Optimization of Load Frequency Control Gain Parameters for Stochastic Microgrid Power System

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Abstract*—Interconnected multi-area microgrids are vital for the future of sustainable and reliable power systems. Effective load frequency control (LFC) is indispensable for ensuring their stable operation. This paper introduces a PID-based LFC system tailored for a stochastic microgrid with diverse power sources, including solar, wind, diesel engine generators, and electrical batteries. The gain parameters of the proposed microgrid PID LFC controller are optimized using genetic algorithms (GA), teaching learning-based optimization (TLBO), and cohort intelligence algorithms. Integral time-multiplied absolute error (ITAE) and integral time-squared error (ITSE) serve as the cost functions for all optimization algorithms. The study evaluated the performance of these optimized microgrid PID LFC configurations under random step load disruptions. Our primary findings reveal that the cohort intelligence-optimized PID LFC controller excels in minimizing computation time (upto 76% and 94% lesser than GA and TLBO respectively) and exhibits superior robust response characteristics. Moreover, the cohort intelligence algorithm requires fewer iterations (upto 66% and 90% lesser than GA and TLBO respectively) and enhances power supply quality within the multi-power microgrid electrical framework, specifically in terms of effective load frequency control.

***Keywords*—Genetic Algorithm; Load Frequency Control; Teaching Learning based Optimization; Cohort Intelligence; Integral Time Absolute Error.**

I. INTRODUCTION

Modern power networks face the challenge of managing diverse energy sources, including conventional and renewable sources such as solar, wind, electrical batteries, and diesel generators. Moreover, micorgrids comprising of unconventional power sources hold the key to the energy independence of remote areas of the planet. These networks are characterized by multiple dynamic power demands and frequent frequency disturbances caused by sudden interruptions in microgrid areas and tie lines. To ensure a stable power supply despite varying loads and power sources, interconnected multi-power microgrid frameworks require effective load frequency control (LFC) mechanisms. Minor load variations can be handled by suitable generators that act as the primary backups in the power management systems. These generators and other regulators are required in the microgrid organization to limit the variation of supply frequency in the interlinked power framework as well as the tie lines to meet the varying demands on the overall power architecture. This regulation mechanism is known as load frequency control that plays a critical role in regulating the power grid and maintaining the required power supply quality [1], [2]. Fig. 1 illustrates the dynamic nature of supply and demand in a multi-microgrid power framework.

While researchers have explored various techniques for LFC in microgrid power systems, recent efforts have focused on soft computing methods that have shown promise in enhancing load frequency control in complex energy systems. These methods include neural networks [3], fuzzy logic [4], adaptive neuro-fuzzy logic control [5], fractional order controller [6]–[9], complex order controller [10]–[13], Grey wolf optimization [14], differential evolution [15], particle swarm optimization [16], ant colony optimization [17], artificial bee colony [18], hybrid optimization [19], imperialist competitive algorithm [20], genetic algorithm [21], [22], teaching-learning based optimization [23]–[26], cohort intelligence optimization [27]–[31]. Researchers have investigated various aspects of complex and fractional order modeling and control in various systems [32]–[45]. These applications include micro and nano particle composite machining, precise control of DC motor, tool/chip interface friction while machining aluminum alloys, position control of Quanser servomotor, lean manufacturing, machined surface roughness, bolted joints, non minimum phase systems and many more [46]–[61]. The above mentioned literature review shows that there is a research gap and an ample scope to explore optimization algorithms for optimal tuning of LFC gain parameter, specifically in case of hybrid power source microgrid application.

This paper addresses the problem statement of 'investigation of selected optimization algorithms to tune PID-based load frequency controller gain parameters for interconnected diesel-solar-battery and diesel-wind-battery power systems'. We em-

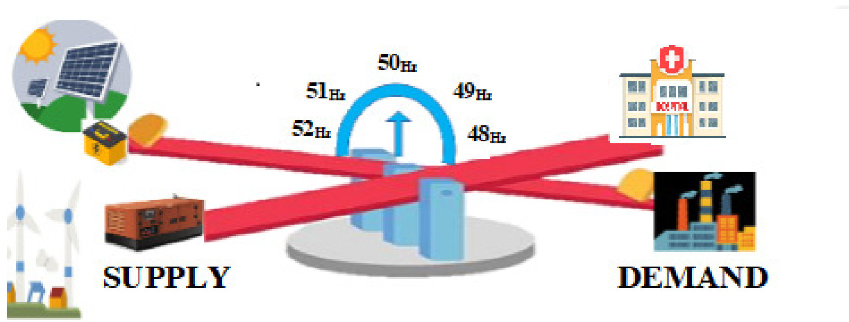

Fig. 1. See saw representation of multi microgrid power system.

ployed genetic algorithms (GA), teaching-learning-based optimization (TLBO), and cohort intelligence optimization (CIO) to tune these parameters. This research aims to:

I Optimize the PID-based load frequency controller gain parameters for the proposed interconnected diesel-solar-battery and diesel-wind-battery power system using various algorithms such as GA, TLBO, and CIO

II Compare the dynamic performances of microgrid PID LFC controllers optimized by GA, TLBO, and CIO using different cost functions such as integral time absolute error(ITAE) and integral time square error(ITSE). Analyze the effectiveness of soft computing solutions across various optimization algorithms by changing the size of the initial solution vector. Validate the effectiveness of optimised controllers by applying random step load perturbations

Exploration of the above mentioned objectives is important from the point of view of facilitating successful microgrid implementations in remote parts of the world that are not well connected to the main supply grids. This study makes the following research contributions:

1) Robust load frequency control in a hybrid multi source microgrid framework
2) Exploration of different optimization algorithms for optimal tuning of the load frequency control gain parameter

The following section 2 gives details of the multi-power interconnected microgrid architecture considered for load frequency control in the present study. Section 3 deals with soft computing techniques. Further, section 4 shows the detailed study of simulation results for the dynamic of microgrid power systems with various scenarios involved in soft computing techniques then followed by a conclusion in section 5.

II. System Under Inspection

In this work, a two-region diesel-wind-battery and diesel-solar-battery microgrid power framework have been investigated. This microgrid power framework comprises an actuator, a diesel generator, and the power organizations integrated with suitable solar, wind, and battery power sources. This specific multi-source microgrid constitution includes a combination of conventional and non-conventional energy sources, which is an ideal state of transition to green energy. This microgrid power scheme was designed using the MATLAB-R2014-32 bit tool, and this proposed model of this framework is displayed in Fig. 2.

