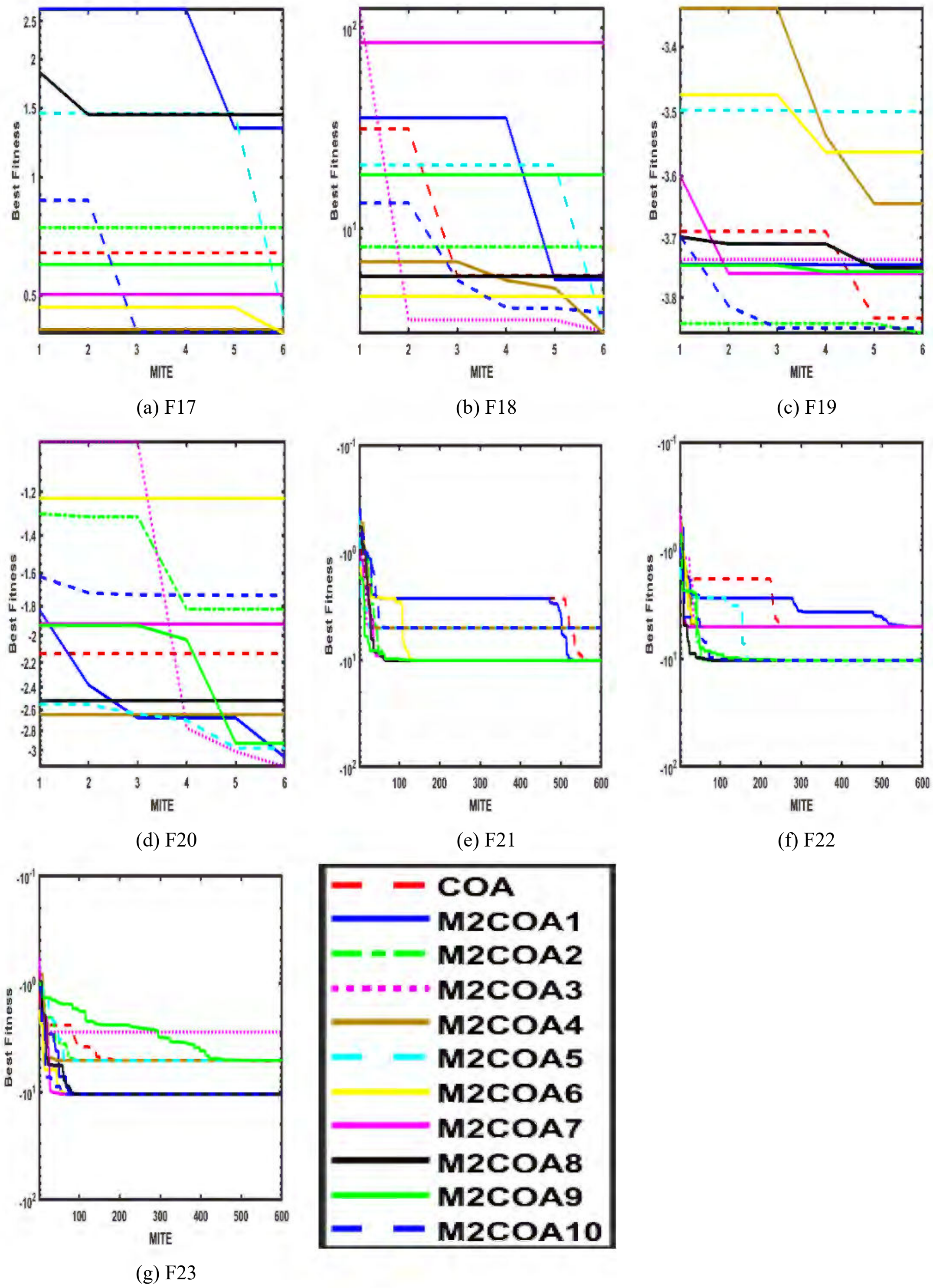


(a) F9 (b) F10 (c) F11

(d) F12 (e) F13 (f) F14

(g) F15 (h) F16

Figure 10: Analysis of F9-F16 for COA and M2COA1-M2COA10

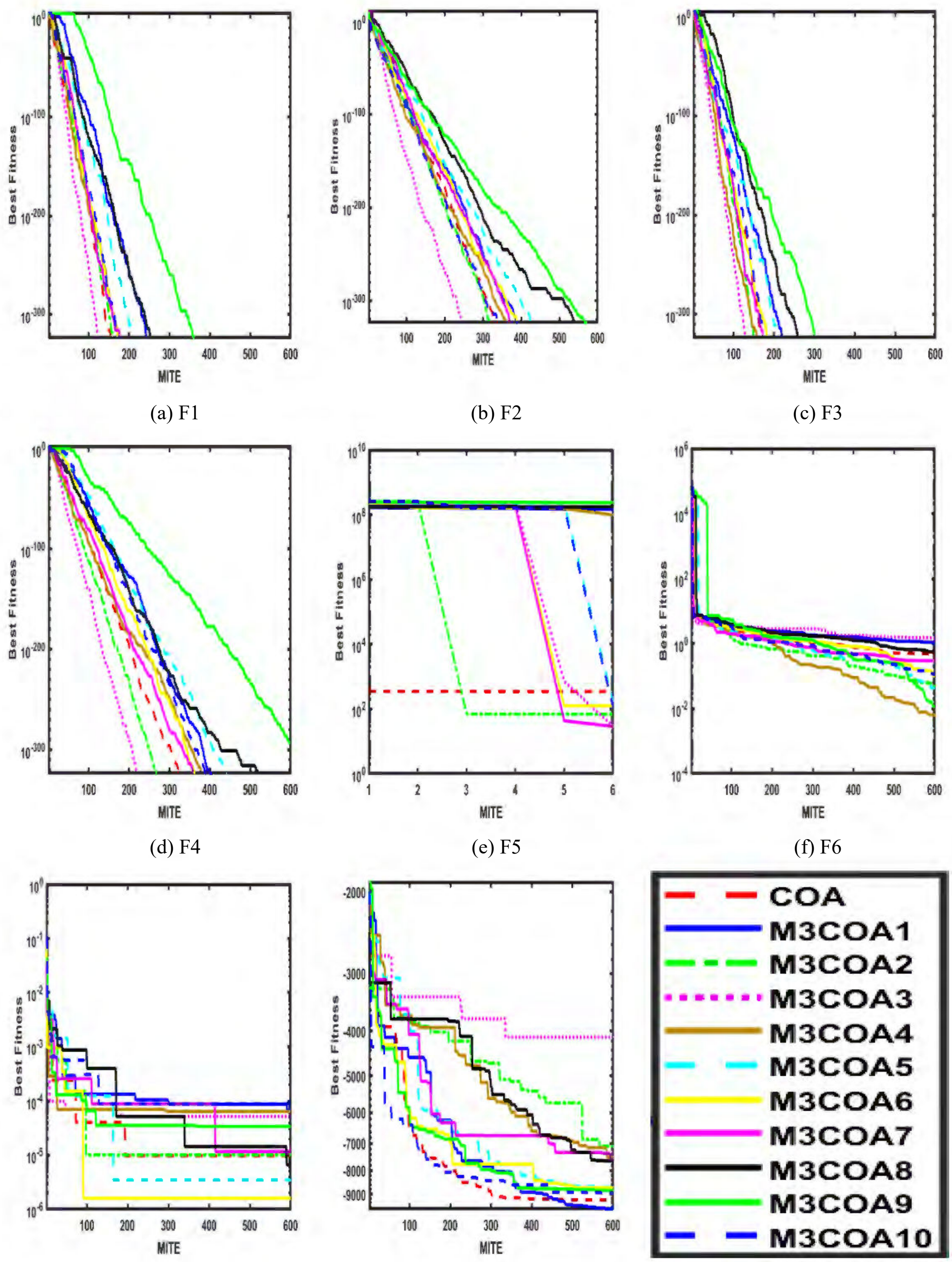


(a) F17 (b) F18 (c) F19

(d) F20 (e) F21 (f) F22

(g) F23

Figure 11: Analysis of F17-F23 for COA and M2COA1-M2COA10



(a) F1 (b) F2 (c) F3

(d) F4 (e) F5 (f) F6

(g) F7 (h) F8

Figure 12: Analysis of F1-F8 for COA and M3COA1-M3COA10

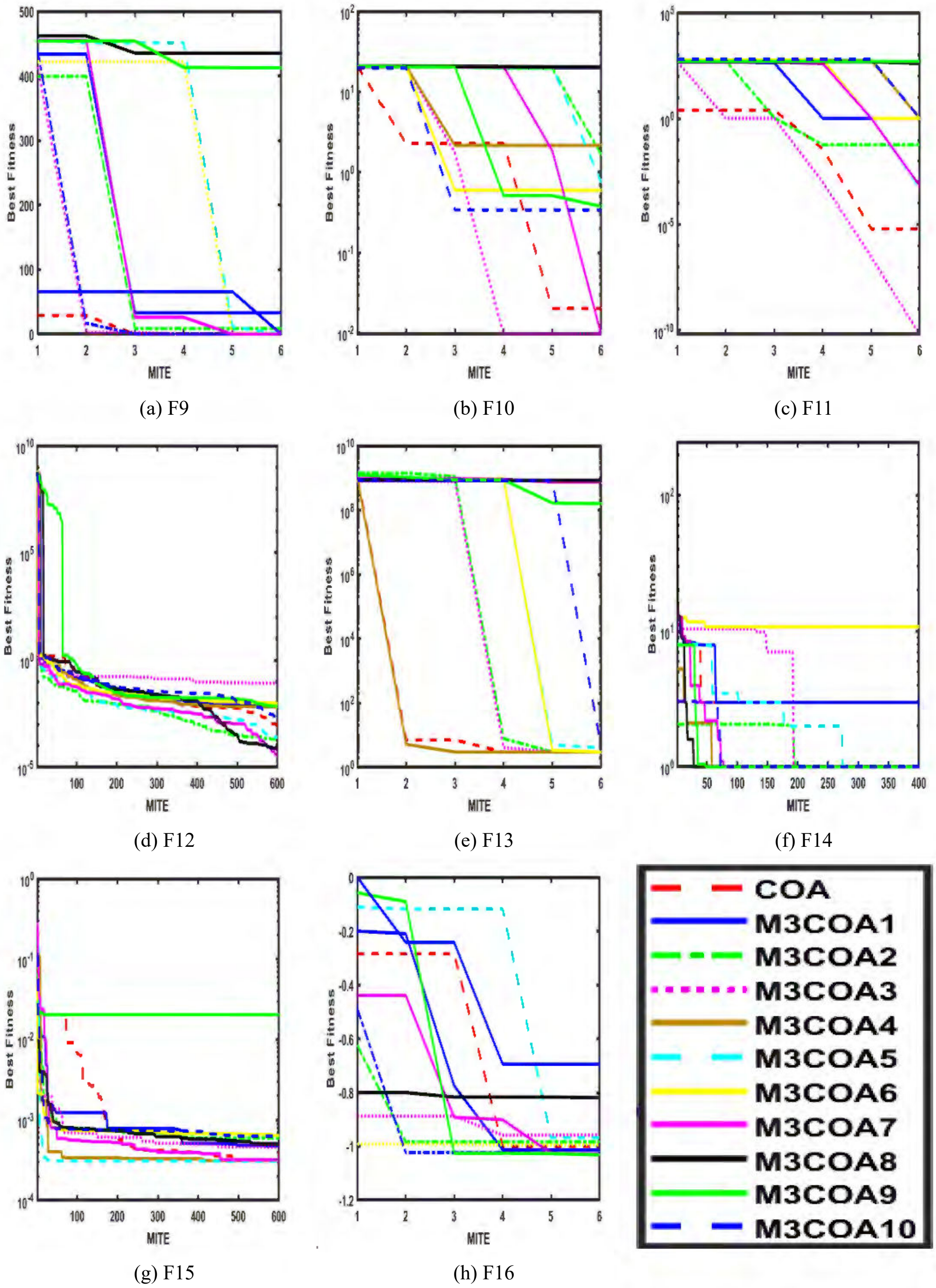
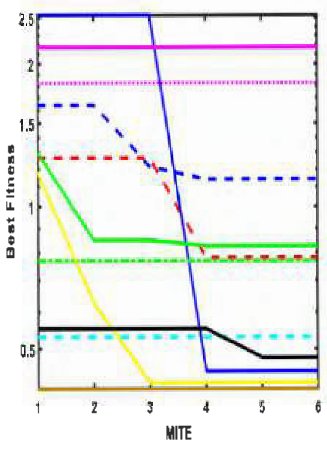
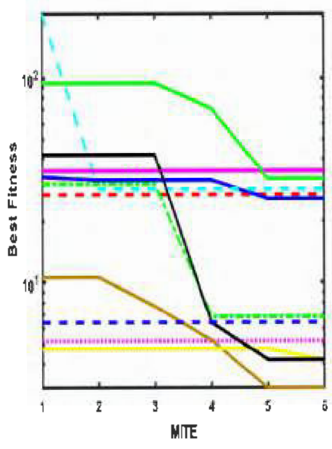


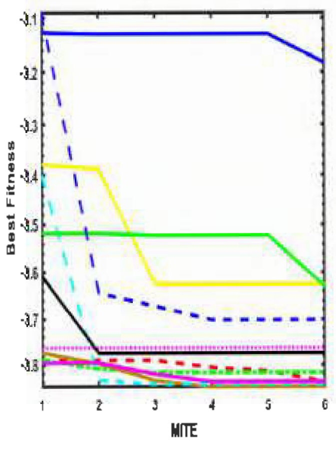
Figure 13: Analysis of F9-F16 for COA and M3COA1-M3COA10



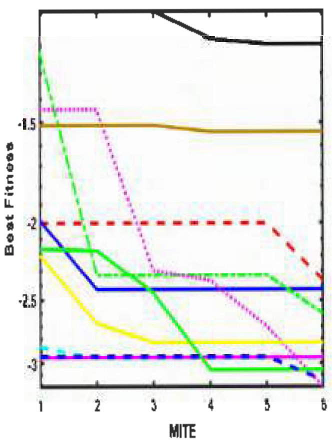
(a) F17



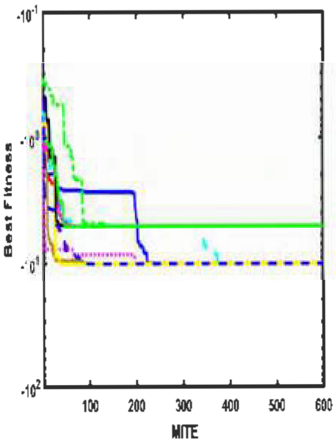
(b) F18



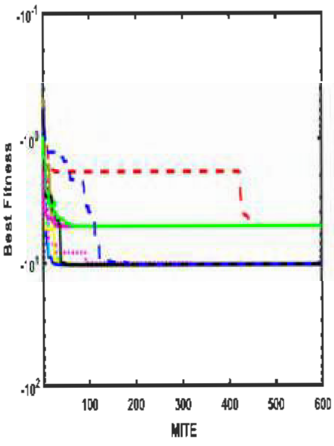
(c) F19



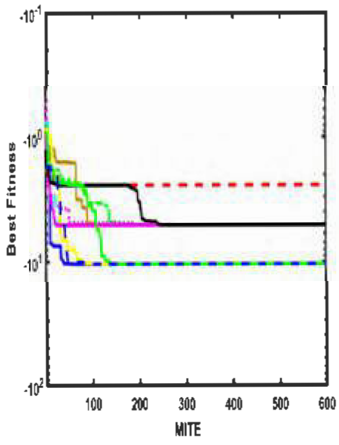
(d) F20



(e) F21



(f) F22



(g) F23

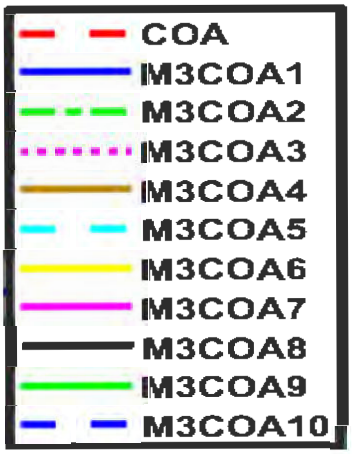
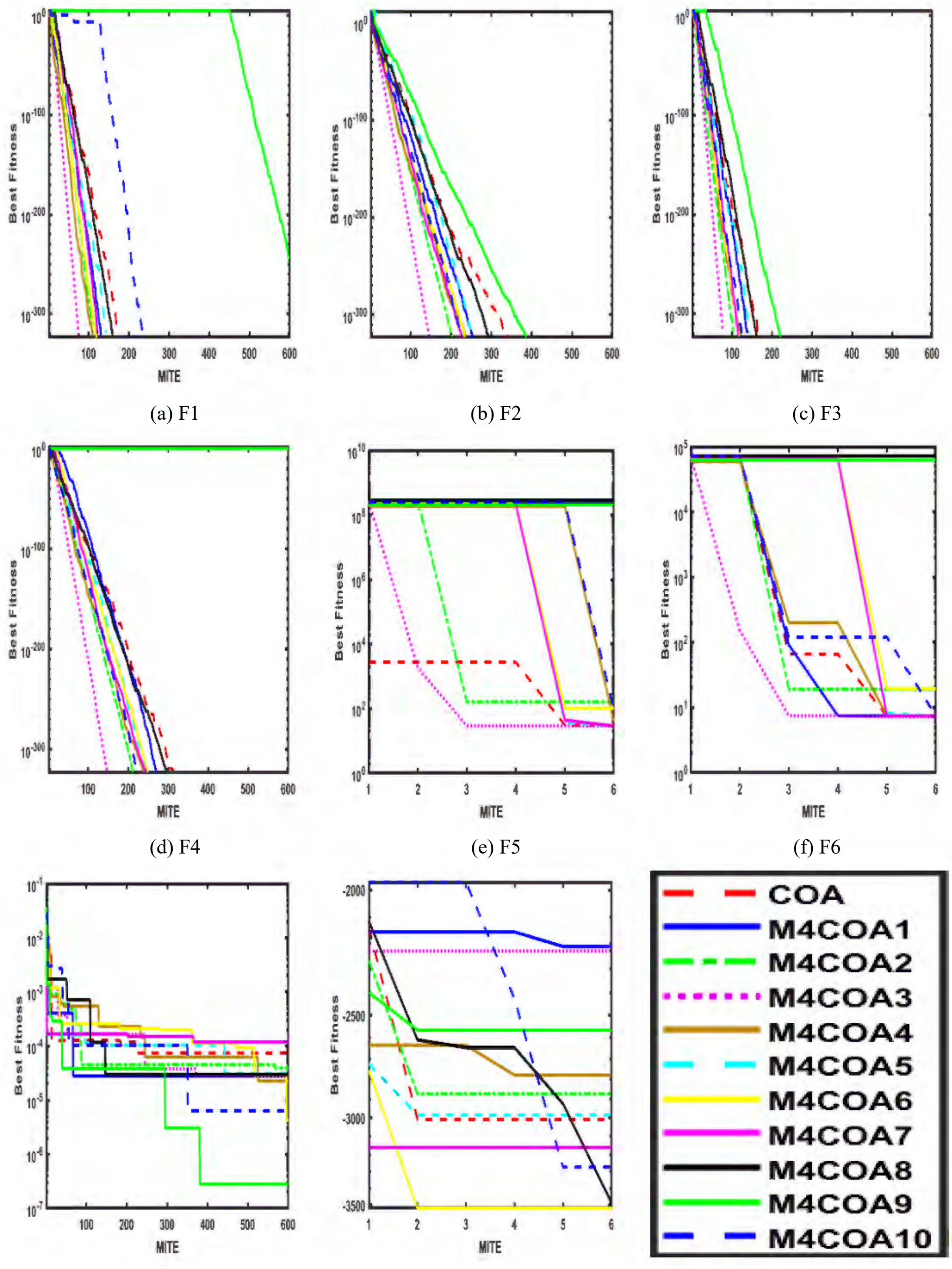