The parameters of the microgrid power system shown in Fig. 2 are given in the appendix. In the current study, PID-based LFC regulators /controllers were utilized in both interconnected microgrid areas. The mathematical expression of the PID LFC regulator is displayed in Eq. (1), where K_p, K_i, and K_d are the controller gains and ACE stands for the area control errors. The area control error refers to the difference between the scheduled/proposed and actual power generation of a microgrid area, considering frequency bias effects.

$$PID = K_p + K_i \int ACE\, dt + K_d \frac{d(ACE)}{dt} \qquad (1)$$

To ensure adequate frequency control as required by several industries, it is mandatory to use auxiliary controllers in the framework. Related literature shows that PID regulators are generally used in industries because of their simplicity in construction. The primary benefit of the PID regulator is that it offers controller boundaries in the coordinate axis framework.

To optimize the design of the regulator, it is additionally important to characterize the cost function to maximize the

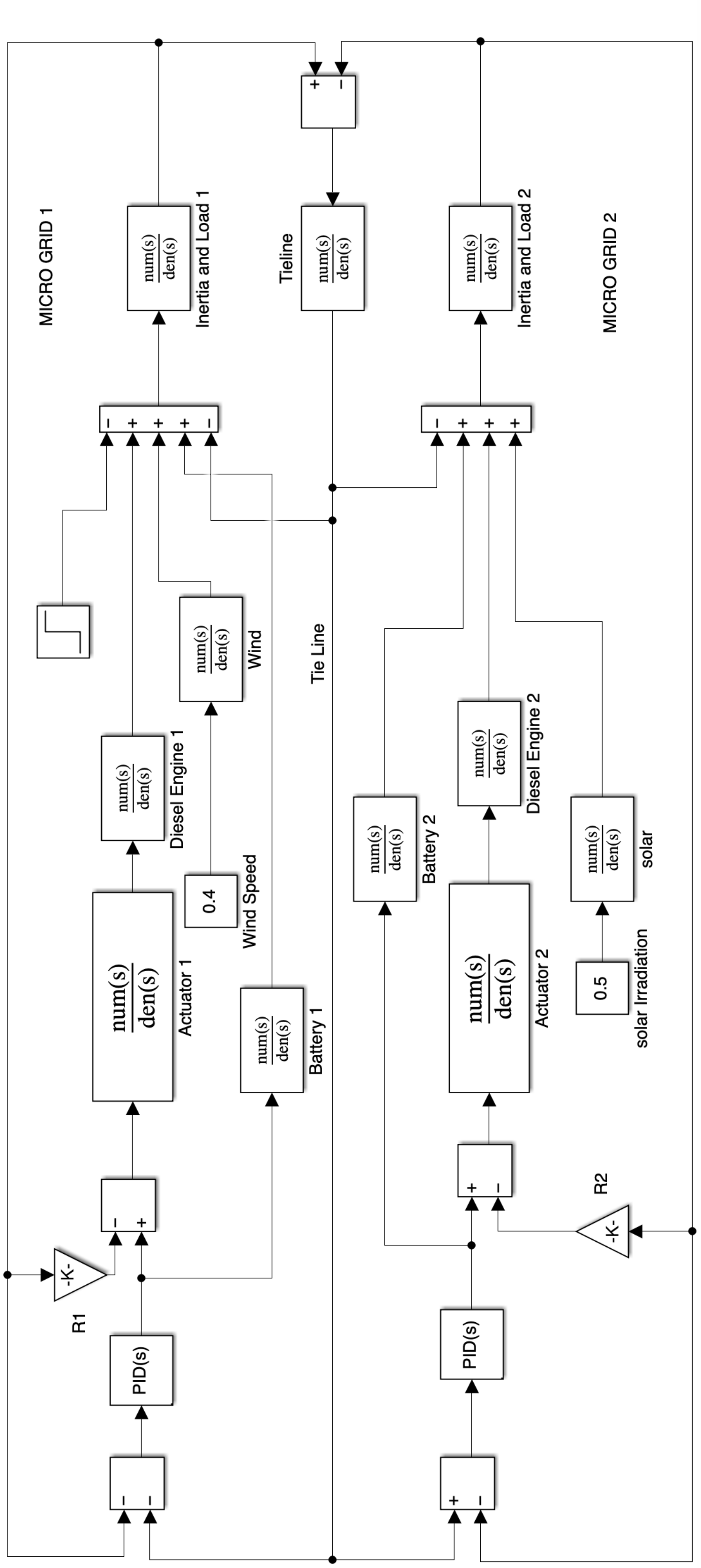

Fig. 2. Matlab Simulink model of the interconnected multi power multi area microgrid power system.

stable performance of the power framework. Cost/fitness function refers to the objective function to be minimized by an optimization algorithm. In this regard, there are different cost functions that may be considered. However, literature shows that the ITAE and ITSE ensure superior performances [20]. The ITAE integrates absolute values of control errors over successive timesteps. The ITSE, on the other hand, integrates the square of control error over successive timesteps. These cost functions ensure improved transient behaviour that is, reduced settling time and oscillations. Furthermore, the proposed framework is also examined with comparisons among the ITAE and ITSE to analyze the best cost function applicable for the microgrid considered in this work. The mathematical representations of ITAE and ITSE for the LFC problem are mentioned in Equations (2) and (3) respectively.

$$ITAE = \int_0^{t_{\text{sim}}} (t \cdot |ACE_1|\, dt) + \int_0^{t_{\text{sim}}} (t \cdot |ACE_2|\, dt) + \int_0^{t_{\text{sim}}} (t \cdot |\Delta P_{\text{tie }12}|\, dt) \tag{2}$$

$$ITSE = \int_0^{t_{\text{sim}}} (t \cdot (ACE_1)^2\, dt) + \int_0^{t_{\text{sim}}} (t \cdot (ACE_2)^2\, dt) + \int_0^{t_{\text{sim}}} (t \cdot (\Delta P_{\text{tie }12})^2\, dt) \tag{3}$$

The following section gives details of the different algorithms employed in this study for microgrid LFC gain parameter optimisation.

III. Soft Computing Algorithms

This section introduces the optimization algorithms considered in the present study. Their specific parameter settings have been tabulated in appendix part (b). These algorithms include socio-inspired as well nature-inspired algorithms, which have been successfully applied across many domains [62], [63].