Figure 14: Analysis of F17-F23 for COA and M3COA1-M3COA10

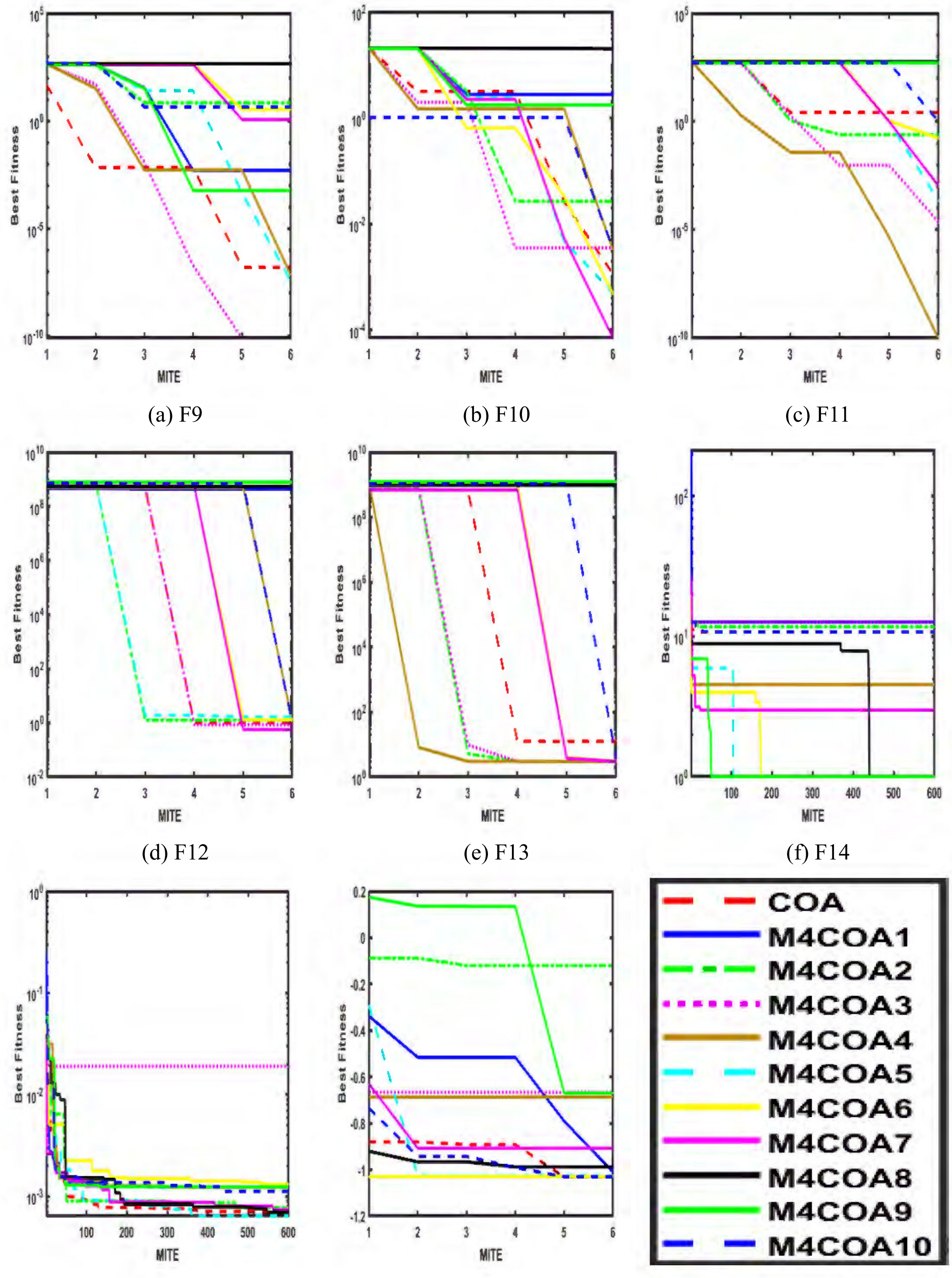


(a) F1 (b) F2 (c) F3

(d) F4 (e) F5 (f) F6

(g) F7 (h) F8

Figure 15: Analysis of F1-F18 for COA and M4COA1-M4COA10

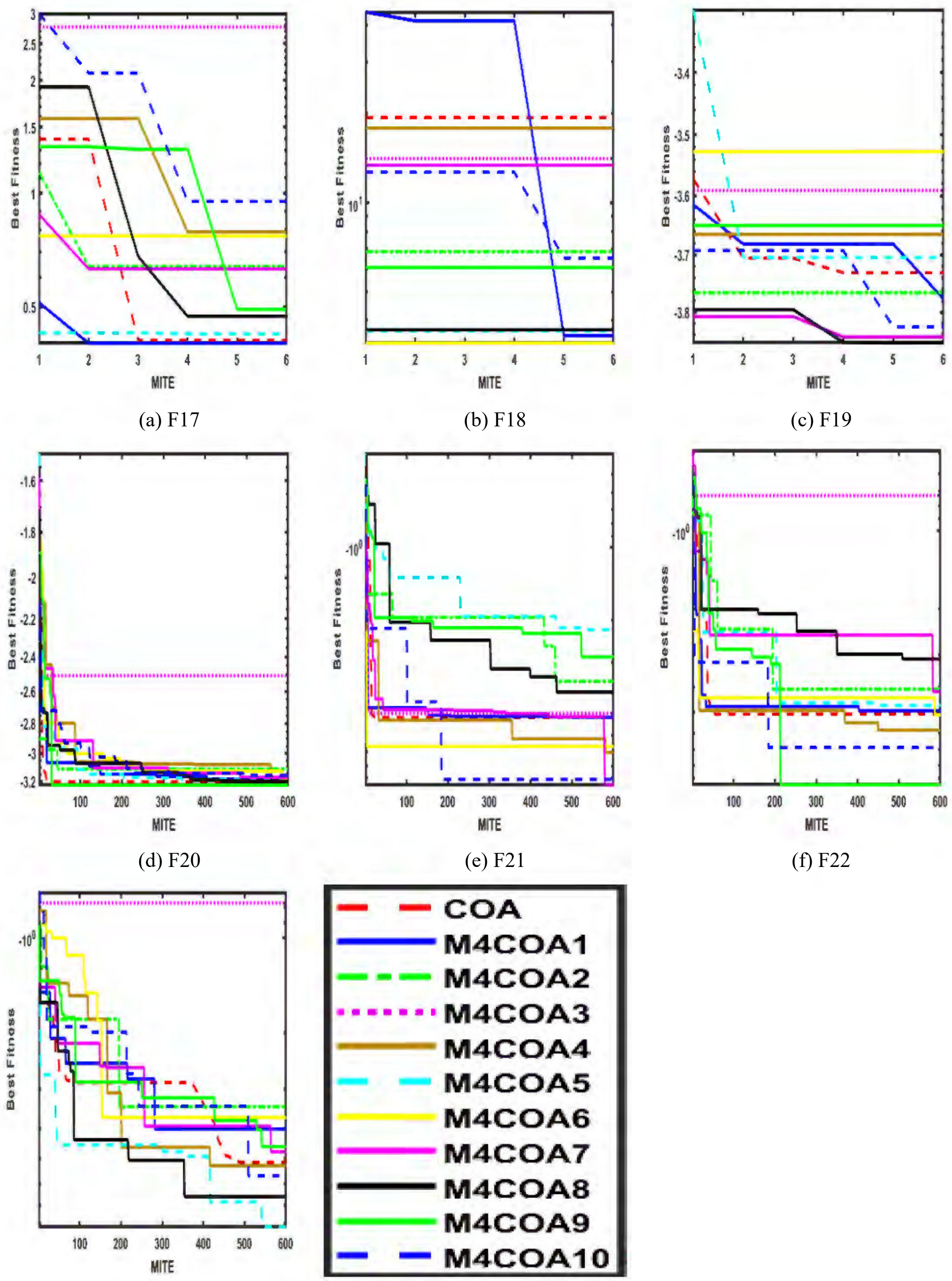


(a) F9 (b) F10 (c) F11

(d) F12 (e) F13 (f) F14

(g) F15 (h) F16

Figure 16: Analysis of F9-F16 for COA and M4COA1-M4COA10



(a) F17 (b) F18 (c) F19

(d) F20 (e) F21 (f) F22

(g) F23

Figure 17: Analysis of F9-F16 for COA and M4COA1-M4COA10

Table 2: Analysis on F1 Function

F1	Average Fitness	STD		Average Fitness	STD
COA	0	0			
M1COA1	0	0	**M2COA1**	0	0
M1COA2	0	0	**M2COA2**	0	0
M1COA3	0	0	**M2COA3**	0	0
M1COA4	0	0	**M2COA4**	0	0
M1COA5	0	0	**M2COA5**	0	0
M1COA6	0	0	**M2COA6**	0	0
M1COA7	0	0	**M2COA7**	0	0
M1COA8	0	0	**M2COA8**	0	0
M1COA9	0	0	**M2COA9**	0	0
M1COA10	0	0	**M2COA10**	0	0
M3COA1	0	0	**M4COA1**	0	0
M3COA2	0	0	**M4COA2**	0	0
M3COA3	0	0	**M4COA3**	0	0
M3COA4	0	0	**M4COA4**	0	0
M3COA5	0	0	**M4COA5**	0	0
M3COA6	0	0	**M4COA6**	0	0
M3COA7	0	0	**M4COA7**	0	0
M3COA8	0	0	**M4COA8**	0.016	0.101
M3COA9	0	0	**M4COA9**	11652.6277	20531.9497
M3COA10	0	0	**M4COA10**	0	0

Table 3: Analysis on F2 Function

F2	Average Fitness	STD		Average Fitness	STD
COA	0	0			
M1COA1	0	0	**M2COA1**	0	0
M1COA2	0	0	**M2COA2**	0	0
M1COA3	0	0	**M2COA3**	0	0
M1COA4	0	0	**M2COA4**	0	0
M1COA5	0	0	**M2COA5**	0	0
M1COA6	0	0	**M2COA6**	0	0
M1COA7	0	0	**M2COA7**	0	0
M1COA8	0	0	**M2COA8**	0	0
M1COA9	1.57E-291	0	**M2COA9**	0	0

M1COA10	0	0	**M2COA10**	0	0
M3COA1	0	0	**M4COA1**	0	0
M3COA2	0	0	**M4COA2**	0	0
M3COA3	0	0	**M4COA3**	0	0
M3COA4	0	0	**M4COA4**	0	0
M3COA5	0	0	**M4COA5**	0	0
M3COA6	0	0	**M4COA6**	0	0
M3COA7	0	0	**M4COA7**	0	0
M3COA8	2.21E-305	0	**M4COA8**	0	0
M3COA9	2.05E-260	0	**M4COA9**	7.203	45.556
M3COA10	0	0	**M4COA10**	0	0

Table 4: Analysis on F3 Function

F3	**Average Fitness**	**STD**		**Average Fitness**	**STD**
COA	0	0			
M1COA1	0	0	**M2COA1**	0	0
M1COA2	0	0	**M2COA2**	0	0
M1COA3	0	0	**M2COA3**	0	0
M1COA4	0	0	**M2COA4**	0	0
M1COA5	0	0	**M2COA5**	0	0
M1COA6	0	0	**M2COA6**	0	0
M1COA7	0	0	**M2COA7**	0	0
M1COA8	0	0	**M2COA8**	0	0
M1COA9	0	0	**M2COA9**	0	0
M1COA10	0	0	**M2COA10**	0	0
M3COA1	0	0	**M4COA1**	0	0
M3COA2	0	0	**M4COA2**	0	0
M3COA3	0	0	**M4COA3**	0	0
M3COA4	0	0	**M4COA4**	0	0
M3COA5	0	0	**M4COA5**	0	0
M3COA6	0	0	**M4COA6**	0	0
M3COA7	0	0	**M4COA7**	0	0
M3COA8	0	0	**M4COA8**	0	0
M3COA9	0	0	**M4COA9**	1.83E+04	2.55E+04
M3COA10	0	0	**M4COA10**	0	0

Table 5: Analysis on F4 Function

F4	Average Fitness	STD		Average Fitness	STD
COA	0	0			
M1COA1	0	0	**M2COA1**	0	0
M1COA2	0	0	**M2COA2**	0	0
M1COA3	0	0	**M2COA3**	0	0
M1COA4	0	0	**M2COA4**	0	0
M1COA5	0	0	**M2COA5**	0	0
M1COA6	0	0	**M2COA6**	0	0
M1COA7	0	0	**M2COA7**	0	0
M1COA8	0	0	**M2COA8**	0	0
M1COA9	2.9777e-313	0	**M2COA9**	0	0
M1COA10	0	0	**M2COA10**	0	0
M3COA1	0	0	**M4COA1**	0	0
M3COA2	0	0	**M4COA2**	0	0
M3COA3	0	0	**M4COA3**	0	0
M3COA4	0	0	**M4COA4**	0	0
M3COA5	0	0	**M4COA5**	0	0
M3COA6	0	0	**M4COA6**	0	0
M3COA7	0	0	**M4COA7**	0	0
M3COA8	5.586e-310	0	**M4COA8**	0	0
M3COA9	3.79E-234	0	**M4COA9**	8.82E-01	3.42E-01
M3COA10	0	0	**M4COA10**	0	0

Table 6: Analysis on F5 Function

F5	Average Fitness	STD		Average Fitness	STD
COA	25.250	0.638			
M1COA1	24.732	0.405	**M2COA1**	26.807	0.943
M1COA2	26.07	0.535	**M2COA2**	27.805	0.772
M1COA3	28.995	0.013	**M2COA3**	28.570	0.346
M1COA4	25.16	0.766	**M2COA4**	27.004	1.127
M1COA5	24.815	0.453	**M2COA5**	26.607	0.979
M1COA6	25.206	0.504	**M2COA6**	26.787	1.096
M1COA7	24.88	0.528	**M2COA7**	26.849	0.814
M1COA8	24.13	0.322	**M2COA8**	25.682	0.489
M1COA9	23.98	0.363	**M2COA9**	27.365	0.662

M1COA10	25.196	0.4332	**M2COA10**	26.550	0.960
M3COA1	26.501	0.815	**M4COA1**	28.510	0.257
M3COA2	27.156	0.728	**M4COA2**	28.725	0.212
M3COA3	28.185	0.377	**M4COA3**	28.925	0.014
M3COA4	26.659	0.648	**M4COA4**	28.675	0.261
M3COA5	26.385	0.696	**M4COA5**	28.479	0.263
M3COA6	26.595	0.604	**M4COA6**	28.651	0.202
M3COA7	26.539	0.609	**M4COA7**	28.562	0.198
M3COA8	26.080	0.661	**M4COA8**	28.507	0.381
M3COA9	26.203	0.736	**M4COA9**	8.15E+07	4.69E+07
M3COA10	26.608	0.766	**M4COA10**	28.506	0.276

Table 7: Analysis on F6 Function

F6	Average Fitness	STD		Average Fitness	STD
COA	0.0089	0.043			
M1COA1	2.367E-04	7.671E-04	**M2COA1**	0.767	0.666
M1COA2	0.27	0.191	**M2COA2**	2.004	0.923
M1COA3	7.036	0.389	**M2COA3**	3.772	0.700
M1COA4	0.026	0.070	**M2COA4**	27.004	0.774
M1COA5	0.001	0.0056	**M2COA5**	0.406	0.347
M1COA6	0.039	0.086	**M2COA6**	1.065	0.679
M1COA7	0.0068	0.039	**M2COA7**	0.938	0.715
M1COA8	2.94E-06	6.78E-06	**M2COA8**	0.058	0.120
M1COA9	3.74E-07	1.75E-07	**M2COA9**	0.437	0.536
M1COA10	0.008	0.0492	**M2COA10**	0.514	0.458
M3COA1	0.238	0.252	**M4COA1**	2.712	0.355
M3COA2	0.461	0.429	**M4COA2**	2.942	0.411
M3COA3	1.332	0.458	**M4COA3**	6.235	0.596
M3COA4	0.238	0.284	**M4COA4**	2.920	0.384
M3COA5	0.151	0.218	**M4COA5**	2.703	0.245
M3COA6	0.178	0.243	**M4COA6**	2.976	0.482
M3COA7	0.132	0.133	**M4COA7**	2.673	0.389
M3COA8	0.084	0.134	**M4COA8**	6.331	1.867
M3COA9	0.012	0.036	**M4COA9**	1.22E+04	2.02E+04
M3COA10	0.229	0.223	**M4COA10**	4.500	2.231

Table 8: Analysis on F7 Function

F7	Average Fitness	STD		Average Fitness	STD
COA	2.13E-05	2.26E-05			
M1COA1	3.493E-05	4.049E-05	**M2COA1**	2.61E-05	2.66E-05
M1COA2	2.43E-05	2.59E-05	**M2COA2**	2.69E-05	2.29E-05
M1COA3	2.43E-05	2.27E-05	**M2COA3**	3.27E-05	2.60E-05
M1COA4	2.62E-05	2.60E-05	**M2COA4**	3.46E-05	2.79E-05
M1COA5	3.05E-05	2.38E-05	**M2COA5**	3.47E-05	3.24E-05
M1COA6	2.19E-05	2.30E-05	**M2COA6**	2.54E-05	2.23E-05
M1COA7	3.37E-05	2.80E-05	**M2COA7**	3.71E-05	4.20E-05
M1COA8	2.94E-05	2.78E-05	**M2COA8**	3.13E-05	2.71E-05
M1COA9	2.58E-05	2.79E-05	**M2COA9**	2.59E-05	2.67E-05
M1COA10	2.63E-05	2.71E-05	**M2COA10**	2.92E-05	2.73E-05
M3COA1	2.96E-05	3.03E-05	**M4COA1**	2.92E-05	2.63E-05
M3COA2	3.45E-05	4.60E-05	**M4COA2**	3.04E-05	2.47E-05
M3COA3	3.04E-05	2.83E-05	**M4COA3**	2.61E-05	2.63E-05
M3COA4	4.34E-05	3.63E-05	**M4COA4**	2.77E-05	2.24E-05
M3COA5	2.50E-05	1.98E-05	**M4COA5**	2.30E-05	2.73E-05
M3COA6	2.18E-05	2.70E-05	**M4COA6**	2.92E-05	2.69E-05
M3COA7	2.62E-05	2.03E-05	**M4COA7**	3.22E-05	3.05E-05
M3COA8	2.30E-05	1.85E-05	**M4COA8**	2.98E-05	2.53E-05
M3COA9	3.99E-05	3.36E-05	**M4COA9**	2.58E-05	2.34E-05
M3COA10	2.90E-05	2.71E-05	**M4COA10**	2.31E-05	1.97E-05

Table 9: Analysis on F8 Function

F8	Average Fitness	STD		Average Fitness	STD
COA	-9.27E+03	5.21E+02			
M1COA1	-9.26E+03	6.20E+02	**M2COA1**	-9.09E+03	1.07E+03
M1COA2	-8.64E+03	6.65E+02	**M2COA2**	-9.10E+03	5.32E+02
M1COA3	-5.77E+03	6.03E+02	**M2COA3**	-7.14E+03	7.93E+02
M1COA4	-9.23E+03	5.19E+02	**M2COA4**	-9.05E+03	9.41E+02
M1COA5	-9.21E+03	4.92E+02	**M2COA5**	-9.07E+03	9.30E+02
M1COA6	-9.16E+03	5.34E+02	**M2COA6**	-9.20E+03	6.85E+02
M1COA7	-9.24E+03	5.45E+02	**M2COA7**	-9.11E+03	6.42E+02
M1COA8	-9.45E+03	5.13E+02	**M2COA8**	-8.66E+03	1.39E+03

M1COA9	-9.57E+03	5.20E+02	**M2COA9**	-5.73E+03	6.45E+02
M1COA10	-9.18E+03	4.98E+02	**M2COA10**	-9.02E+03	7.02E+02
M3COA1	-8.23E+03	8.36E+02	**M4COA1**	-4.11E+03	3.20E+02
M3COA2	-7.00E+03	1.16E+03	**M4COA2**	-3.78E+03	2.86E+02
M3COA3	-4.21E+03	6.28E+02	**M4COA3**	-2.73E+03	3.92E+02
M3COA4	-7.86E+03	1.05E+03	**M4COA4**	-4.14E+03	3.14E+02
M3COA5	-8.01E+03	1.08E+03	**M4COA5**	-4.19E+03	2.79E+02
M3COA6	-7.66E+03	1.26E+03	**M4COA6**	-4.03E+03	3.53E+02
M3COA7	-7.87E+03	1.21E+03	**M4COA7**	-4.12E+03	4.03E+02
M3COA8	-8.57E+03	8.15E+02	**M4COA8**	-4.38E+03	3.98E+02
M3COA9	-8.80E+03	5.80E+02	**M4COA9**	-4.42E+03	9.72E+00
M3COA10	-7.74E+03	1.08E+03	**M4COA10**	-4.11E+03	3.72E+02

Table 10: Analysis on F9 Function

F9	**Average Fitness**	**STD**		**Average Fitness**	**STD**
COA	0	0			
M1COA1	0	0	**M2COA1**	0	0
M1COA2	0	0	**M2COA2**	0	0
M1COA3	0	0	**M2COA3**	0	0
M1COA4	0	0	**M2COA4**	0	0
M1COA5	0	0	**M2COA5**	0	0
M1COA6	0	0	**M2COA6**	0	0
M1COA7	0	0	**M2COA7**	0	0
M1COA8	0	0	**M2COA8**	0	0
M1COA9	0	0	**M2COA9**	0	0
M1COA10	0	0	**M2COA10**	0	0
M3COA1	0	0	**M4COA1**	0	0
M3COA2	0	0	**M4COA2**	0	0
M3COA3	0	0	**M4COA3**	0	0
M3COA4	0	0	**M4COA4**	0	0
M3COA5	0	0	**M4COA5**	0	0
M3COA6	0	0	**M4COA6**	0	0
M3COA7	0	0	**M4COA7**	0	0
M3COA8	0	0	**M4COA8**	0	0
M3COA9	0	0	**M4COA9**	6.415	9.718
M3COA10	0	0	**M4COA10**	0	0

Table 11: Analysis on F10 Function

F10	Average Fitness	STD		Average Fitness	STD
COA	8.88E-16	0			
M1COA1	8.88E-16	0	M2COA1	8.88E-16	0
M1COA2	8.88E-16	0	M2COA2	8.88E-16	0
M1COA3	8.88E-16	0	M2COA3	8.88E-16	0
M1COA4	8.88E-16	0	M2COA4	8.88E-16	0
M1COA5	8.88E-16	0	M2COA5	8.88E-16	0
M1COA6	8.88E-16	0	M2COA6	8.88E-16	0
M1COA7	8.88E-16	0	M2COA7	8.88E-16	0
M1COA8	8.88E-16	0	M2COA8	8.88E-16	0
M1COA9	8.88E-16	0	M2COA9	8.88E-16	0
M1COA10	8.88E-16	0	M2COA10	8.88E-16	0
M3COA1	8.88E-16	0	M4COA1	8.88E-16	0
M3COA2	8.88E-16	0	M4COA2	8.88E-16	0
M3COA3	8.88E-16	0	M4COA3	8.88E-16	0
M3COA4	8.88E-16	0	M4COA4	8.88E-16	0
M3COA5	8.88E-16	0	M4COA5	8.88E-16	0
M3COA6	8.88E-16	0	M4COA6	8.88E-16	0
M3COA7	8.88E-16	0	M4COA7	8.88E-16	0
M3COA8	8.88E-16	0	M4COA8	2.05E-09	1.29E-08
M3COA9	8.88E-16	0	M4COA9	1.305	0.853
M3COA10	8.88E-16	0	M4COA10	8.88E-16	0

Table 12: Analysis on F11 Function

F11	Average Fitness	STD		Average Fitness	STD
COA	0	0			
M1COA1	0	0	M2COA1	0	0
M1COA2	0	0	M2COA2	0	0
M1COA3	0	0	M2COA3	0	0
M1COA4	0	0	M2COA4	0	0
M1COA5	0	0	M2COA5	0	0
M1COA6	0	0	M2COA6	0	0
M1COA7	0	0	M2COA7	0	0
M1COA8	0	0	M2COA8	0	0

M1COA9	0	0	**M2COA9**	0	0
M1COA10	0	0	**M2COA10**	0	0
M3COA1	0	0	**M4COA1**	0	0
M3COA2	0	0	**M4COA2**	0	0
M3COA3	0	0	**M4COA3**	0	0
M3COA4	0	0	**M4COA4**	0	0
M3COA5	0	0	**M4COA5**	0	0
M3COA6	0	0	**M4COA6**	0	0
M3COA7	0	0	**M4COA7**	0	0
M3COA8	0	0	**M4COA8**	0	0
M3COA9	0	0	**M4COA9**	171.74	213.93
M3COA10	0	0	**M4COA10**	0	0

Table 13: Analysis on F12 Function

F12	Average Fitness	STD		Average Fitness	STD
COA	0.002	0.003			
M1COA1	0.000	0.000	**M2COA1**	0.021	0.015
M1COA2	0.008	0.007	**M2COA2**	0.092	0.080
M1COA3	1.535	0.277	**M2COA3**	0.356	0.134
M1COA4	0.001	0.002	**M2COA4**	0.066	0.069
M1COA5	0.000	0.002	**M2COA5**	0.021	0.028
M1COA6	0.001	0.003	**M2COA6**	0.033	0.029
M1COA7	0.000	0.000	**M2COA7**	0.035	0.038
M1COA8	0.000	0.001	**M2COA8**	0.001	0.004
M1COA9	0.000	0.000	**M2COA9**	0.022	0.030
M1COA10	0.000	0.001	**M2COA10**	0.014	0.015
M3COA1	0.004	0.006	**M4COA1**	0.512	0.395
M3COA2	0.009	0.008	**M4COA2**	1.016	0.537
M3COA3	0.045	0.024	**M4COA3**	0.828	0.166
M3COA4	0.005	0.007	**M4COA4**	0.638	0.526
M3COA5	0.004	0.006	**M4COA5**	0.479	0.350
M3COA6	0.006	0.007	**M4COA6**	0.907	0.547
M3COA7	0.007	0.010	**M4COA7**	0.409	0.090
M3COA8	0.002	0.004	**M4COA8**	0.586	0.425
M3COA9	0.002	0.003	**M4COA9**	1.287E+08	5.994E+07
M3COA10	0.003	0.005	**M4COA10**	0.549	0.433

Table 14: Analysis on F13 Function

F13	Average Fitness	STD		Average Fitness	STD
COA	1.706	0.210			
M1COA1	1.498	0.321	**M2COA1**	2.213	0.511
M1COA2	2.055	0.222	**M2COA2**	2.523	0.360
M1COA3	2.999	0.002	**M2COA3**	2.931	0.134
M1COA4	1.714	0.237	**M2COA4**	2.618	0.358
M1COA5	1.646	0.297	**M2COA5**	2.236	0.459
M1COA6	1.799	0.200	**M2COA6**	2.439	0.392
M1COA7	1.760	0.249	**M2COA7**	2.546	0.337
M1COA8	1.143	0.283	**M2COA8**	1.589	0.705
M1COA9	1.109	0.418	**M2COA9**	1.419	0.488
M1COA10	1.703	0.2608	**M2COA10**	2.241	0.448
M3COA1	2.660	0.508	**M4COA1**	2.904	0.330
M3COA2	2.566	0.326	**M4COA2**	2.940	0.171
M3COA3	2.873	0.276	**M4COA3**	2.995	0.004
M3COA4	2.664	0.391	**M4COA4**	2.877	0.383
M3COA5	2.716	0.590	**M4COA5**	2.981	0.006
M3COA6	2.607	0.416	**M4COA6**	2.982	0.007
M3COA7	2.519	0.731	**M4COA7**	2.979	0.002
M3COA8	2.473	0.701	**M4COA8**	2.862	0.402
M3COA9	2.030	0.224	**M4COA9**	3.81E+08	1.46E+08
M3COA10	2.550	0.658	**M4COA10**	2.982	0.008

Table 15: Analysis on F14 Function

F14	Average Fitness	STD		Average Fitness	STD
COA	2.322	2.948			
M1COA1	1.635	2.186	**M2COA1**	1.879	2.616
M1COA2	3.873	3.890	**M2COA2**	2.615	3.217
M1COA3	8.152	3.765	**M2COA3**	5.000	3.456
M1COA4	2.806	3.731	**M2COA4**	2.764	3.184
M1COA5	3.292	3.853	**M2COA5**	2.879	3.842
M1COA6	1.815	2.203	**M2COA6**	3.447	3.797
M1COA7	2.370	2.941	**M2COA7**	2.297	2.946
M1COA8	1.242	1.544	**M2COA8**	2.980	3.690

M1COA9	1.048	0.314	**M2COA9**	2.682	3.052
M1COA10	2.711	3.4880	**M2COA10**	1.883	2.212
M3COA1	3.099	3.786	**M4COA1**	4.925	5.132
M3COA2	5.339	5.132	**M4COA2**	7.858	4.302
M3COA3	7.859	5.690	**M4COA3**	10.641	2.920
M3COA4	6.388	5.584	**M4COA4**	9.934	4.175
M3COA5	3.926	4.622	**M4COA5**	7.432	5.024
M3COA6	3.247	3.991	**M4COA6**	7.511	4.945
M3COA7	4.458	5.075	**M4COA7**	6.386	4.965
M3COA8	2.065	2.745	**M4COA8**	2.136	3.030
M3COA9	4.410	5.004	**M4COA9**	3.008	3.777
M3COA10	4.021	4.788	**M4COA10**	8.019	5.128

Table 16: Analysis on F15 Function

F15	**Average Fitness**	**STD**		**Average Fitness**	**STD**
COA	6.3E-04	3.1E-04			
M1COA1	4.0E-03	7.6E-03	**M2COA1**	1.6325E-03	4.3614E-03
M1COA2	2.8E-03	6.0E-03	**M2COA2**	2.5085E-03	6.0323E-03
M1COA3	5.5E-03	6.6E-03	**M2COA3**	6.0969E-03	8.9063E-03
M1COA4	2.0E-03	5.3E-03	**M2COA4**	2.0340E-03	5.2905E-03
M1COA5	3.0E-03	6.6E-03	**M2COA5**	2.0443E-03	5.2899E-03
M1COA6	2.7E-03	6.0E-03	**M2COA6**	1.5292E-03	4.3836E-03
M1COA7	1.6E-03	4.2E-03	**M2COA7**	1.0315E-03	3.1418E-03
M1COA8	2.7E-03	6.1E-03	**M2COA8**	1.5612E-03	4.3737E-03
M1COA9	2.0E-03	5.3E-03	**M2COA9**	7.0234E-04	2.3325E-04
M1COA10	1.1E-03	3.1E-03	**M2COA10**	1.0143E-03	3.1445E-03
M3COA1	1.5E-03	4.4E-03	**M4COA1**	8.564E-04	0
M3COA2	1.6E-03	4.4E-03	**M4COA2**	9.325E-04	0
M3COA3	4.0E-04	1.7E-04	**M4COA3**	1.376E-02	1.252E-02
M3COA4	1.0E-03	3.1E-03	**M4COA4**	8.004E-04	0
M3COA5	4.7E-04	1.3E-04	**M4COA5**	7.774E-04	0
M3COA6	5.2E-04	2.1E-04	**M4COA6**	8.688E-04	0
M3COA7	9.9E-04	3.1E-03	**M4COA7**	7.784E-04	0
M3COA8	1.5E-03	4.4E-03	**M4COA8**	8.199E-04	0
M3COA9	3.1E-03	6.6E-03	**M4COA9**	7.570E-04	0
M3COA10	1.6E-03	4.4E-03	**M4COA10**	8.754E-04	0

Table 17: Analysis on F16 Function

F16	Average Fitness	STD		Average Fitness	STD
COA	-1.032	1.38E-16			
M1COA1	-1.032	6.16E-17	**M2COA1**	-1.032	2.36E-16
M1COA2	-1.032	6.30E-15	**M2COA2**	-1.032	1.55E-16
M1COA3	-1.009	0.094	**M2COA3**	-1.032	7.95E-17
M1COA4	-1.032	2.51E-16	**M2COA4**	-1.032	2.33E-16
M1COA5	-1.032	1.01E-16	**M2COA5**	-1.032	3.04E-16
M1COA6	-1.032	6.16E-17	**M2COA6**	-1.032	4.18E-16
M1COA7	-1.032	1.01E-16	**M2COA7**	-1.032	3.30E-16
M1COA8	-1.032	2.16E-16	**M2COA8**	-1.032	3.55E-15
M1COA9	-1.032	1.55E-16	**M2COA9**	-1.032	3.00E-14
M1COA10	-1.032	8.71E-17	**M2COA10**	-1.032	2.75E-16
M3COA1	-1.032	1.33E-14	**M4COA1**	-1.032	8.95E-06
M3COA2	-1.032	2.52E-13	**M4COA2**	-1.032	1.75E-04
M3COA3	-1.032	2.95E-08	**M4COA3**	-0.895	2.70E-01
M3COA4	-1.032	1.42E-14	**M4COA4**	-1.032	3.79E-05
M3COA5	-1.032	4.36E-15	**M4COA5**	-1.032	3.04E-05
M3COA6	-1.032	9.96E-15	**M4COA6**	-1.032	6.41E-05
M3COA7	-1.032	6.84E-15	**M4COA7**	-1.032	1.35E-05
M3COA8	-1.032	3.78E-15	**M4COA8**	-1.032	5.89E-06
M3COA9	-1.032	1.60E-15	**M4COA9**	-1.032	7.98E-06
M3COA10	-1.032	9.66E-15	**M4COA10**	-1.032	1.13E-05

Table 18: Analysis on F17 Function

F17	Average Fitness	STD		Average Fitness	STD
COA	0.398	7.51E-09			
M1COA1	0.398	1.37E-11	**M2COA1**	0.398	1.41E-09
M1COA2	0.398	2.99E-07	**M2COA2**	0.398	9.59E-09
M1COA3	0.413	0.061	**M2COA3**	0.398	6.41E-11
M1COA4	0.398	1.49E-07	**M2COA4**	0.398	5.00E-09
M1COA5	0.398	3.47E-11	**M2COA5**	0.398	1.53E-08
M1COA6	0.398	3.36E-08	**M2COA6**	0.398	2.21E-08
M1COA7	0.398	1.70E-13	**M2COA7**	0.398	7.01E-09
M1COA8	0.398	0	**M2COA8**	0.398	1.47E-06

M1COA9	0.398	1.53E-12	**M2COA9**	0.398	4.13E-05
M1COA10	0.398	5.56E-10	**M2COA10**	0.398	9.87E-10
M3COA1	0.398	2.20E-07	**M4COA1**	0.399	4.56E-03
M3COA2	0.398	7.04E-07	**M4COA2**	0.424	6.98E-02
M3COA3	0.398	2.70E-06	**M4COA3**	0.776	2.98E-01
M3COA4	0.398	1.68E-07	**M4COA4**	0.402	1.06E-02
M3COA5	0.398	1.63E-07	**M4COA5**	0.405	2.68E-02
M3COA6	0.398	6.19E-08	**M4COA6**	0.423	7.14E-02
M3COA7	0.398	8.17E-06	**M4COA7**	0.404	1.83E-02
M3COA8	0.398	1.70E-06	**M4COA8**	0.409	3.44E-02
M3COA9	0.398	7.05E-07	**M4COA9**	0.415	7.85E-02
M3COA10	0.398	9.98E-08	**M4COA10**	0.416	6.61E-02