A. Genetic Algorithm (GA)

The GA is a technique for optimizing constraint-unconstrained problems and is based on Darwin's principle of survival of the fittest. It was developed by John Holland in 1965. Genetic algorithms are generally used to generate better solutions through optimization for random search problems by depending on bio-influenced operators like reproduction, crossover, mutation, and best solution selection. From an initial population of probable solutions, a set of chromosomes or solution features are selected which can be mutated and altered to generate new offspring or solutions. The chromosomes are represented as binary strings of 0s and 1s, although other encoding forms are also possible. The success of GM depends on the proper selection and initialization of the genetic operators as well as conditions of heuristics and termination. Generally, GA provides good optimal solutions but a few deficiencies have also been observed in GA performances such as the higher consumption of computation time, no guarantee of obtaining a global optimum, difficult selection of the stopping criterion, and multiple trials required to arrive at the best optimal solution of a problem. In a nutshell, GA replicates the process of natural selection of best survivors/performers of a species to reproduce and generate newer generations having progressively better members. GA was selected for the microgrid controller parameter optimization because it provides optimal or near optimal solutions in a relatively shorter computation timespans [64]–[68].

B. Teaching Learning based Optimization (TLBO)

TLBO is a stochastic society-based technique suggested by Rao et.al in 2011. The knowledge transfer process inspires the TLBO algorithm in a classroom environment. The main user-defined parameters for optimization are the teacher/student size and the number of training cycles. The design of this algorithm consists of two phases particularly the teacher phase and the learner phase. In the teacher phase, new results are produced using the previous best result and the population's mean. Secondly, a greedy option is applied i.e. the new results are accepted if it is superior to the previous result. Thereafter, in the learner phase, the new result is produced using a partner result again followed by the greedy option. Partner result is considered for new result generation only in the learner phase, not in the teacher phase. Furthermore, all remaining results undergo the teacher phase followed by the learner phase.

The teaching phase is defined as follows,

$$X_{\text{new}} = X + r \cdot (X_{\text{best}} - \text{TeXmean}) \tag{4}$$

Learning phase is defined as follows,

$$X_{\text{new}} = X + r \cdot (X - X_p) \quad \text{if} \quad f < f_p \tag{5}$$

$$X_{\text{new}} = X - r \cdot (X - X_p) \quad \text{if} \quad f \geq f_p \tag{6}$$

Where X= current result, X_{new}=new result, X_{best}= teacher, X_{mean}= mean of initial results, Te= teaching element either 1 or 2, r= random number between 0 and 1 for each variable, X_p= partner result, f= fitness of current result, and f_{new} = fitness of partner result. The basic step-wise design procedure of teaching-learning-based optimization is given as follows:

- Step 1: Fix the population size Np, decision variables, upper and lower limits, and maximum iterations T
- Step 2: Generate random solutions within the domain of decision variables and find the fitness function
- Step 3: Select teacher, xbest and determine the mean of the class xmean
- Step 4: Determine the new solution for the teacher phase of the first student

Step 5: Apply corner boundary strategies if the new solution violates the bounds
Step 6: Evaluate the fitness of the bounded solution
Step 7: Perform the greedy option to update the population
Step 8: Select the partner solution
Step 9: Find the new solution through the learner phase
Step 10: Evaluate the fitness values of the bounded solution
Step 11: Perform the greedy selection to update the population

The TLBO algorithm simulates a teacher-learner based classroom environment for optimising single objective problems effectively. It was used in the present study because of its inherent simplicity of requiring minimal prameters for tuning [69]–[74].

C. Cohort Intelligence Optimization (CIO)

CIO is a socio-influenced self-regulating algorithm that comprises inherent, self-accomplished, and rational training iterations, which was developed by Kulkarni in 2013. In this algorithm, each society is a set of self-involved members (cohorts), and every member is devoted to developing and improving himself. Development of knowledge among cohorts is possible through training from each other. Furthermore, training is attained through communication and as well through a championship among the members. It is essential to indicate that this training may lead to an abrupt development in members' attitudes. Anyhow, it is also possible for certain individuals that training and further development are gradual. In a group of learners, some students will learn quickly whereas others will be very slow while learning. So there are basically slow learners and fast learners. This is because training and associative development depend upon the member being trained as well as the member whose qualities the trainee is trying to follow or trying to adapt. As the members are trained, the opportunities for improving the member solutions increase.

The cohort intelligence optimization algorithm supplies design procedure is outlined as follows:

Step 1: Initialize the cohort(C), decision variables, upper and lower limits, and maximum iterations T
Step 2: Controller gain values (cohort characters) are negotiated for all cohorts as cost functions using ITAE / ITSE
Step 3: The chance of every cohort being followed by another, the cohort is calculated based on the fitness function. Others follow the cohort with the best fitness function.
Step 4: The entire cohort group updates its fitness function parameters by expanding or lowering them within the prescribed limits.
Step 5: Convergence is decided based on the most permissible iterations or the minimum changes between successive cohort behaviours between training iterations.

CIO optimizes system performance based on the progressive mutual learning and competitive behaviour of the solution candidates, or cohorts. CIO was used in the present work because it involves relatively lesser functional evaluations per iteration, consumes reasonable computation time and is generally robust throughout the optimization process [75]–[80].

IV. Result Analysis

In the study, firstly the transfer function design of the interdependent microgrid power framework was created in a Matlab environment [81] as displayed in Fig. 2. Two distinct PID LFC regulators were designed for every microgrid unit to regulate the variation in frequencies and tie-line power. The gain values of the PID regulator were optimized by using the following soft computing techniques GA, TLBO, and CIO. Further, the effectiveness of numerical computations has been addressed by adjusting the size of the chromosome in GA / Population size in TLBO and Cohort numbers in CIO by considering various scenarios namely S1, S2, S3 for ITAE employed cost function and S4, S5, S6 for ITSE used cost function. These scenarios included three, ten and 50 chromosomes (GA), population (TLBO) and cohorts (CIO) respectively. Table I clearly shows that the CIO-based technique takes very less computation time than GA and TLBO algorithms for all the scenarios (S1-S6). Additionally, it may be noticed that CIO consumes lesser iterations for getting the best solutions for both cost functions, as well. These findings establish the superiority of CIO over GA and TLBO in case of single objective optimization problems such as the microgrid LFC control problem investigated in the present work.

The optimal gain values of the two areas PID LFC regulators are mentioned in Table II. The ITAE and ITSE determined in Eqs. (4-5) were assessed by simulating the microgrid model for a 1% step load in area 1. The simulated response of the system with both regulators is shown in Figs. 3- 29. All figure captions point out the best performing scenario for each algorithm along with the specific distinguishing performance criteria such as overshoots, undershoots and/or settling time. The resultant response metrics, for example, settling time and oscillations for ITAE and ITSE are listed in Table IV. Furthermore, the associated performances are discussed in the following sections.

A. ITAE cost function results

1) Genetic algorithm performance through ITAE cost function: Figs. 3, 4 and 5 represent the system performance of the genetic algorithm based on Integral Time Absolute Error through initial chromosome selections of 3, 10, and 50. It takes 600, 213 and 158 iterations to get the best solutions in 35, 33 and 123 minutes respectively. From these results, the best of the best solution is noticed in the case of 10 chromosomes selection for the corresponding 213 iterations in 33 minutes. These results show that GA consumes lesser iterations as

TABLE I

OPTIMIZATION PARAMETERS OF VARIOUS ALGORITHMS FOR SOLAR / WIND / BATTERY / DIESEL GENERATOR BASED MICRO GRID

Particulars	Cost Function	Chromosome/ Population / Cohort	Iteration 1000 / 100 / 50			Computation Time in (minutes)			Best Cost Function		
			GA	TLBO	CIO	GA	TLBO	CIO	GA	TLBO	CIO
Scenario 1 (S1)		3 / 3 / 3	600	1000	203	35	32	9.53	5.055	2.726	2.4609
Scenario 2 (S2)	ITAE	10 / 10 /10	213	100	100	33	53	15.05	2.420	2.417	2.4952
Scenario 3 (S3)		50 / 50 /50	158	50	50	123	85	20.83	2.418	2.417	3.1262
Scenario 4 (S4)		3 / 3 / 3	444	1000	105	21	84	5.1	0.127	0.039	0.0492
Scenario 5 (S5)	ITSE	10 / 10 /10	146	100	100	32	46	17	0.039	0.039	0.0425
Scenario 6 (S6)		50 / 50 /50	126	50	50	168	98	76	0.039	0.039	0.0422

TABLE II

OPTIMIZED LFC CONTROLLER GAIN VALUES OF THE PROPOSED ALGORITHM /MICROGRID SYSTEM

			Controller Gain Values					
Cost Function	Algorithm	Size	Area 1			Area 2		
			Kp1	Ki1	Kd1	Kp2	Ki2	Kd2
		3	0.99666	0.50938	0.41267	0.93394	0.99993	0.38212
	GA	10	1	1	0.00093753	0.84614	0.99999	0.0017237
		50	0.99999	1	0.00008117	0.81247	1	0.0000113
		3	0.96908	0.9995	0.0014573	0.95049	0.99934	0.054337
ITAE	TLBO	10	1	1	0.0000456	0.81208	1	0
		50	0.83898	0.87971	0.016234	0.93353	0.88032	0.15672
		3	0.98738	0.99959	0.00042683	0.99478	0.99896	0.013131
	CIO	10	0.9945	0.99198	0.060044	0.95175	0.99676	0.11902
		50	0.94026	0.96887	0.23177	0.97671	0.8755	0.15785
		3	0.47949	0.93976	0.23247	1	0.34266	0.11291
	GA	10	0.99611	0.99999	0.0024644	0.99996	0.99987	
		50	0.99998	0.99997	0.0000472	0.99998	0.99999	0.0025128
		3	1	1	0.0000881	1	1	3.7772e-15
ITSE	TLBO	10	1	1	7.7479e-07	1	0.99999	0
		50	1	1	7.586e-07	1	1	1.9094e-07
		3	0.94578	0.97925	0.014913	0.9981	0.83656	0.41845
	CIO	10	0.98591	0.97803	0.01059	0.96447	0.93392	0.0088369
		50	0.96424	0.99391	0.014287	0.9754	0.97448	0.088334

higher number of chromosomes are selected. However, the computation times generally rise with increasing chromosomes, indicating higher functional evaluations per iteration for higher chromosomal counts. A few trials of varying choromosomal counts are necessary to arrive at optimal solutions.

2) Teaching Learning-Based Optimization performance through ITAE cost function: Figs. 6, 7 and 8 present the performance of Teaching Learning Based Optimization using the Integral Time Absolute Error through initial populations of 3, 10, and 50 for 1000, 100 and 50 iterations respectively to attain the best solutions in 32, 53 and 85 minutes respectively. From these results, the best of the best solution is observed at population size 3 for the corresponding 1000 iterations in 32 minutes. These ITAE results show that TLBO consumes lesser iterations as higher initial population is selected. However, the computation times generally rise with increasing population, indicating higher functional evaluations per iteration for greater populations. A few trials of varying initial populations are necessary to arrive at optimal solutions.

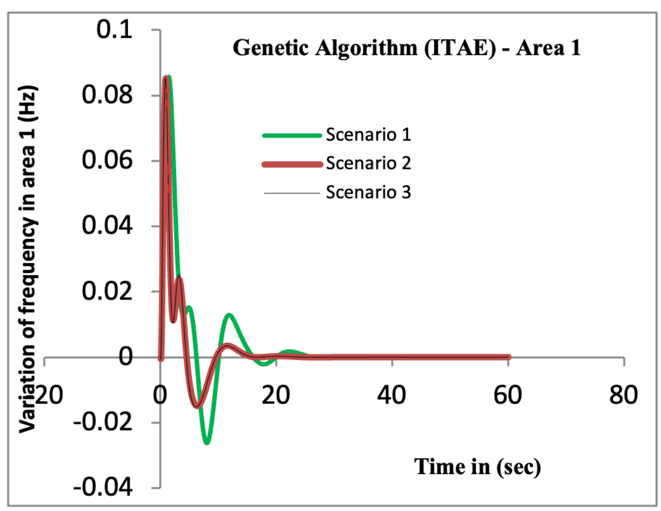

Fig. 3. GA (ITAE) based multi micro grid power system responses in area 1: best responses (lower undershoots) by S2 and S3 (10 and 50 choromosomes respectively).

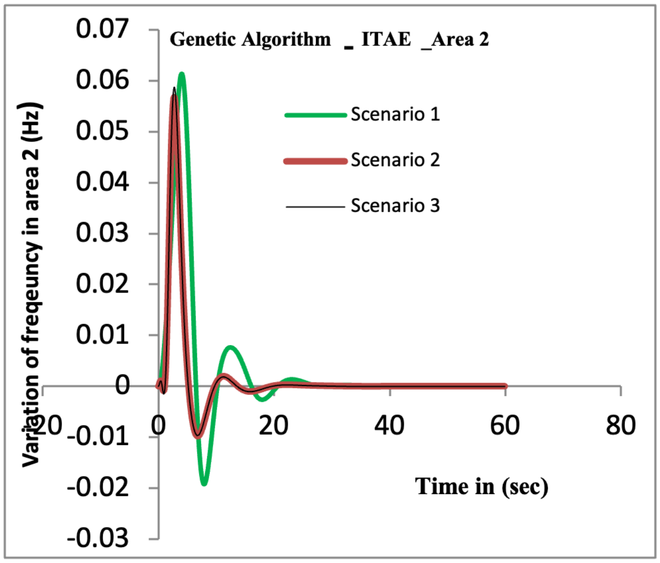

Fig. 4. GA (ITAE) based multi micro grid power system responses in area 2: best responses (lower undershoots and overshoots) by S2 and S3 (10 and 50 choromosomes respectively).