Table 19: Analysis on F18 Function

F18	**Average Fitness**	**STD**		**Average Fitness**	**STD**
COA	3	8.38E-13			
M1COA1	3	5.83E-15	**M2COA1**	3	4.12E-11
M1COA2	3	1.77E-09	**M2COA2**	3	6.35E-13
M1COA3	5	5.330	**M2COA3**	3	1.30E-14
M1COA4	3	6.45E-13	**M2COA4**	3	3.18E-12
M1COA5	3	8.54E-15	**M2COA5**	3	2.87E-11
M1COA6	3	6.76E-14	**M2COA6**	3	3.79E-12
M1COA7	3	5.35E-15	**M2COA7**	3	2.23E-12
M1COA8	3	1.76E-15	**M2COA8**	3	2.84E-09
M1COA9	3	4.30E-15	**M2COA9**	3	7.44E-07
M1COA10	3	7.68E-15	**M2COA10**	3	1.08E-12
M3COA1	3	7.91E-11	**M4COA1**	3	1.72E-04
M3COA2	3	1.25E-10	**M4COA2**	3	4.53E-03
M3COA3	3	3.94E-08	**M4COA3**	6	2.69E+00
M3COA4	3	3.65E-11	**M4COA4**	3	2.52E-04
M3COA5	3	2.58E-11	**M4COA5**	3	1.73E-04
M3COA6	3	1.34E-10	**M4COA6**	3	3.69E-04
M3COA7	3	2.25E-11	**M4COA7**	3	7.67E-05
M3COA8	3	6.82E-11	**M4COA8**	3	3.38E-09
M3COA9	3	6.05E-12	**M4COA9**	3	1.39E-05
M3COA10	3	2.45E-09	**M4COA10**	3	1.66E-04

Table 20: Analysis on F19 Function

F19	Average Fitness	STD		Average Fitness	STD
COA	-3.863	1.78E-14			
M1COA1	-3.863	1.25E-03	**M2COA1**	-3.863	3.30E-14
M1COA2	-3.863	1.48E-12	**M2COA2**	-3.863	1.08E-14
M1COA3	-3.858	1.30E-02	**M2COA3**	-3.863	1.86E-15
M1COA4	-3.863	3.58E-14	**M2COA4**	-3.863	5.41E-14
M1COA5	-3.863	2.16E-15	**M2COA5**	-3.863	1.25E-03
M1COA6	-3.863	4.44E-15	**M2COA6**	-3.863	1.28E-13
M1COA7	-3.863	2.26E-15	**M2COA7**	-3.863	1.39E-13
M1COA8	-3.863	2.64E-15	**M2COA8**	-3.863	3.98E-13
M1COA9	-3.863	2.30E-15	**M2COA9**	-3.863	1.45E-11
M1COA10	-3.863	2.13E-15	**M2COA10**	-3.863	7.41E-14
M3COA1	-3.863	2.89E-11	**M4COA1**	-3.862	3.27E-04
M3COA2	-3.863	6.41E-10	**M4COA2**	-3.863	5.53E-03
M3COA3	-3.863	8.00E-06	**M4COA3**	-3.698	1.23E-01
M3COA4	-3.863	1.25E-03	**M4COA4**	-3.863	1.92E-03
M3COA5	-3.863	4.93E-12	**M4COA5**	-3.863	3.65E-04
M3COA6	-3.863	6.97E-12	**M4COA6**	-3.863	1.39E-03
M3COA7	-3.863	2.29E-10	**M4COA7**	-3.863	4.11E-04
M3COA8	-3.863	6.91E-13	**M4COA8**	-3.863	1.15E-07
M3COA9	-3.863	6.85E-13	**M4COA9**	-3.863	1.47E-04
M3COA10	-3.863	3.32E-12	**M4COA10**	-3.862	6.39E-04

Table 21: Analysis on F20 Function

F20	Average Fitness	STD		Average Fitness	STD
COA	-3.260	0.066			
M1COA1	-3.280	0.057	**M2COA1**	-3.282	0.060
M1COA2	-3.294	0.054	**M2COA2**	-3.263	0.068
M1COA3	-3.242	0.085	**M2COA3**	-3.285	0.059
M1COA4	-3.274	0.059	**M2COA4**	-3.276	0.061
M1COA5	-3.256	0.065	**M2COA5**	-3.280	0.057
M1COA6	-3.261	0.063	**M2COA6**	-3.265	0.065
M1COA7	-3.265	0.060	**M2COA7**	-3.267	0.063
M1COA8	-3.267	0.063	**M2COA8**	-3.259	0.065
M1COA9	-3.257	0.063	**M2COA9**	-3.319	0.019

M1COA10	-3.267	0.063	**M2COA10**	-3.280	0.057
M3COA1	-3.286	0.056	**M4COA1**	0.033	0.028
M3COA2	-3.275	0.057	**M4COA2**	-3.084	0.075
M3COA3	-3.273	0.060	**M4COA3**	-2.267	0.453
M3COA4	-3.294	0.050	**M4COA4**	-3.168	0.028
M3COA5	-3.280	0.057	**M4COA5**	-3.178	0.029
M3COA6	-3.274	0.059	**M4COA6**	-3.144	0.040
M3COA7	-3.278	0.056	**M4COA7**	-3.168	0.045
M3COA8	-3.262	0.060	**M4COA8**	-3.197	0.050
M3COA9	-3.283	0.056	**M4COA9**	-3.219	0.041
M3COA10	-3.283	0.055	**M4COA10**	-3.156	0.033

Table 22: Analysis on F21 Function

F21	**Average Fitness**	**STD**		**Average Fitness**	**STD**
COA	-7.86	2.563			
M1COA1	-7.86	2.750	**M2COA1**	-8.183	2.600
M1COA2	-8.38	2.637	**M2COA2**	-7.195	2.786
M1COA3	-6.62	3.325	**M2COA3**	-6.853	2.525
M1COA4	-8.34	2.538	**M2COA4**	-6.730	2.774
M1COA5	-8.29	2.553	**M2COA5**	-7.733	2.577
M1COA6	-8.23	2.516	**M2COA6**	-6.777	2.890
M1COA7	-7.69	2.987	**M2COA7**	-6.919	2.745
M1COA8	-6.86	2.813	**M2COA8**	-8.370	2.461
M1COA9	-7.69	2.827	**M2COA9**	-8.496	2.416
M1COA10	-6.97	2.675	**M2COA10**	-7.663	2.546
M3COA1	-7.987	2.552	**M4COA1**	-5.421	2.027
M3COA2	-7.532	2.549	**M4COA2**	-4.314	1.647
M3COA3	-7.032	2.464	**M4COA3**	-1.634	1.582
M3COA4	-7.986	2.552	**M4COA4**	-5.928	1.644
M3COA5	-8.751	2.305	**M4COA5**	-5.570	2.214
M3COA6	-7.221	2.544	**M4COA6**	-4.632	1.999
M3COA7	-7.732	-5.055	**M4COA7**	-4.970	2.119
M3COA8	-8.494	2.417	**M4COA8**	-5.473	1.993
M3COA9	-8.751	2.305	**M4COA9**	-6.803	2.094
M3COA10	-7.859	2.569	**M4COA10**	-5.675	2.175

Table 23: Analysis on F22 Function

F22	Average Fitness	STD		Average Fitness	STD
COA	-8.40	2.632			
M1COA1	-7.25	3.120	**M2COA1**	-7.241	2.966
M1COA2	-7.69	2.938	**M2COA2**	-7.694	2.935
M1COA3	-6.48	3.476	**M2COA3**	-6.366	2.590
M1COA4	-8.17	2.836	**M2COA4**	-6.840	2.868
M1COA5	-8.15	2.826	**M2COA5**	-6.922	2.774
M1COA6	-7.67	2.935	**M2COA6**	-7.694	2.936
M1COA7	-7.98	2.723	**M2COA7**	-8.186	2.745
M1COA8	-8.03	3.148	**M2COA8**	-7.551	2.932
M1COA9	-8.00	3.041	**M2COA9**	-8.989	2.390
M1COA10	-7.85	2.785	**M2COA10**	-8.008	2.847
M3COA1	-7.878	2.688	**M4COA1**	-5.980	2.100
M3COA2	-7.612	2.688	**M4COA2**	-4.017	1.324
M3COA3	-7.130	2.674	**M4COA3**	-1.566	1.485
M3COA4	-7.480	2.678	**M4COA4**	-4.915	1.941
M3COA5	-7.745	2.691	**M4COA5**	-5.409	2.012
M3COA6	-8.144	2.661	**M4COA6**	-4.525	1.260
M3COA7	-8.043	2.650	**M4COA7**	-4.978	1.494
M3COA8	-8.315	2.600	**M4COA8**	-5.798	1.815
M3COA9	-8.243	2.688	**M4COA9**	-6.793	1.889
M3COA10	-7.435	2.641	**M4COA10**	-4.908	1.905

Table 24: Analysis on F23 Function

F23	Average Fitness	STD		Average Fitness	STD
COA	-8.11	2.883			
M1COA1	-8.72	2.875	**M2COA1**	-8.353	2.905
M1COA2	-8.14	3.070	**M2COA2**	-7.505	3.337
M1COA3	-6.04	3.429	**M2COA3**	-7.210	3.323
M1COA4	-8.59	2.881	**M2COA4**	-6.910	3.050
M1COA5	-6.96	3.029	**M2COA5**	-7.748	3.026
M1COA6	-8.29	2.820	**M2COA6**	-8.004	3.061
M1COA7	-7.28	3.229	**M2COA7**	-9.355	2.427
M1COA8	-7.59	3.383	**M2COA8**	-9.263	2.417
M1COA9	-7.50	3.156	**M2COA9**	-9.825	1.804

M1COA10	-7.65	2.959	**M2COA10**	-7.971	2.732
M3COA1	-8.309	2.777	**M4COA1**	-4.953	1.802
M3COA2	-8.209	2.687	**M4COA2**	-3.683	1.083
M3COA3	-7.914	2.690	**M4COA3**	-1.430	1.148
M3COA4	-7.828	2.734	**M4COA4**	-5.009	1.380
M3COA5	-7.832	2.738	**M4COA5**	-4.962	1.377
M3COA6	-8.646	2.590	**M4COA6**	-4.564	1.285
M3COA7	-7.562	2.725	**M4COA7**	-4.716	1.245
M3COA8	-8.315	2.714	**M4COA8**	-5.821	1.715
M3COA9	-9.017	2.506	**M4COA9**	-6.339	1.535
M3COA10	-7.826	2.745	**M4COA10**	-5.106	1.642

4.1.2. EHAS Analysis

The performance analysis for the proposed chaotic variants of COA for Electro-Hydraulic Actuator System is presented for multiple variation of noise levels m(k), population (P) and iterations (MITE). MATLAB software was used to carryout simulations, we take input signal as zero mean unit variance as long as noise taken as constant variance normal distribution signal. EH-AS model parameters documented in this paper was extracted from [68] as follows:

$$A(c) = 1 - 1.781n^{-1} + 0.9148n^{-2} - 0.1333n^{-3} \tag{32}$$

$$F(c) = 0.02439n^{-1} - 0.0276n^{-2} + 0.01095n^{-3} \tag{33}$$

The parameter settings for EH-AS is shown in Table 25.

Table 25: Parameter setting for both models

Methods	**Parameters**
AO	$\alpha = 0.1, \delta = 0.1$ [69]
CO	No parameter is tuned [55]
COA	$Q_3 = 3$ [26]
M1COA M2COA M3COA M4COA	$Q_3 = 3, C_{map} = 0.7$
RSA	$\alpha = 0.1, \beta = 0.1$ [70]
WOA	$a = [2 \;\; 0]$ [59]

The following Table 26-28 represents the overall performance of AO, CO, COA, WOA, RSA, M1COA1, M1COA2, M1COA3, M1COA4, M1COA5, M1COA6, M1COA7, M1COA8, M1COA9, M1COA10, M2COA1, M2COA2, M2COA3, M2COA4, M2COA5, M2COA6, M2COA7, M2COA8, M2COA9, M2COA10, M3COA1, M3COA2, M3COA3, M3COA4, M3COA5, M3COA6, M3COA7, M3COA8, M3COA9, M3COA10, M4COA1, M4COA2, M4COA3, M4COA4, M4COA5, M4COA6, M4COA7, M4COA8, M4COA9, and M4COA10 in terms of estimated best value and best fitness for different ($1.9\times10^{-1}, 1.9\times10^{-2}, 1.9\times10^{-3}$) noise levels. It has been concluded that all the values of m(k), M1COA1 to M4COA10 are capable to attain the best value against AO, CO, COA, WSA, and RSA. It is concluded form the Table that the fitness value of AO, CO, COA, WOA, RSA, M1COA1, M1COA2, M1COA3, M1COA4, M1COA5, M1COA6, M1COA7, M1COA8,

M1COA9, M1COA10, M2COA1, M2COA2, M2COA3, M2COA4, M2COA5, M2COA6, M2COA7, M2COA8, M2COA9, M2COA10, M3COA1, M3COA2, M3COA3, M3COA4, M3COA5, M3COA6, M3COA7, M3COA8, M3COA9, M3COA10, M4COA1, M4COA2, M4COA3, M4COA4, M4COA5, M4COA6, M4COA7, M4COA8, M4COA9, and M4COA10 increases with the increase in noise levels m(k). However, when the fitness value increases the EH-AS identification parameters diverts form the true value.

The values of algorithm extracted from the simulation results are P=56, MITE=600 and m(k)= $1.9\times10^{-1}, 1.9\times10^{-2}, 1.9\times10^{-3}$. The convergence curves of AO, CO, COA, WOA, RSA, M1COA1, M1COA2, M1COA3, M1COA4, M1COA5, M1COA6, M1COA7, M1COA8, M1COA9, M1COA10, M2COA1, M2COA2, M2COA3, M2COA4, M2COA5, M2COA6, M2COA7, M2COA8, M2COA9, M2COA10, M3COA1, M3COA2, M3COA3, M3COA4, M3COA5, M3COA6, M3COA7, M3COA8, M3COA9, M3COA10, M4COA1, M4COA2, M4COA3, M4COA4, M4COA5, M4COA6, M4COA7, M4COA8, M4COA9, and M4COA10 are presented in the Figure (18 (a-i) - 22 (a-i)). It is determined from the figure that by the increase in the m(k) there is also an increase in the fitness.

For all values of m(k) Figures 23 (a-d)-25(a-d) shows the convergence curves of AO, CO, COA, WOA, RSA, M1COA1, M1COA2, M1COA3, M1COA4, M1COA5, M1COA6, M1COA7, M1COA8, M1COA9, M1COA10, M2COA1, M2COA2, M2COA3, M2COA4, M2COA5, M2COA6, M2COA7, M2COA8, M2COA9, M2COA10, M3COA1, M3COA2, M3COA3, M3COA4, M3COA5, M3COA6, M3COA7, M3COA8, M3COA9, M3COA10, M4COA1, M4COA2, M4COA3, M4COA4, M4COA5, M4COA6, M4COA7, M4COA8, M4COA9, and M4COA10. By the results it is determined from the results the fitness value increases with the increase in m(k). However, M1COA1-M1COA10, M2COA1-M2COA10, M3COA1-M3COA10 and M4COA1-M4COA10 has the fitness value lower than AO, CO, COA, WOA and RSA.

Figures 26 (a-d)-28 (a-d) represents the statistical curves of M1COA1-M1COA10, M2COA1-M2COA10, M3COA1-M3COA10, M4COA1-M4COA10, AO, CO, COA, WOA, and RSA for 40 different runs. It has been verified the Figure 26-28 that M1COA1-M1COA10, M2COA1-M2COA10, M3COA1-M3COA10, M4COA1-M4COA10 has lowest fitness value against AO, CO, COA, WSA, and RSA.

Table 29 shows the performance of AO, CO, COA, WOA, RSA, M1COA1, M1COA2, M1COA3, M1COA4, M1COA5, M1COA6, M1COA7, M1COA8, M1COA9, M1COA10, M2COA1, M2COA2, M2COA3, M2COA4, M2COA5, M2COA6, M2COA7, M2COA8, M2COA9, M2COA10, M3COA1, M3COA2, M3COA3, M3COA4, M3COA5, M3COA6, M3COA7, M3COA8, M3COA9, M3COA10, M4COA1, M4COA2, M4COA3, M4COA4, M4COA5, M4COA6, M4COA7, M4COA8, M4COA9, and M4COA10 for Friedman test rank analysis. It has been concluded from the Table 29 that M1COA9 stood first in term of ranking then all other methods.

Table 30 represents the overall performance of AO, CO, COA, WOA, RSA, M1COA1, M1COA2, M1COA3, M1COA4, M1COA5, M1COA6, M1COA7, M1COA8, M1COA9, M1COA10, M2COA1, M2COA2, M2COA3, M2COA4, M2COA5, M2COA6, M2COA7, M2COA8, M2COA9, M2COA10, M3COA1, M3COA2, M3COA3, M3COA4, M3COA5, M3COA6, M3COA7, M3COA8, M3COA9, M3COA10, M4COA1, M4COA2, M4COA3, M4COA4, M4COA5, M4COA6, M4COA7, M4COA8, M4COA9, and M4COA10 in terms of average execution time and standard deviation (STD), at different noise levels (m(k)= $1.9\times10^{-1}, 1.9\times10^{-2}, 1.9\times10^{-3}$) for 40 independent executions. It is observed from Table 30 that chaotic variants of COA attains comparable execution time[67].

Table 26: Analysis of EH-AS estimated weights with respect to m(k)= 1.9×10^{-3}

Methods	**Weights**						**Best Fitness**
AO	-0.4738	-0.3339	-0.2356	0.0231	0.0164	-0.0070	1.06E-04
CO	-0.9649	-0.0205	-0.0199	0.0107	0.0038	0.0071	4.47E-05
COA	-1.8012	0.8981	-0.0951	0.0249	-0.0267	0.0089	3.10E-06
WSA	-1.8347	0.7846	0.0536	0.0194	-0.0111	-0.0046	4.31E-05
RSA	-1.0468	-0.0003	0.0061	0.0114	0.0022	0.0000	6.03E-05
M1COA1	-1.5846	0.5753	0.0108	0.0241	-0.0202	0.0057	3.73E-06
M1COA2	-1.3685	0.2205	0.1477	0.0235	-0.0145	0.0018	5.65E-06
M1COA3	-0.2105	-0.3054	-0.5076	0.0145	0.0123	0.0184	1.44E-04
M1COA4	-1.7869	0.9021	-0.1122	0.0250	-0.0260	0.0091	2.99E-06
M1COA5	-1.5609	0.5665	-0.0049	0.0236	-0.0198	0.0063	3.90E-06
M1COA6	-1.5433	0.5787	-0.0347	0.0231	-0.0198	0.0074	4.41E-06
M1COA7	-1.6964	0.7805	-0.0836	0.0241	-0.0237	0.0085	3.15E-06
M1COA8	-1.8075	0.9666	-0.1578	0.0241	-0.0267	0.0107	2.85E-06
M1COA9	-1.7632	0.8718	-0.1068	0.0244	-0.0254	0.0092	2.95E-06
M1COA10	-1.6613	0.7417	-0.0803	0.0243	-0.0218	0.0069	3.52E-06
M2COA1	-1.6626	0.7591	-0.0968	0.0239	-0.0226	0.0085	3.33E-06
M2COA2	-1.7303	0.7617	-0.0289	0.0253	-0.0245	0.0067	3.38E-06

M2COA3	-1.2552	-0.0245	0.2811	0.0248	-0.0117	-0.0021	7.01E-06
M2COA4	-1.9136	1.1918	-0.2788	0.0238	-0.0295	0.0138	2.97E-06
M2COA5	-1.6568	0.6916	-0.0318	0.0243	-0.0223	0.0070	3.40E-06
M2COA6	-1.9287	1.1729	-0.2430	0.0241	-0.0299	0.0132	2.86E-06
M2COA7	-1.8234	0.9960	-0.1704	0.0244	-0.0266	0.0104	2.92E-06
M2COA8	-1.6354	0.7890	-0.1559	0.0235	-0.0214	0.0092	4.11E-06
M2COA9	-2	1.4732	-0.4821	0.0213	-0.0362	0.0234	1.02E-05
M2COA10	-1.5132	0.4433	0.0690	0.0243	-0.0192	0.0043	4.36E-06
M3COA1	-1.9952	1.3557	-0.3614	0.0234	-0.0323	0.0167	3.33E-06
M3COA2	-1.6543	0.7567	-0.1016	0.0237	-0.0227	0.0094	3.62E-06
M3COA3	-1.5428	0.7176	-0.1778	0.0206	-0.0172	0.0101	7.47E-06
M3COA4	-1.4422	0.3923	0.0481	0.0236	-0.0168	0.0044	4.89E-06
M3COA5	-1.6480	0.6444	0.0058	0.0248	-0.0218	0.0056	3.61E-06
M3COA6	-1.7136	0.8814	-0.1690	0.0237	-0.0240	0.0102	3.32E-06
M3COA7	-1.7277	0.7743	-0.0438	0.0246	-0.0244	0.0076	3.20E-06
M3COA8	-1.8569	0.9741	-0.1129	0.0244	-0.0283	0.0107	3.19E-06
M3COA9	-1.7497	0.8236	-0.0717	0.0249	-0.0256	0.0087	3.12E-06
M3COA10	-1.5383	0.5856	-0.0486	0.0237	-0.0178	0.0052	4.74E-06
M4COA1	-2.0000	1.0522	-0.0362	0.0296	-0.0365	0.0054	6.46E-05
M4COA2	-1.1285	0.1409	-0.0009	0.0110	0.0081	0.0038	7.35E-05
M4COA3	-0.1818	-0.1934	-0.7667	0.0341	0.0107	-0.0373	1.33E-03
M4COA4	-1.6596	0.8445	-0.1943	0.0295	-0.0190	-0.0008	2.36E-05
M4COA5	-1.3857	0.2071	0.1661	0.0172	-0.0117	0.0030	1.87E-05
M4COA6	-2.0000	0.9972	-0.0134	0.0384	-0.0483	0.0076	6.77E-05

M4COA7	-1.9610	1.6706	-0.7097	0.0151	-0.0291	0.0265	3.59E-05
M4COA8	-1.4039	0.1301	0.2991	0.0291	-0.0110	-0.0052	2.62E-05
M4COA9	-2	0.8926	0.0976	0.0147	-0.0363	0.0127	1.09E-04
M4COA10	-2	0.8438	0.1284	0.0276	-0.0352	0.0045	6.94E-05

Table 27: Analysis of EH-AS estimated weights with respect to m(k)= 1.9×10^{-2}

Methods	**Weights**						**Best Fitness**
AO	-1.1125	0.1535	-0.0122	0.0218	-0.0010	0.0183	4.21E-04
CO	-1.0253	0.0191	0.0150	0.0190	0.0182	-0.0055	4.00E-04
COA	-1.4992	0.4705	0.0406	0.0200	-0.0032	0.0008	2.67E-04
WSA	-1.0282	-0.2585	0.3007	0.0246	-0.0054	0.0052	3.56E-04
RSA	-1.2677	0.0001	0.3007	0	0	0.0224	3.91E-04
M1COA1	-1.5004	0.4697	0.0427	0.0204	-0.0035	0.0006	2.67E-04
M1COA2	-1.4084	0.3351	0.0872	0.0191	-0.0030	0.0031	2.70E-04
M1COA3	-0.8184	-0.2144	-0.0163	-0.0054	0.0115	0.0112	7.78E-04
M1COA4	-1.4935	0.4539	0.0514	0.0201	-0.0025	-0.0001	2.67E-04
M1COA5	-1.4854	0.4418	0.0557	0.0200	-0.0028	0.0004	2.67E-04
M1COA6	-1.5008	0.4727	0.0400	0.0206	-0.0036	0.0005	2.67E-04
M1COA7	-1.4834	0.4360	0.0597	0.0200	-0.0028	0.0004	2.67E-04
M1COA8	-1.4944	0.4573	0.0490	0.0205	-0.0033	0.0003	2.67E-04
M1COA9	-1.4960	0.4623	0.0457	0.0202	-0.0033	0.0006	2.67E-04
M1COA10	-1.4878	0.4440	0.0559	0.0197	-0.0034	0.0012	2.67E-04
M2COA1	-1.4882	0.4393	0.0608	0.0208	-0.0031	-0.0003	2.67E-04
M2COA2	-1.5225	0.5141	0.0202	0.0212	-0.0046	0.0008	2.67E-04
M2COA3	-1.3965	0.3027	0.1095	0.0147	0.0009	0.0042	2.74E-04

M2COA4	-1.4915	0.4490	0.0549	0.0200	-0.0033	0.0008	2.67E-04
M2COA5	-1.5059	0.4792	0.0388	0.0208	-0.0036	0.0002	2.67E-04
M2COA6	-1.5167	0.5162	0.0119	0.0211	-0.0040	0.0008	2.67E-04
M2COA7	-1.4898	0.4528	0.0488	0.0202	-0.0030	0.0005	2.67E-04
M2COA8	-1.4913	0.4534	0.0508	0.0208	-0.0027	-0.0004	2.67E-04
M2COA9	-1.4115	0.3802	0.0527	0.0248	-0.0029	0.0006	2.79E-04
M2COA10	-1.4852	0.4434	0.0541	0.0200	-0.0028	0.0005	2.98E-04
M3COA1	-1.5002	0.4820	0.0301	0.0209	-0.0045	0.0013	2.67E-04
M3COA2	-1.4969	0.4585	0.0504	0.0211	-0.0039	0.0002	2.67E-04
M3COA3	-1.3807	0.2156	0.1831	0.0182	0.0000	0.0002	2.73E-04
M3COA4	-1.4786	0.4456	0.0448	0.0195	-0.0023	0.0008	2.67E-04
M3COA5	-1.5008	0.4659	0.0467	0.0205	-0.0036	0.0005	2.67E-04
M3COA6	-1.5100	0.4907	0.0304	0.0206	-0.0043	0.0010	2.67E-04
M3COA7	-1.4901	0.4664	0.0352	0.0197	-0.0016	-0.0001	2.67E-04
M3COA8	-1.4905	0.4508	0.0515	0.0199	-0.0028	0.0003	2.67E-04
M3COA9	-1.5028	0.4810	0.0335	0.0205	-0.0035	0.0005	2.67E-04
M3COA10	-1.4698	0.4046	0.0777	0.0195	-0.0023	0.0003	2.67E-04
M4COA1	-2.0000	0.9310	0.0599	0.0094	-0.0035	-0.0046	4.73E-04
M4COA2	-1.1160	-0.1448	0.2864	0.0034	-0.0037	0.0200	4.21E-04
M4COA3	-0.4163	0.0038	-0.5231	-0.0480	0.0584	0.0607	2.28E-03
M4COA4	-1.1471	0.0096	0.1762	0.0170	-0.0012	0.0157	3.56E-04
M4COA5	-1.1741	-0.0146	0.1978	0.0124	-0.0046	0.0160	3.37E-04
M4COA6	-1.3763	0.7355	-0.3560	0.0289	0.0117	-0.0153	5.09E-04
M4COA7	-1.6658	0.8517	-0.1603	0.0302	-0.0073	0.0050	3.62E-04
M4COA8	-0.8846	-0.7243	0.6250	-0.0040	0.0308	-0.0077	4.30E-04
M4COA9	-2	2	-1.0300	0.0399	-0.0387	0.0238	6.64E-04

M4COA10	-1.3055	0.3679	-0.0035	0.0175	-0.0048	0.0221	4.48E-04

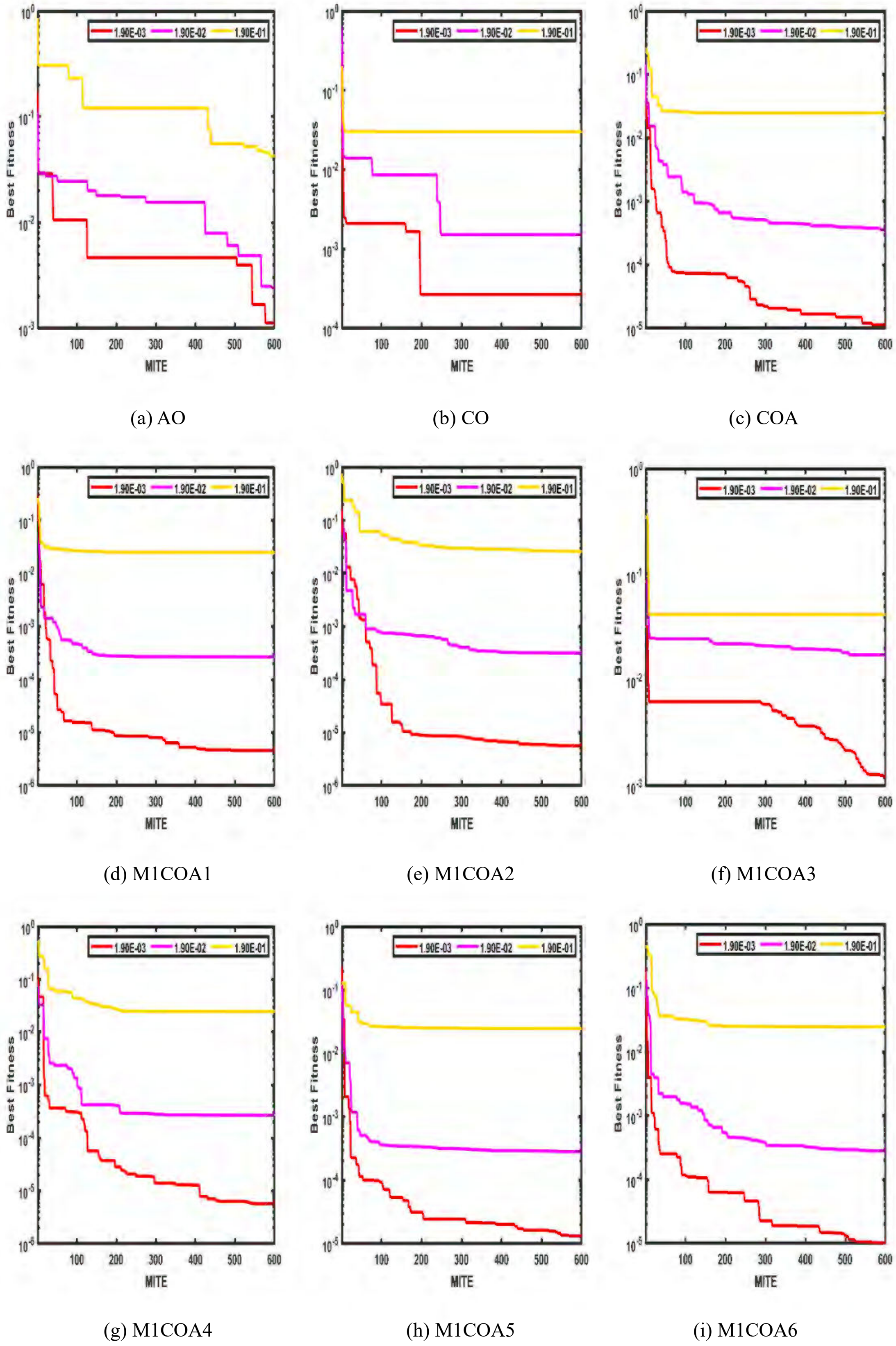
Table 28: Analysis of EH-AS estimated weights with respect to m(k)= 1.9×10^{-1}

Methods	**Weights**						**Best Fitness**
AO	-1.3234	0.2142	0.1473	0.0070	0.1370	-0.0307	2.53E-02
CO	-0.9798	-0.3936	0.4185	-0.1756	0.2425	0.0487	3.01E-02
COA	-1.3813	0.3173	0.1043	-0.0315	0.1540	-0.0178	2.47E-02
WOA	-1.2150	0.1450	0.1179	0.0181	0.0407	0.0741	2.75E-02
RSA	-1.3352	0.3793	0	0	0.1157	0	2.57E-02
M1COA1	-1.3794	0.3139	0.1059	-0.0313	0.1535	-0.0173	2.47E-02
M1COA2	-1.3879	0.3306	0.0974	-0.0295	0.1525	-0.0191	2.47E-02
M1COA3	-0.8305	-0.1524	0.0095	-0.0012	0.0795	0.0858	3.86E-02
M1COA4	-1.3807	0.3152	0.1058	-0.0317	0.1537	-0.0174	2.47E-02
M1COA5	-1.3799	0.3146	0.1056	-0.0313	0.1537	-0.0177	2.47E-02
M1COA6	-1.3806	0.3160	0.1050	-0.0309	0.1534	-0.0177	2.47E-02
M1COA7	-1.3815	0.3177	0.1041	-0.0307	0.1532	-0.0178	2.47E-02
M1COA8	-1.3803	0.3155	0.1051	-0.0311	0.1534	-0.0176	2.47E-02
M1COA9	-1.3801	0.3153	0.1051	-0.0312	0.1534	-0.0175	2.47E-02
M1COA10	-1.3820	0.3187	0.1036	-0.0311	0.1536	-0.0178	2.47E-02
M2COA1	-1.3783	0.3124	0.1063	-0.0316	0.1537	-0.0172	2.47E-02
M2COA2	-1.3803	0.3155	0.1052	-0.0309	0.1534	-0.0178	2.47E-02
M2COA3	-1.3748	0.3023	0.1131	-0.0351	0.1554	-0.0157	2.47E-02
M2COA4	-1.3790	0.3109	0.1085	-0.0308	0.1542	-0.0188	2.47E-02
M2COA5	-1.3845	0.3223	0.1025	-0.0296	0.1524	-0.0182	2.47E-02
M2COA6	-1.3788	0.3129	0.1062	-0.0314	0.1540	-0.0177	2.47E-02

M2COA7	-1.3810	0.3165	0.1048	-0.0308	0.1538	-0.0184	2.47E-02
M2COA8	-1.3834	0.3224	0.1021	-0.0299	0.1533	-0.0171	2.47E-02
M2COA9	-1.5111	0.4811	0.0725	-0.0421	0.2008	-0.0545	2.56E-02
M2COA10	-1.3819	0.3196	0.1027	-0.0315	0.1534	-0.0172	2.47E-02
M3COA1	-1.4053	0.3656	0.0802	-0.0301	0.1545	-0.0193	2.47E-02
M3COA2	-1.3887	0.3367	0.0922	-0.0284	0.1505	-0.0167	2.47E-02
M3COA3	-1.3776	0.3135	0.1040	-0.0414	0.1601	-0.0161	2.47E-02
M3COA4	-1.3787	0.3114	0.1080	-0.0316	0.1529	-0.0165	2.47E-02
M3COA5	-1.3784	0.3110	0.1081	-0.0298	0.1528	-0.0182	2.47E-02
M3COA6	-1.3768	0.3076	0.1100	-0.0311	0.1543	-0.0180	2.47E-02
M3COA7	-1.3834	0.3222	0.1014	-0.0299	0.1536	-0.0190	2.47E-02
M3COA8	-1.3829	0.3208	0.1023	-0.0303	0.1536	-0.0186	2.47E-02
M3COA9	-1.3810	0.3148	0.1067	-0.0317	0.1554	-0.0187	2.47E-02
M3COA10	-1.3843	0.3223	0.1021	-0.0299	0.1537	-0.0190	2.47E-02
M4COA1	-1.5021	0.4681	0.0449	-0.0295	0.2568	-0.1730	2.88E-02
M4COA2	-1.7689	1.2051	-0.3909	0.0403	0.0330	0.0864	3.78E-02
M4COA3	-1.5283	0.8014	-0.1809	-0.3196	0.1881	0.2406	5.77E-02
M4COA4	-1.0064	-0.0709	0.1277	-0.1916	0.2749	0.1065	3.47E-02
M4COA5	-2	1.2433	-0.1874	-0.0132	0.1520	-0.0505	3.61E-02
M4COA6	-1.1727	0.1008	0.1516	-0.1540	0.2793	0.0656	3.11E-02
M4COA7	-1.2176	0.3271	-0.0528	-0.2179	0.0904	0.2972	4.10E-02
M4COA8	-1.6345	0.6770	0.0075	-0.0457	0.0660	0.0479	2.99E-02
M4COA9	-1.6503	0.3884	0.2913	-0.0085	0.1793	-0.1717	3.47E-02
M4COA10	-1.6192	0.3355	0.3177	-0.0069	0.1253	-0.0628	3.07E-02

Table 29: Friedman test of Statistical curves of CO, COA, WOA, RSA, M1COA1-M1COA10, M2COA1-M2COA10, M3COA1-M3COA10, and M4COA1-M4COA10.