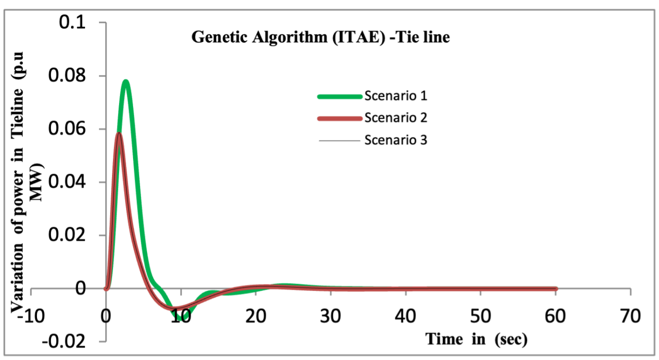

Fig. 5. GA (ITAE) based multi micro grid power system responses in tie line: best responses (lower undershoots and overshoots) by S2 and S3 (10 and 50 choromosomes respectively).

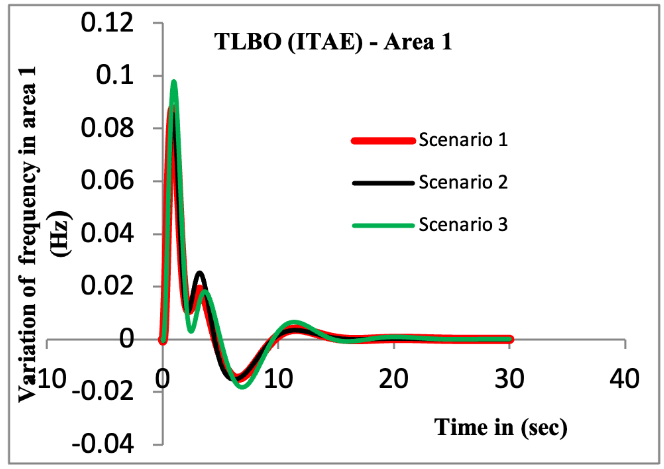

Fig. 6. TLBO (ITAE) based multi micro grid power system responses in area 1: best responses (lower undershoots and overshoots) by S1 and S2 (3 and 10 population size respectively).

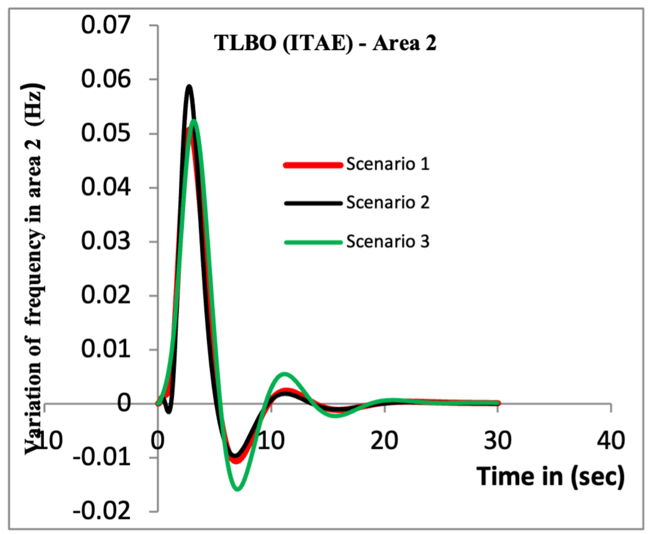

Fig. 7. TLBO (ITAE) based multi micro grid power system responses in area 2: best response (lower undershoot and overshoot) by S1 (3 population size).

3) Cohort Intelligence performance through ITAE cost function: Figs. 9, 10 and 11 produce the superior performance of cohort intelligence based on Integral Time Absolute Error through initial cohort selections of 3, 10 and 50. It takes 203, 100 and 50 iterations, to obtain the best solutions in 9.53, 15.05 and 20.83 minutes respectively. From these results, the best of the best solution is noticed at cohort selection 3 for the corresponding 203 iterations in 9.53 minutes. These results show that CIO consumes lesser iterations as higher cohorts are selected. However, the computation times generally rise with increasing cohorts, indicating higher functional evaluations per iteration for more cohorts. A few trials of varying cohorts are necessary to arrive at optimal solutions.

B. ITSE cost function results

1) Genetic algorithm performance through ITSE as cost function: Figs. 15, 16 and 17 show the performances of the genetic algorithm optimized PID LFC multigrid controllers based on Integral Time Squared Error through the initial chromosome selections of 3, 10, and 50. It takes 444, 146 and 126 iterations respectively similarly obtaining the best solutions in 21, 32 and 168 minutes respectively. From these results, the best of the best solution is noticed at 50 chromosomes for the corresponding 126 iterations in 168 minutes. These ITSE results also show that GA consumes lesser iterations as higher number of chromosomes are selected. The computation times generally

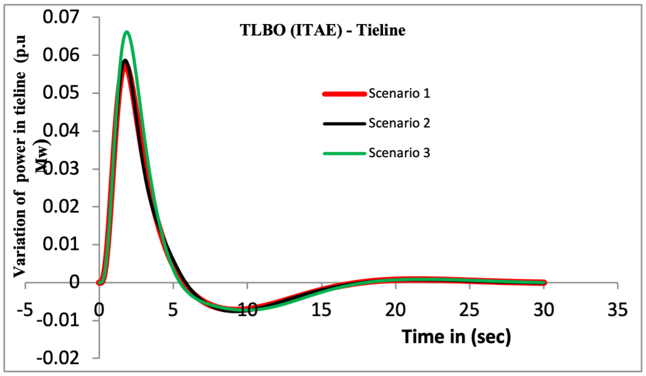

Fig. 8. TLBO (ITAE) based multi micro grid power system responses in tie line: best responses (lower overshoots) by S1 and S2 (3 and 10 population size respectively).

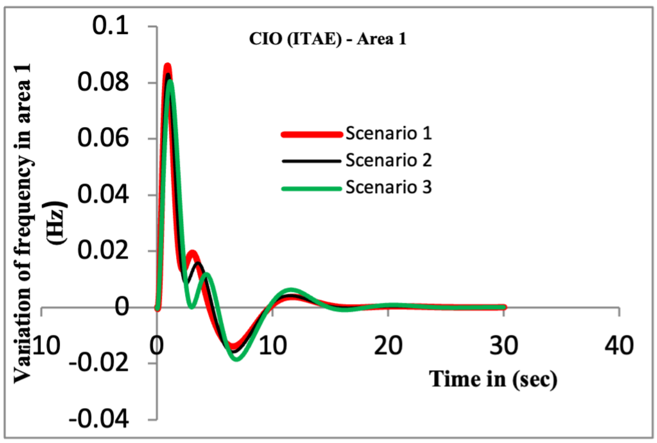

Fig. 9. CIO (ITAE) based multi micro grid power system responses in area 1: best responses (lower undershoots and overshoots) by S1 and S2 (3 and 10 cohorts respectively).