Methods	Ranksum	Rank	Methods	Ranksum	Rank	Methods	Ranksum	Rank
AO	242	44	**M2COA1**	125.5	7	**M3COA6**	170	26
CO	196	31	**M2COA2**	166.5	24	**M3COA7**	147	17
COA	136	11	**M2COA3**	191	30	**M3COA8**	134	10
WOA	236	44	**M2COA4**	143	14	**M3COA9**	167	25
RSA	225	42	**M2COA5**	141	13	**M3COA10**	149	18
M1COA1	112.5	3	**M2COA6**	131	9	**M4COA1**	197	32
M1COA2	181.5	27	**M2COA7**	130	8	**M4COA2**	202	33
M1COA3	206	34	**M2COA8**	145	16	**M4COA3**	210	34
M1COA4	116	4	**M2COA9**	188	29	**M4COA4**	196	31
M1COA5	122	6	**M2COA10**	152	19	**M4COA5**	202	33
M1COA6	143	14	**M3COA1**	153	20	**M4COA6**	211	37
M1COA7	121	5	**M3COA2**	164	22	**M4COA7**	213	38
M1COA8	106	2	**M3COA3**	183	28	**M4COA8**	211	37
M1COA9	**102**	**1**	**M3COA4**	153	20	**M4COA9**	223	40
M1COA10	139	12	**M3COA5**	166	23	**M4COA10**	235	41

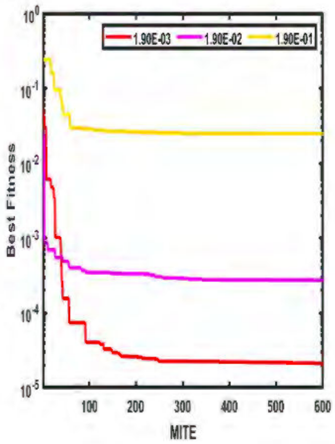


(a) AO (b) CO (c) COA

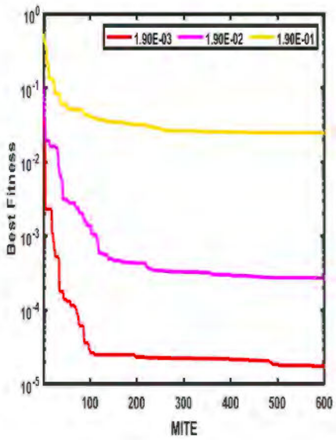
(d) M1COA1 (e) M1COA2 (f) M1COA3

(g) M1COA4 (h) M1COA5 (i) M1COA6

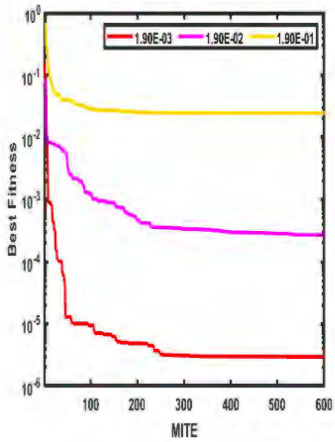
Figure 18: Convergence curves for AO, CO, COA and M1COA1-M1COA6



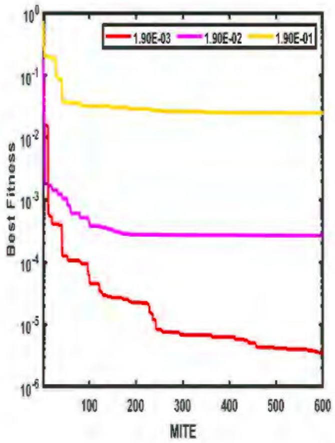
(a) M1COA7



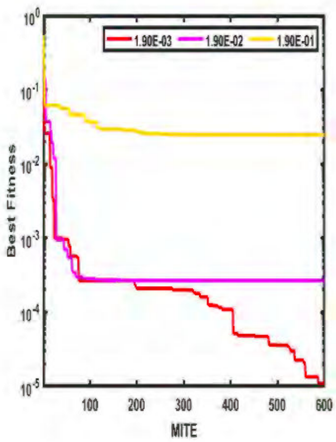
(b) M1COA8



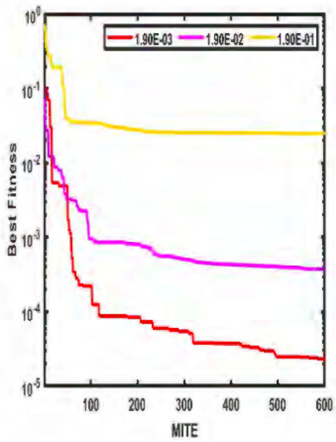
(c) M1COA9



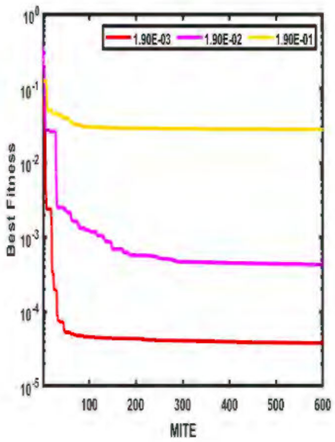
(d) M1COA10



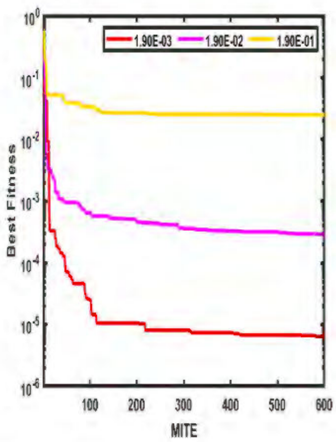
(e) M2COA1



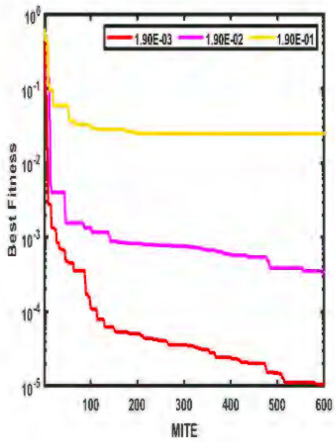
(f) M2COA2



(g) M2COA3

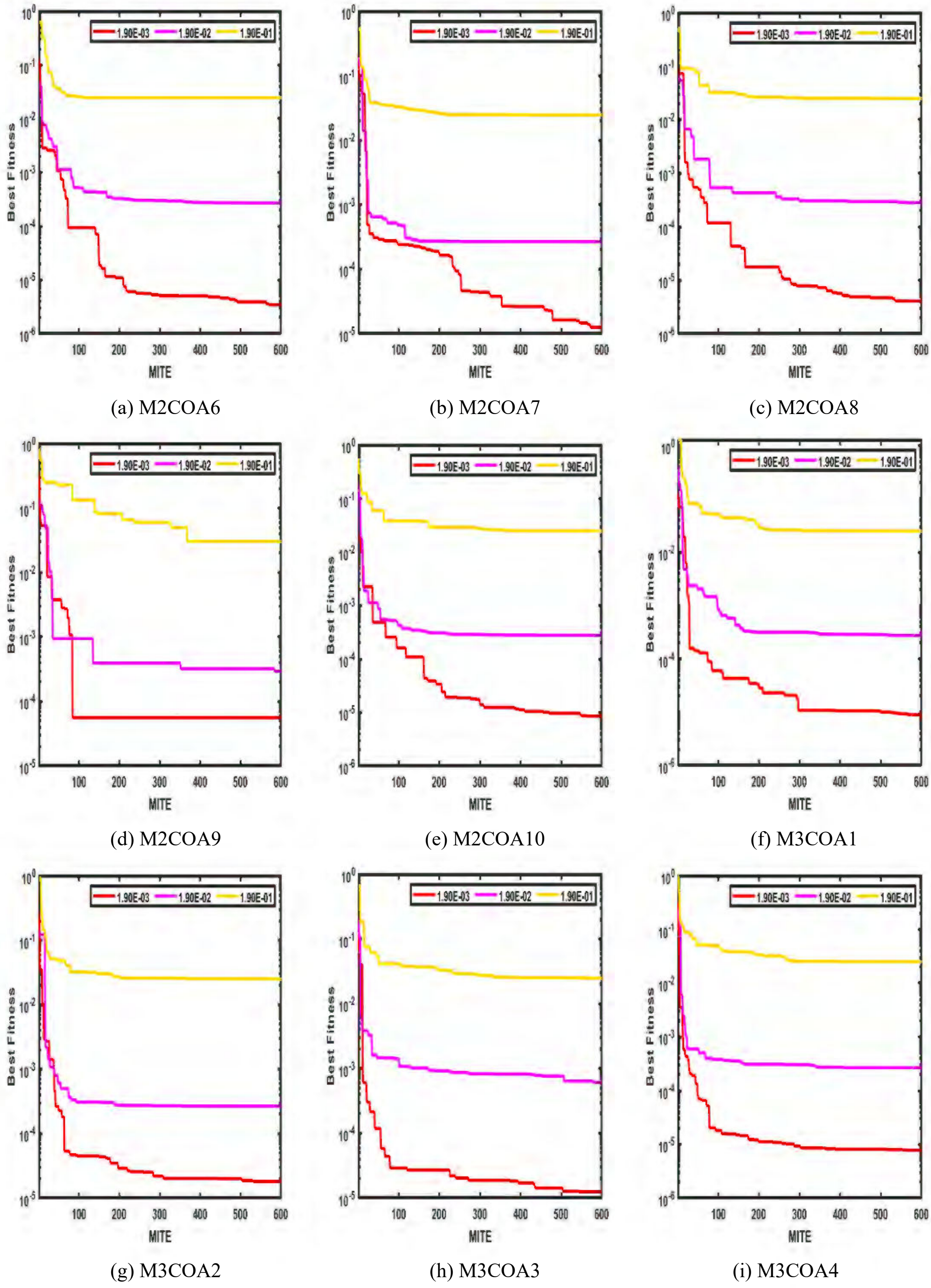


(h) M2COA4



(i) M2COA5

Figure 19: Convergence curves for M1COA7-M1COA10 and M2COA1-M2COA5

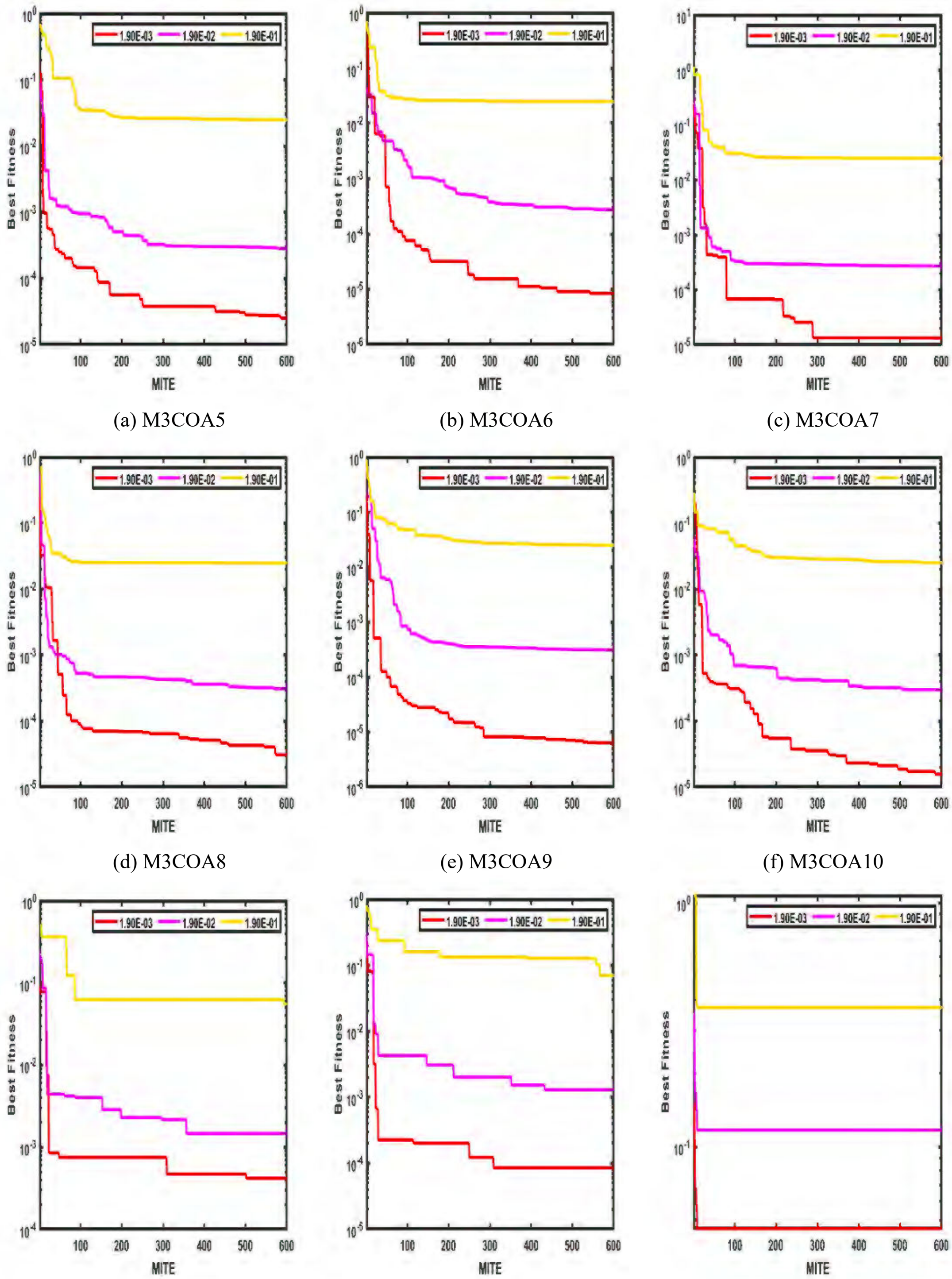


(a) M2COA6 (b) M2COA7 (c) M2COA8

(d) M2COA9 (e) M2COA10 (f) M3COA1

(g) M3COA2 (h) M3COA3 (i) M3COA4

Figure 20: Convergence curves for M2COA6-M2COA10 and M3COA1-M3COA4



(a) M3COA5 (b) M3COA6 (c) M3COA7

(d) M3COA8 (e) M3COA9 (f) M3COA10

(g) M4COA1 (h) M4COA2 (i) M4COA3

Figure 21: Convergence curves for M3COA5-M3COA10 and M4COA1-M4COA3

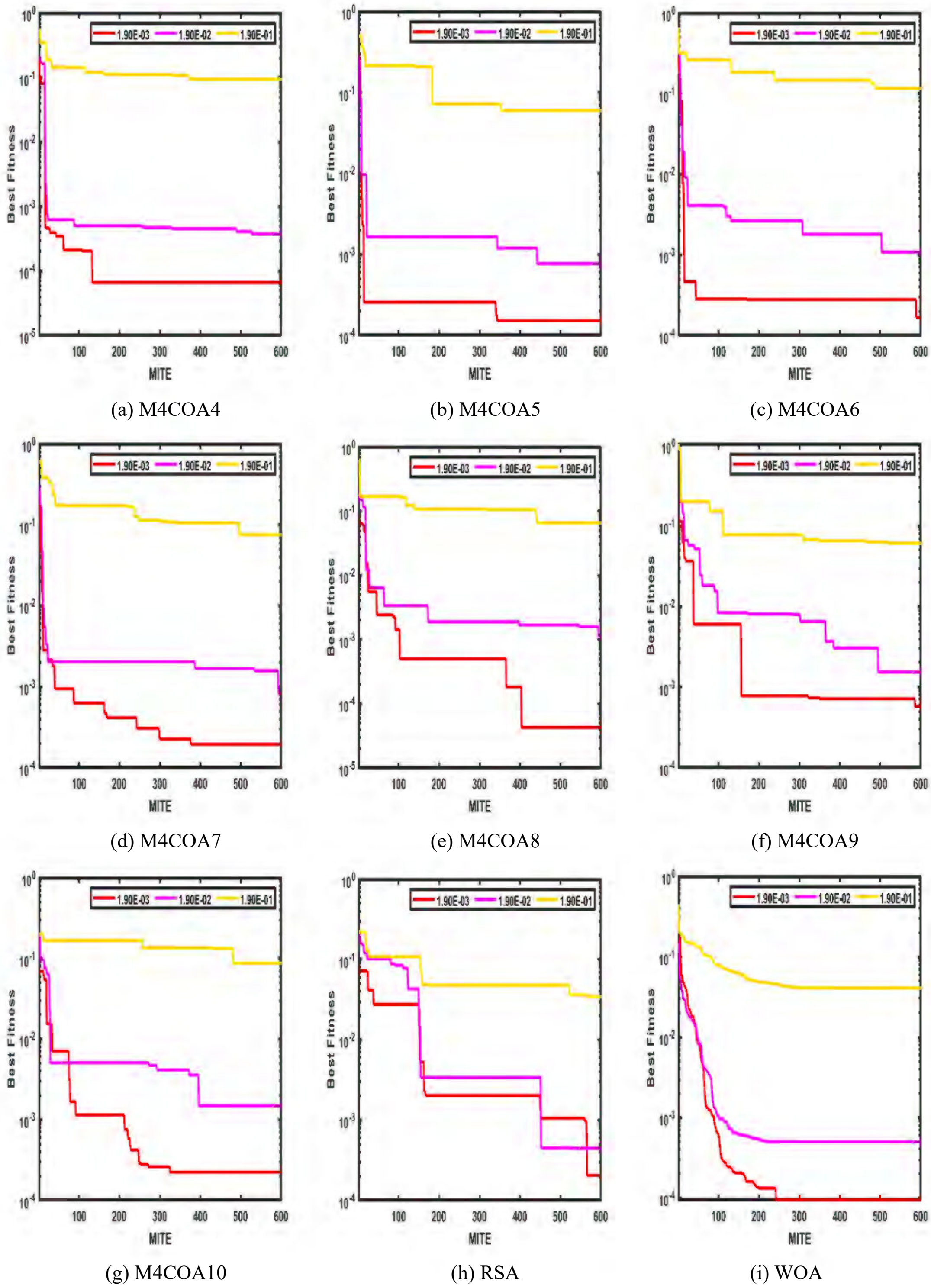
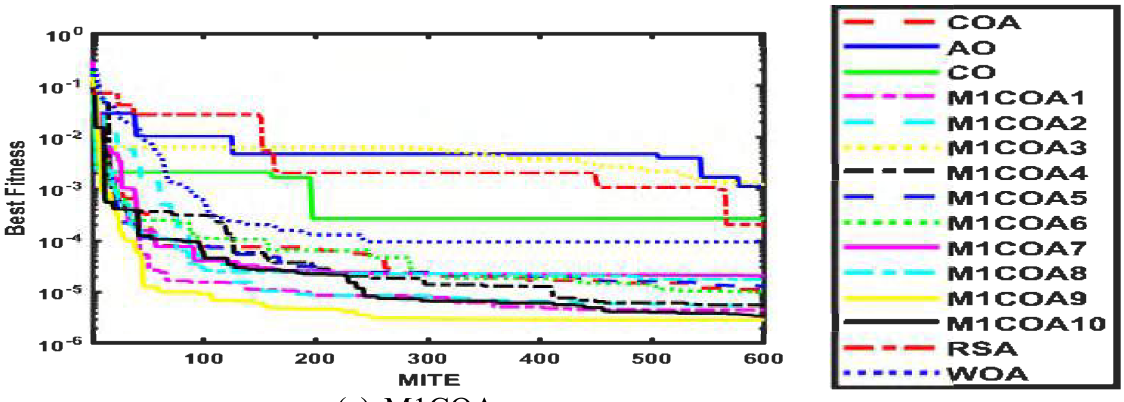
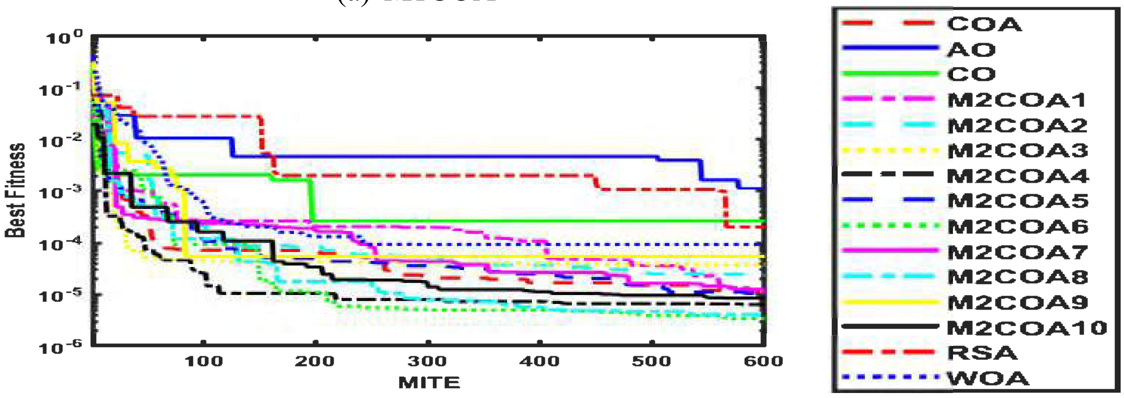