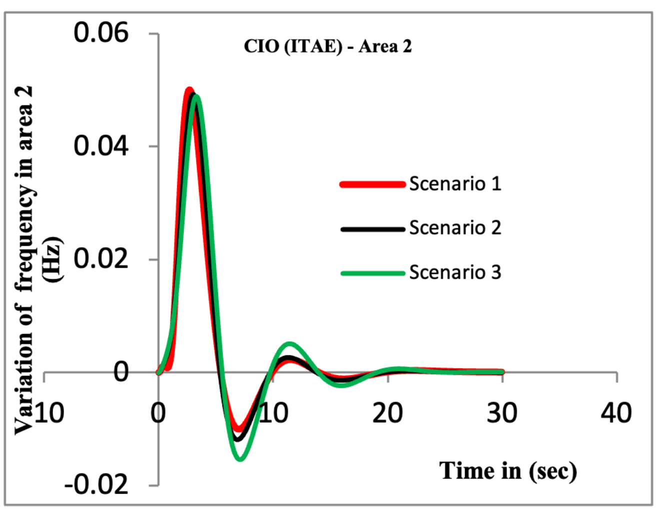

Fig. 10. CIO (ITAE) based multi micro grid power system responses in area 2: best responses (lower undershoots and overshoots) by S1 and S2 (3 and 10 cohorts respectively).

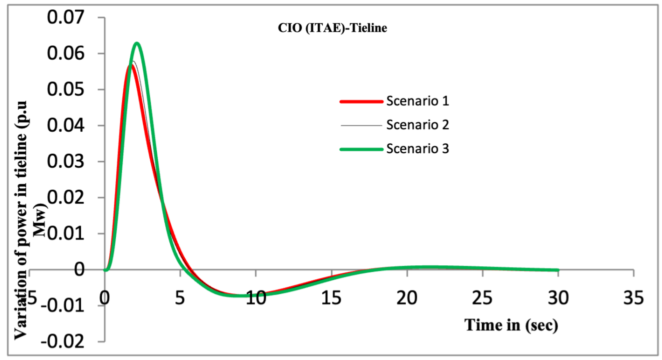

Fig. 11. CIO (ITAE) based multi micro grid power system responses in tie line: best response (lower undershoot and overshoot) by S1 (3 cohorts respectively).

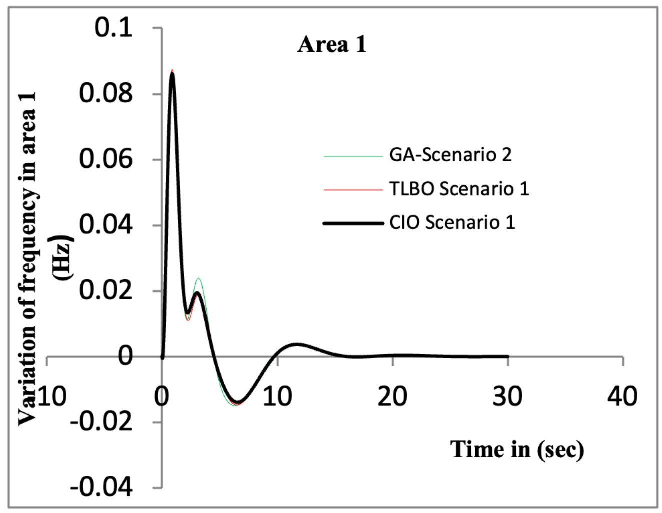

Fig. 12. GA, TLBO and CIO based ITAE optimised multi micro grid power system responses in area 1: best response (lower undershoot and overshoot) by CIO

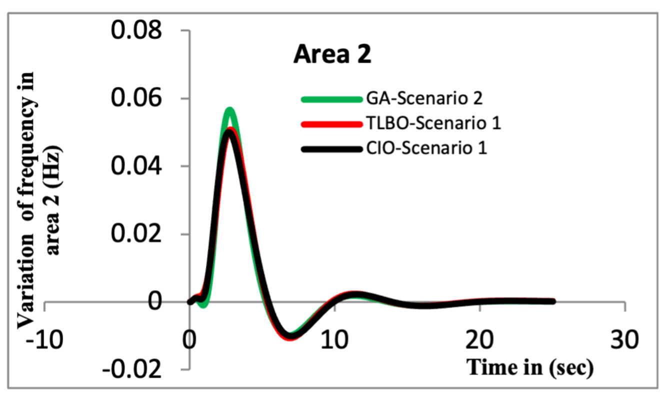

Fig. 13. GA, TLBO and CIO based ITAE optimised multi micro grid power system responses in area 2: best response (lower undershoot and overshoot) by CIO

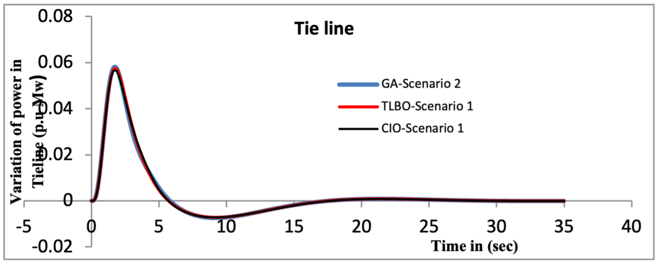

Fig. 14. GA, TLBO and CIO based ITAE optimised multi micro grid power system responses in tie line: best response (lower undershoot and overshoot) by CIO

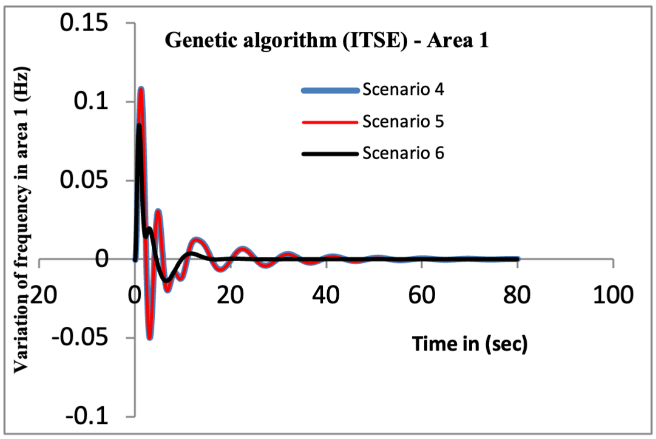

Fig. 15. GA (ITSE) optimised multi micro grid power system responses in area 1: best response (lower undershoot and overshoot) by S6 (50 choromosomes).

rise with increasing chromosomes, indicating higher functional evaluations per iteration for higher chromosomal counts. A few trials of varying choromosomal counts are necessary to arrive at optimal solutions.