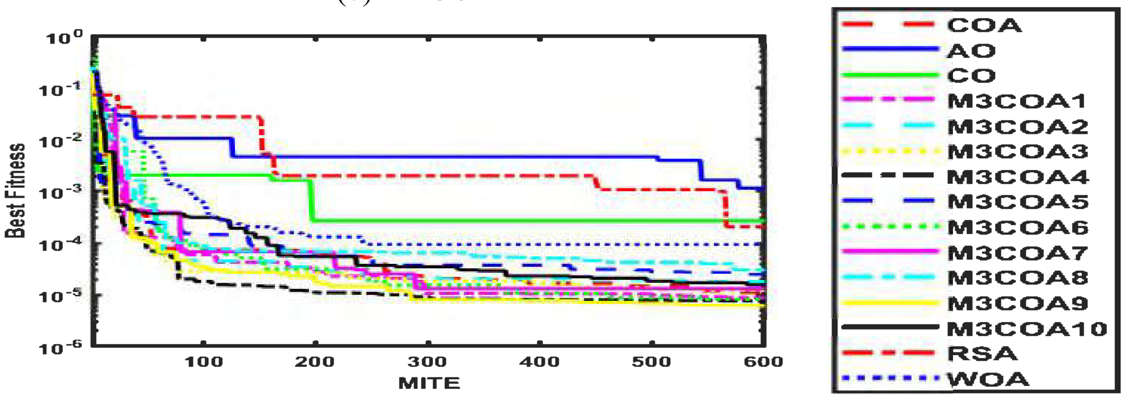
Figure 22: Convergence curves for M4COA4-M4COA10, RSA and WOA



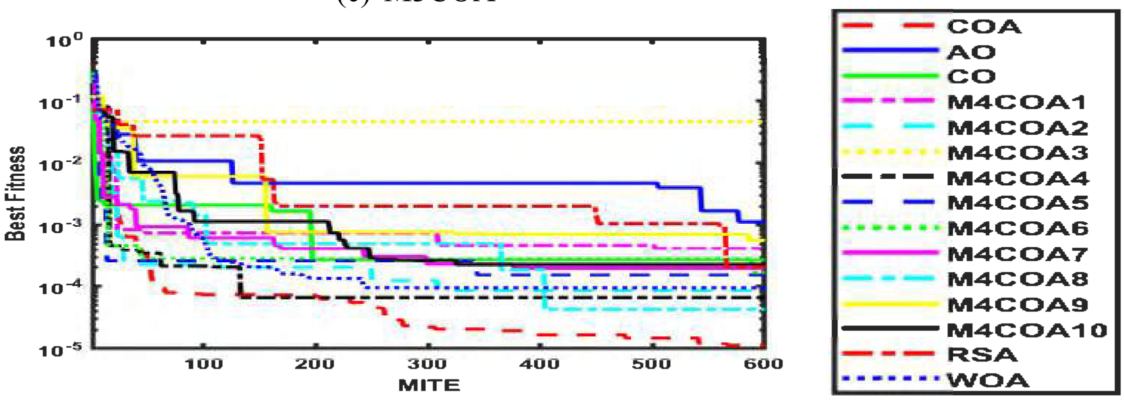
(a) M1COA



(b) M2COA

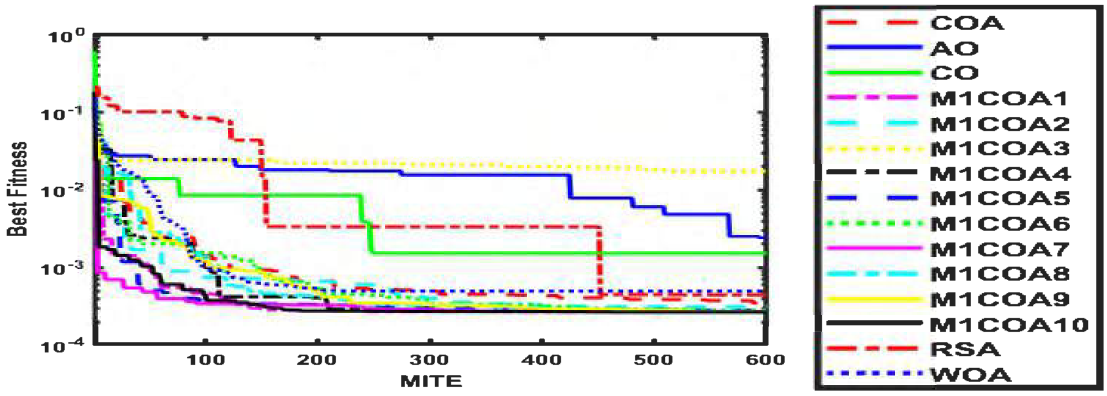


(c) M3COA

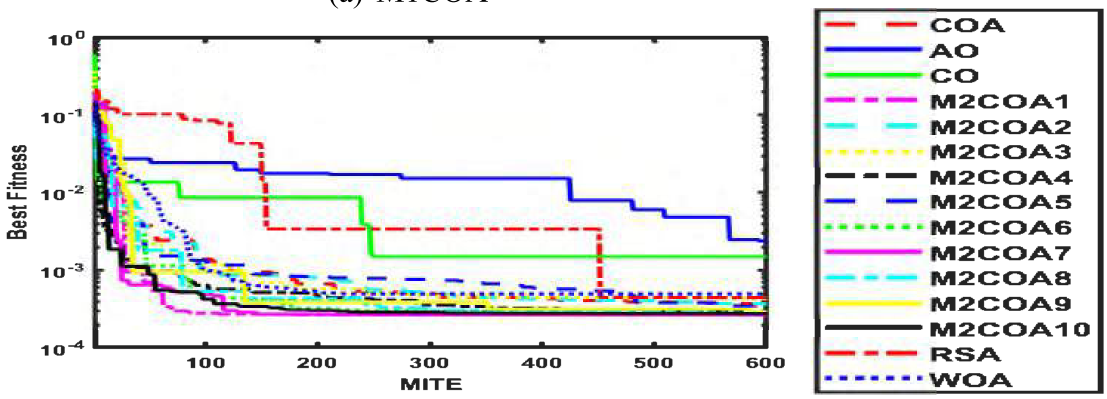


(d) M4COA

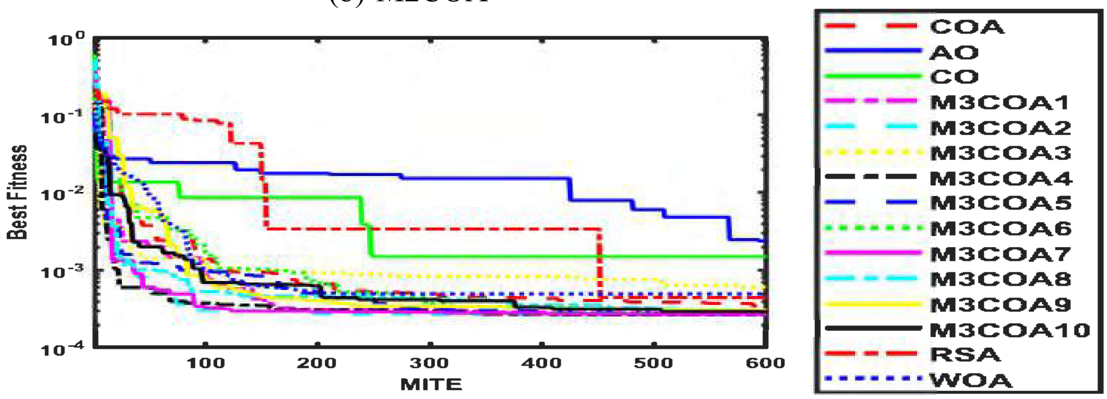
Figure 23: Convergence curves of M1COA1-M1COA10, M2COA1-M2COA10, M3COA1-M3COA10, M4COA1-M4COA10, CO, COA, WOA, and RSA at noise level m(k) $= 1.9\times10^{-3}$



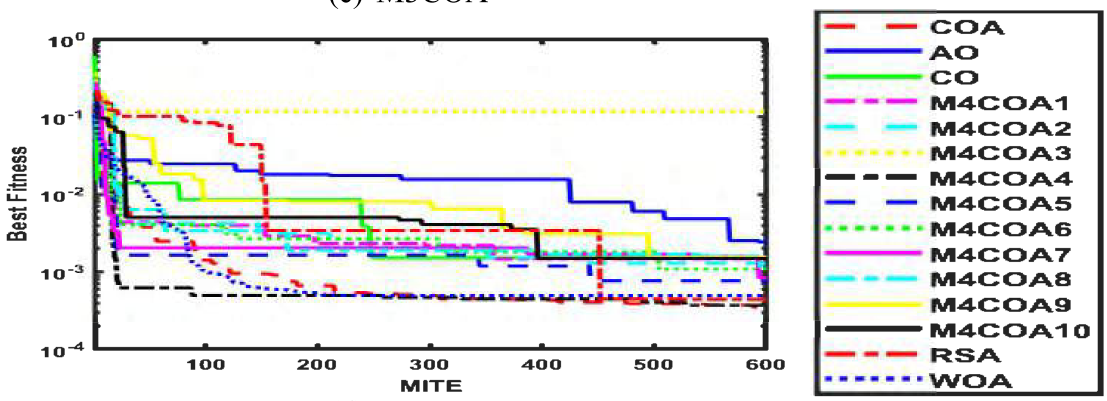
(a) M1COA



(b) M2COA

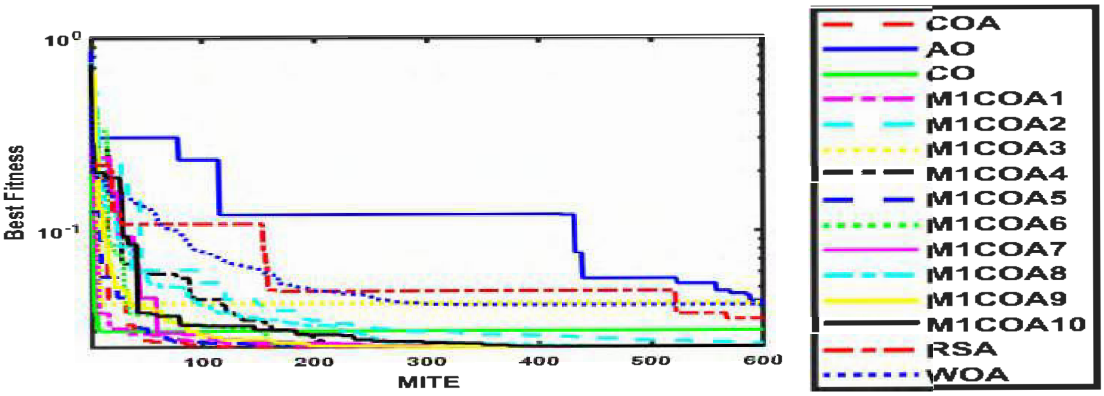


(c) M3COA

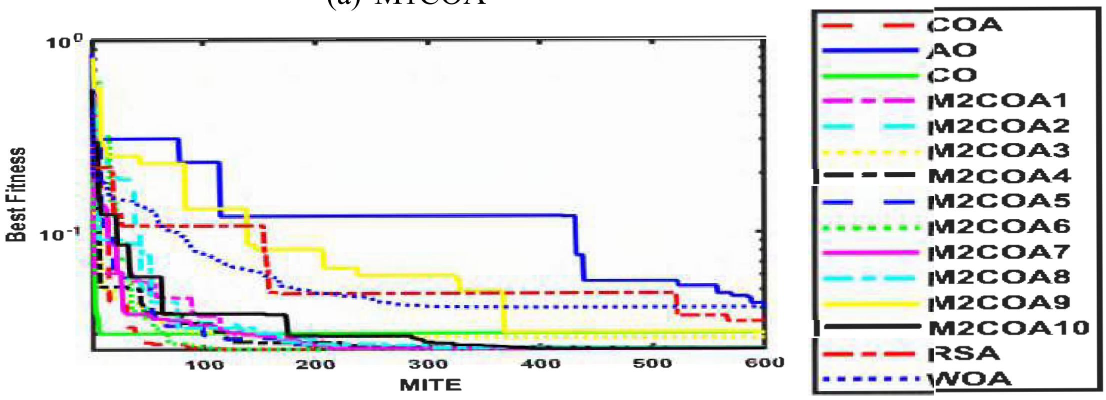


(d) M4COA

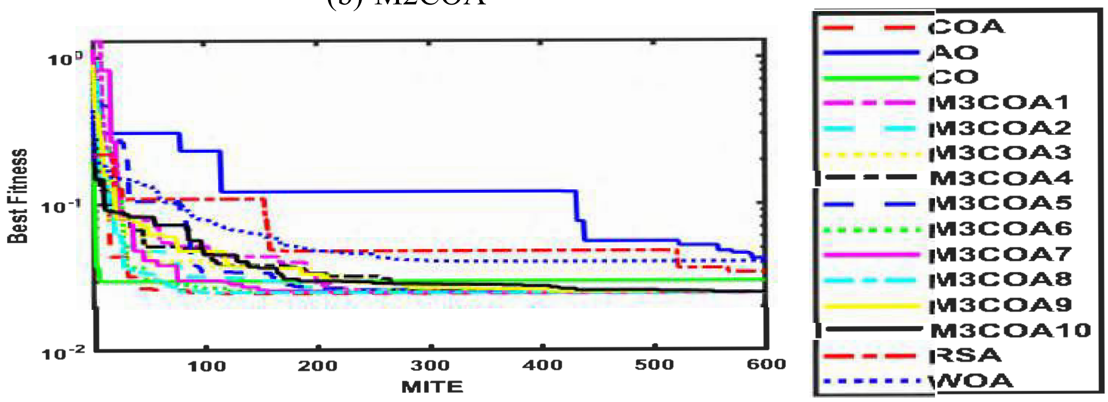
Figure 24: Convergence curves of M1COA1-M1COA10, M2COA1-M2COA10, M3COA1-M3COA10, M4COA1-M4COA10, CO, COA, WOA, and RSA at noise level m(k) = 1.9×10^{-2}



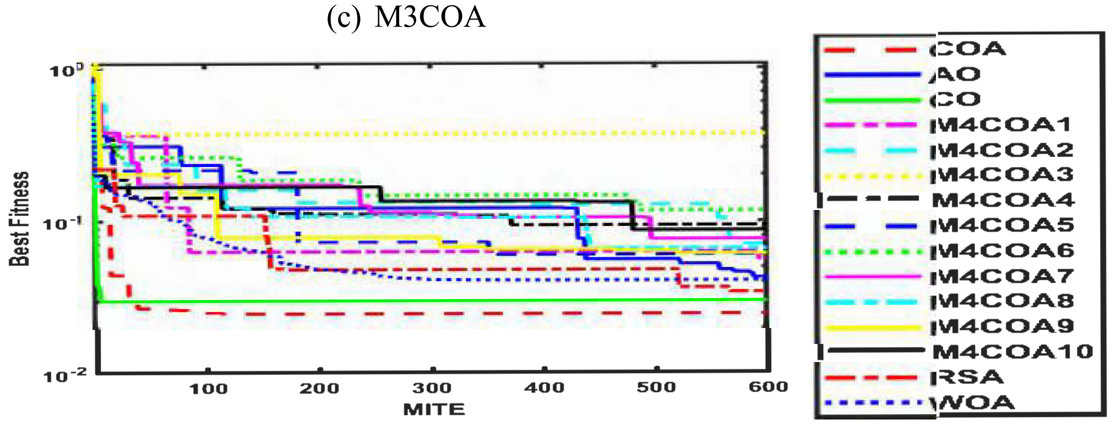
(a) M1COA



(b) M2COA



(c) M3COA



(d) M4COA

Figure 25: Convergence curves of M1COA1-M1COA10, M2COA1-M2COA10, M3COA1-M3COA10, M4COA1-M4COA10, CO, COA, WOA, and RSA at noise level m(k) = 1.9×10^{-1}

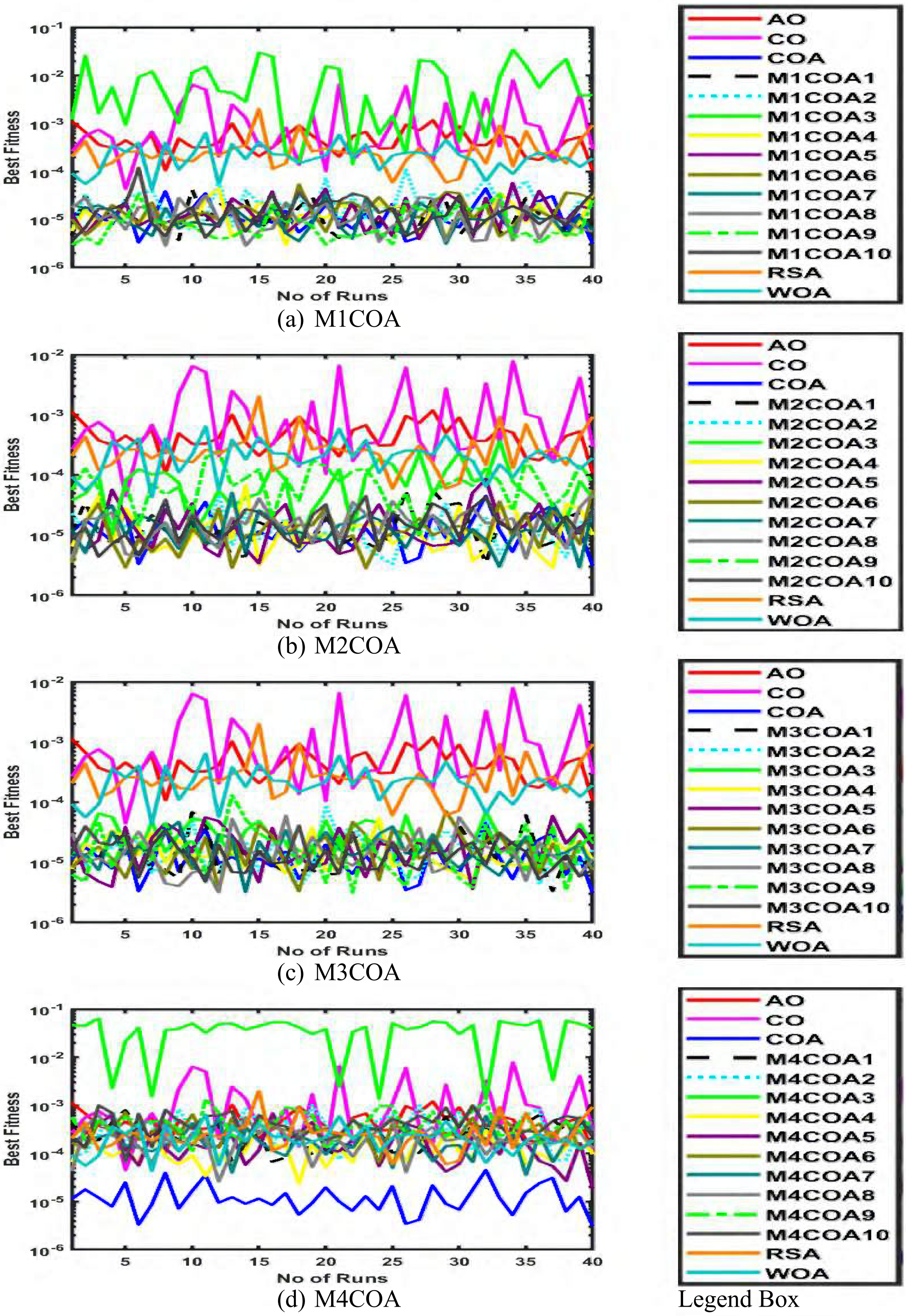
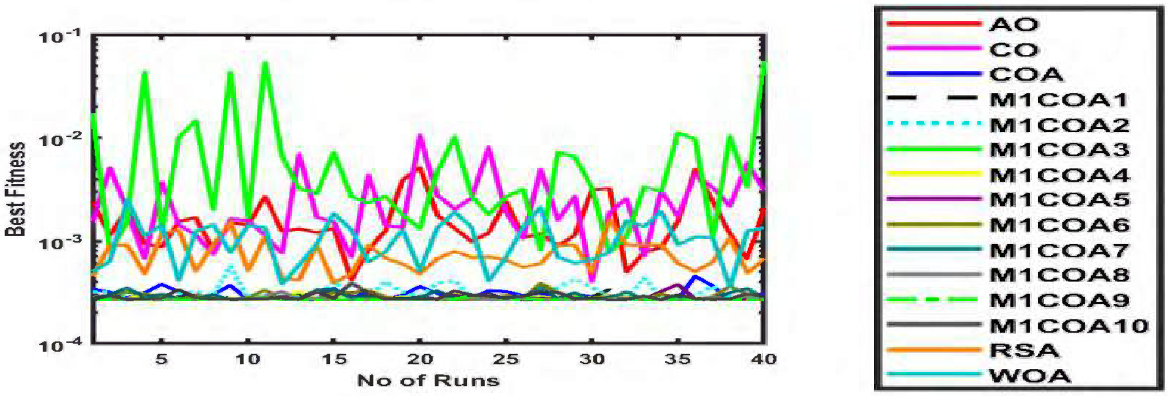
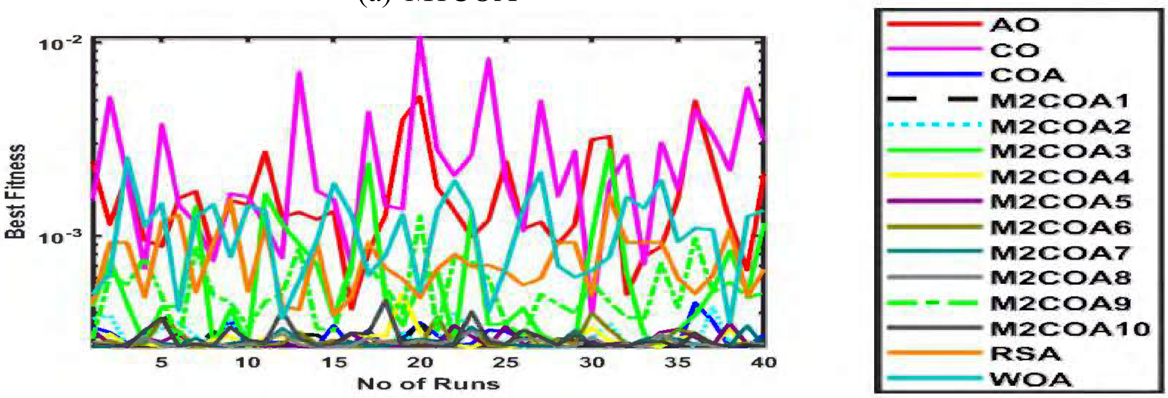


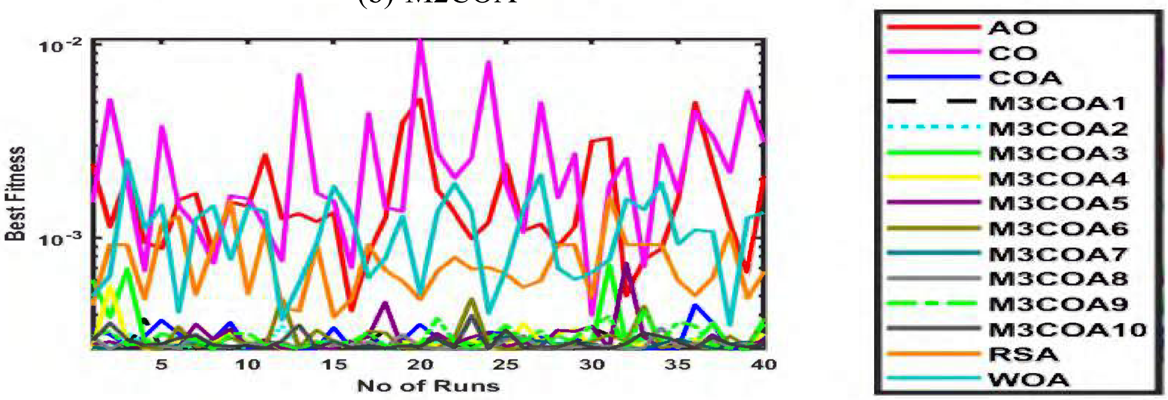
Figure 26: Statistical curves of M1COA1-M1COA10, M2COA1-M2COA10, M3COA1-M3COA10, M4COA1-M4COA10, CO, COA, WOA, and RSA at noise level m(k) = 1.9×10^{-3}



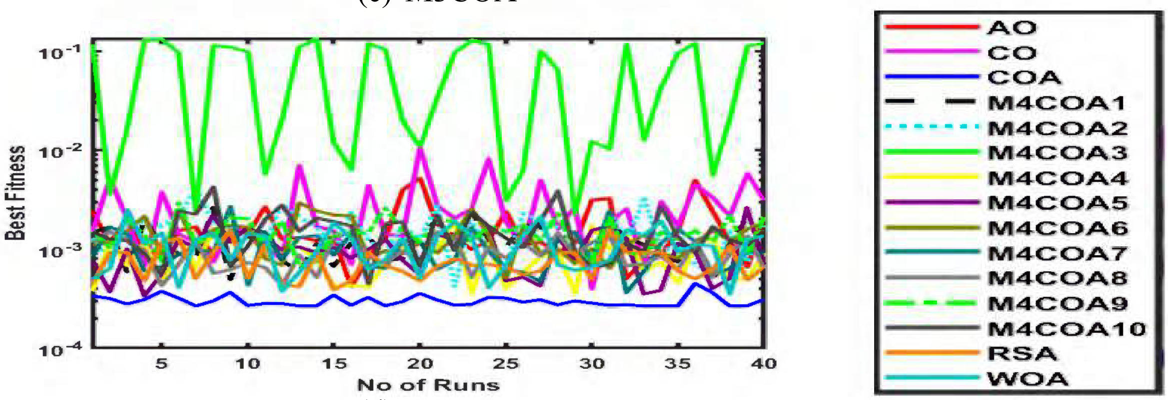
(a) M1COA



(b) M2COA

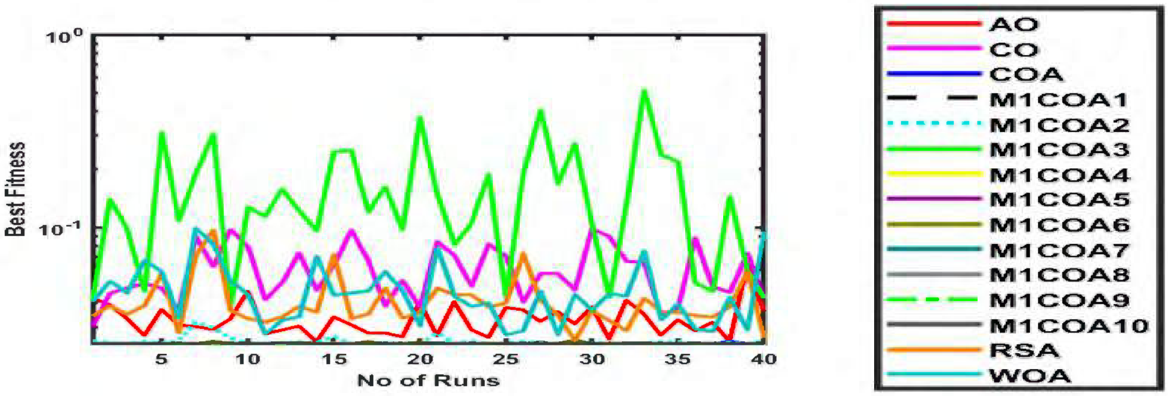


(c) M3COA

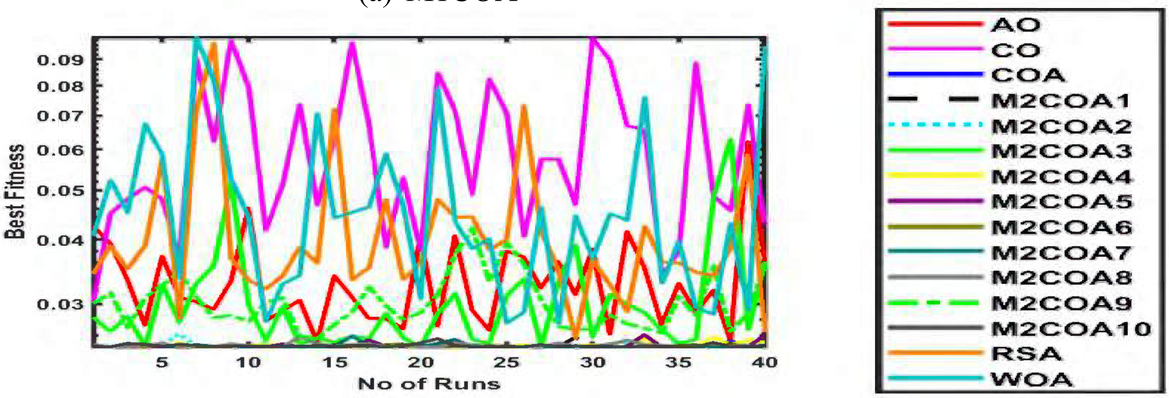


(d) M4COA

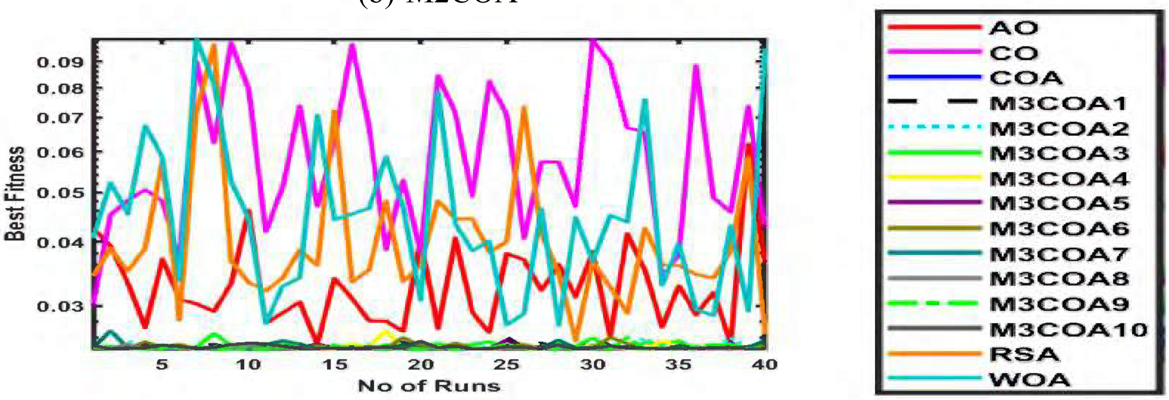
Figure 27: Statistical curves of M1COA1-M1COA10, M2COA1-M2COA10, M3COA1-M3COA10, M4COA1-M4COA10, CO, COA, WOA, and RSA at noise level m(k) = 1.9×10^{-2}



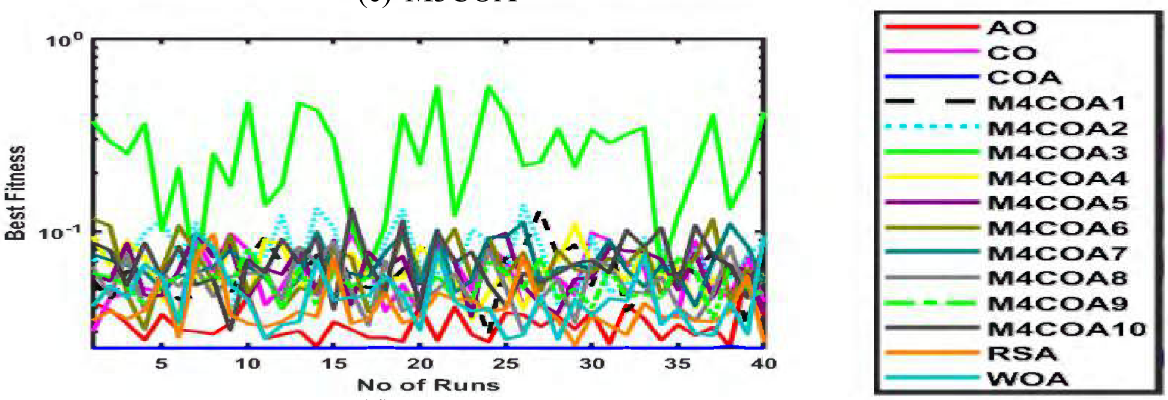
(a) M1COA



(b) M2COA



(c) M3COA



(d) M4COA

Figure 28: Statistical curves of M1COA1-M1COA10, M2COA1-M2COA10, M3COA1-M3COA10, M4COA1-M4COA10, CO, COA, WOA, and RSA at noise level m(k) $= 1.9\times10^{-1}$

Table 30: Complexity analysis of M1COA1-M1COA10, M2COA1-M2COA10, M3COA1-M3COA10, M4COA1-M4COA10, CO, COA, WOA, and RSA.

Methods	Avg_Time	STD	Methods	Avg_Time	STD	Methods	Avg_Time	STD
AO	3.1620	0.1474	**M2COA1**	2.5553	0.0640	**M3COA6**	2.5825	0.1317
CO	3.5616	0.1823	**M2COA2**	2.5711	0.1424	**M3COA7**	2.5975	0.2804
COA	2.5934	0.1998	**M2COA3**	2.5632	0.0859	**M3COA8**	2.5946	0.2425
WOA	1.8466	0.0646	**M2COA4**	2.5669	0.0945	**M3COA9**	2.5915	0.2036
RSA	2.4244	0.0894	**M2COA5**	2.5674	0.0923	**M3COA10**	2.5547	0.0854
M1COA1	2.4950	0.1589	**M2COA6**	2.5630	0.0904	**M4COA1**	2.4847	0.1027
M1COA2	2.6816	0.1051	**M2COA7**	2.5675	0.0832	**M4COA2**	2.6687	0.0509
M1COA3	2.9421	0.1365	**M2COA8**	2.5603	0.0930	**M4COA3**	2.9662	0.1959
M1COA4	2.5305	0.1221	**M2COA9**	2.5616	0.1018	**M4COA4**	2.5564	0.1913
M1COA5	2.4715	0.1240	**M2COA10**	2.6056	0.2489	**M4COA5**	2.4943	0.1683
M1COA6	2.5621	0.1484	**M3COA1**	2.5749	0.1289	**M4COA6**	2.5604	0.1144
M1COA7	2.5334	0.2687	**M3COA2**	2.5870	0.2137	**M4COA7**	2.5061	0.1598
M1COA8	2.3161	0.1806	**M3COA3**	2.5710	0.1388	**M4COA8**	2.2884	0.1104
M1COA9	2.2623	0.1038	**M3COA4**	2.5663	0.1193	**M4COA9**	2.2269	0.0676
M1COA10	2.6022	0.2602	**M3COA5**	2.5610	0.0781	**M4COA10**	2.5528	0.0753

CHAPTER 5

CONCLUSIONS AND FUTURE WORK

5.1. Conclusions

- The swarm intelligence algorithm based Chaotic Crayfish Optimization Algorithm is proposed for the identification of Electro Hydraulic Actuator System.
- The chaotic variants of COA are developed by integrating ten well established chaotic maps (Chebyshev, Circle, Gauss, Iterative, Logistic, Piecewise, Sine, Singer, Sinusoidal and Tent) in the temperature stage, summer resort stage and foraging stage of COA.
- Statistical complexity and convergence analysis on multiple independent executions verifies the reliability of M1COA9 for EH-AS identification against AO, CO, COA, WOA, RSA, M1COA1, M1COA2, M1COA3, M1COA4, M1COA5, M1COA6, M1COA7, M1COA8, M1COA10, M2COA1, M2COA2, M2COA3, M2COA4, M2COA5, M2COA6, M2COA7, M2COA8, M2COA9, M2COA10, M3COA1, M3COA2, M3COA3, M3COA4, M3COA5, M3COA6, M3COA7, M3COA8, M3COA9, M3COA10, M4COA1, M4COA2, M4COA3, M4COA4, M4COA5, M4COA6, M4COA7, M4COA8, M4COA9, and M4COA10.

5.2 Future Work

- In future various newly developed optimization methods will be explored for EH-AS identification [71], [72], [73].

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