2) Teaching Learning-Based Optimization performance through ITSE cost function: Figs. 18, 19 and 20 depict the performances of Teaching Learning Based Optimization optimized PID LFC multigrid controllers using the Integral Time Squared Error through initial population selections of 3, 10, and 50 consuming 1000, 100 and 50 iterations, respectively to attain the best solutions in 84, 46 and 98 minutes respectively. From these results, the best of the best solution is observed at population 3 for the corresponding 1000 iterations in 84 minutes. These ITSE results show that TLBO consumes lesser iterations as higher initial population is selected. However, the computation times generally rise with increasing population, indicating higher functional evaluations per iteration for greater populations. A few trials of varying initial populations are necessary to arrive at optimal solutions.

3) Cohort Intelligence performance through ITSE cost function: Figs. 21, 22 and 23 display the performances of cohort intelligence optimized PIDLFC architectures on Integral Time

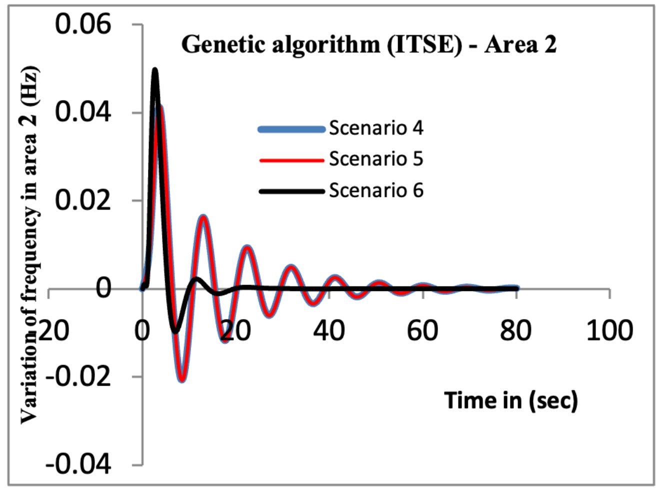

Fig. 16. GA (ITSE) optimised multi micro grid power system responses in area 2: best response (lower undershoot and overshoot) by S6 (50 choromosomes).

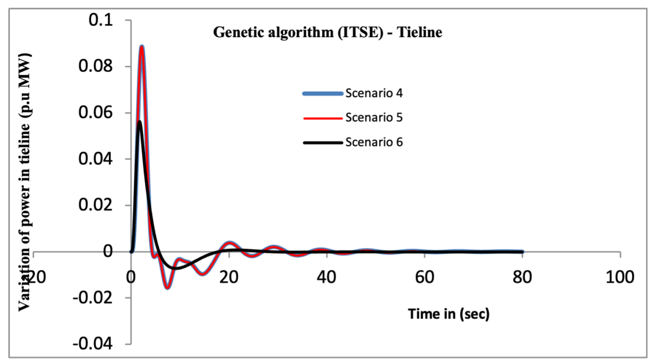

Fig. 17. GA (ITSE) optimised multi micro grid power system responses in tie line: best response (lower undershoot and overshoot) by S6 (50 choromosomes).

Squared Error through initial cohorts selections of 3, 10, and 50. This algorithm consumes 105, 100 and 50 iterations, to accomplish the best solutions in 5.1, 17, 76 minutes respectively. From these results, the best of the best solution is seen at 50 cohorts for the corresponding 203 iterations in 76 minutes. These ITSE results show that CIO consumes lesser iterations as higher cohorts are selected. However, the computation times generally rise with increasing cohorts, indicating higher functional evaluations per iteration for more cohorts. A few trials of varying cohorts are necessary to arrive at optimal solutions.

C. Main findings

From Figs. 12, 13, 14 and 24, 25 and 26 and Table III, it is evident that the Cohort intelligence-based PID regulator gives better results compared to GA and TLBO in terms of lower undershoots and overshoots of the system responses. These findings reiterate the superiority of CIO over GA and TLBO in case of single objective optimization problems such as

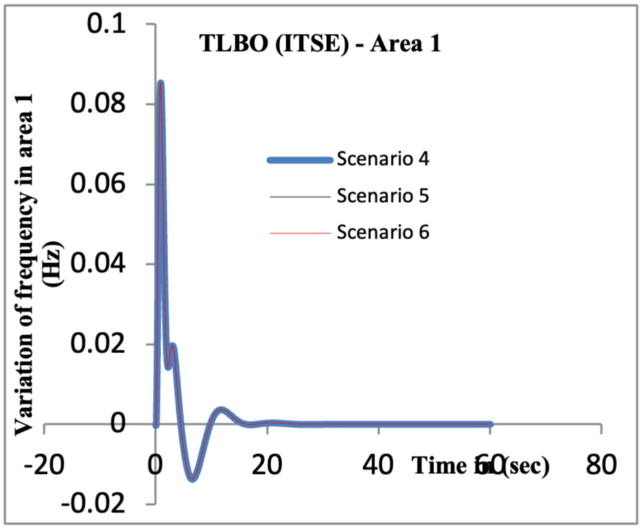

Fig. 18. TLBO (ITSE) optimised multi micro grid power system responses in area 1: best responses (same under and overshoots) by S4, S5 and S6 (3, 10 and 50 population sizes).

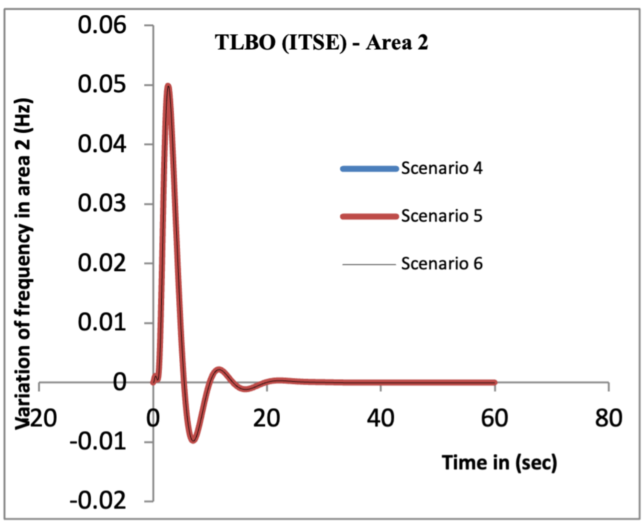

Fig. 19. TLBO (ITSE) optimised multi micro grid power system responses in area 2: best responses (same under and overshoots) by S4, S5 and S6 (3, 10 and 50 population sizes).

the microgrid LFC control problem investigated in the present work. Figs. 27, 28 and 29 examine the improvement of ITAE-based cohort intelligence optimized results as compared to the ITSE-based cohort intelligence regulator. In other words, CIO algorithm employed with ITAE cost function provides better LFC control results as compared to CIO-ITSE. This result indicates that consideration of absolute errors as cost function leads to more optimal solutions in LFC control as opposed to squared errors, which prove slightly less effective in optimal solution approximations. In a similar study [69], the authors used GA, TLBO, CIO and Differential Evolution (DE) to optimize PID

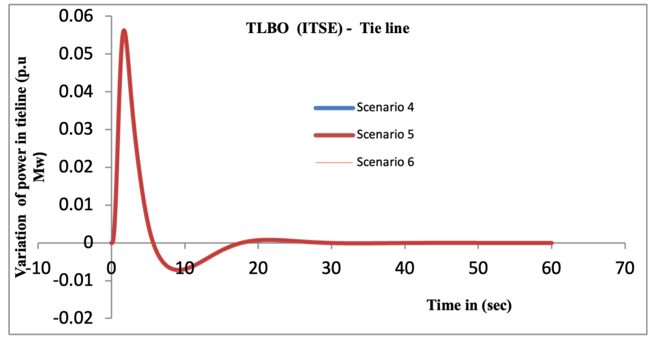

Fig. 20. TLBO (ITSE) optimised multi micro grid power system responses in tie line: best responses (same under and overshoots) by S4, S5 and S6 (3, 10 and 50 population sizes).

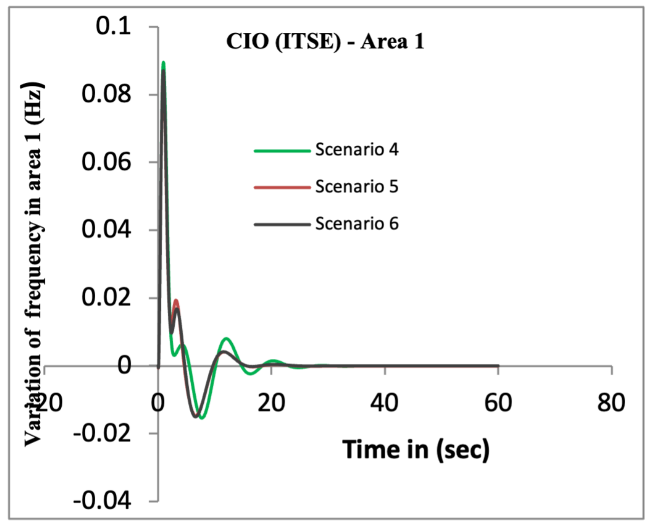

Fig. 21. Cohort Intelligence based ITSE optimised multi micro grid power system responses in area 1: best response (lower overshoots) by S6 (50 cohorts).

regulator of a multisource single area power framework. This study also found that the CIO based minimization of the ITAE cost function yielded the lowest response settling time and oscillations in case of multi-controller multi-source single area framework. The CIO-ISE (integral squared error) provided the best dynamic response in case of single-controller multi-source single area framework. Further, the potential of the proposed CIO-optimised regulator is shown in the present study by giving it random step load perturbations in Figs. 30 (step load inputs) and 31 (microgrid system response for area 1, area 2 and tie line). These results show that the LFC microgrid controller tuned with CIO optimized parameters is quite robust and stable in the presence of step load perturbation inputs, making it suitable for microgrid applications.

The rate of improvement of the cohort intelligence optimized PID LFC performance is compared with the genetic algorithm (Sl-66%, S2-53%, S3-68%, S4-76%, S5-32%, S6-60%) and

TABLE III
REPORT OF FIGURES FOR TRANSIENT PERFORMANCE ANALYSIS

Figure number	**Best transient behaviour**	**Best response**	**Best of Best response**
Fig. 3	Undershoot	S2,S3	
Fig. 4	Both undershoot and overshoot	S2,S3	S2
Fig. 5	Both undershoot and overshoot	S2,S3	
Figure 6	Both undershoot and overshoot	S1,S2	
Figure 7	Both undershoot and overshoot	S1	S1
Fig. 8	Overshoot	S1,S2	
Fig. 9	Both undershoot and overshoot	S1,S2	
Fig. 10	Both undershoot and overshoot	S1,S2	S1
Fig. 11	Both undershoot and overshoot	S1	
Fig. 12	Both undershoot and overshoot	CIO	
Fig. 13	Both undershoot and overshoot	CIO	CIO - (S1)
Fig. 14	Both undershoot and overshoot	CIO	
Fig. 15	Both undershoot and overshoot	S6	
Fig. 16	Both undershoot and overshoot	S6	S6
Fig. 17	Both undershoot and overshoot	S6	
Fig. 18	Same for all	S4,S5,S6	
Fig. 19	Same for all	S4,S5,S6	S4
Fig. 20	Same for all	S4,S5,S6	
Fig. 21	Overshoot	S6	
Fig. 22	Both undershoot and overshoot	S5,S6	S6
Fig. 23	Undershoot	S5,S6	
Fig. 24	Overshoot	CIO	
Fig. 25	Overshoot	CIO	CIO-(S6)
Fig. 26	Same for all	CIO	
Fig. 27	Both undershoot and overshoot	ITAE	
Fig. 28	Undershoot,overshoot and settling time	ITAE	ITAE
Fig. 29	Overshoot	ITAE	

TABLE IV
TRANSIENT PERFORMANCE ANALYSIS UNDER SCENARIOS 1 & 6

Particulars	Cost Function	Areas	Settling Time in (Sec)			Peak Overshoot in (Hz / p.u.MW)			Peak undershoot (Hz / p.u.MW)		
			GA	TLBO	CIO	GA	TLBO	CIO	GA	TLBO	CIO
Scenario 1 (S1)	ITAE	Del F1	36	24	24	0.086	0.088	0.085	0.025	0.015	0.015
		Del F2	37	28	27	0.06	0.05	0.05	0.02	0.01	0.01
		Tie line	34	30	30	0.08	0.06	0.055	0.01	0.01	0.007
Scenario 6 (S6)	ITSE	Del F1	28	24	24	0.085	0.085	0.085	0.015	0.015	0.015
		Del F2	33	31	33	0.05	0.05	0.05	0.01	0.01	0.01
		Tie line	40	30	30	0.056	0.055	0.055	0.007	0.007	0.007

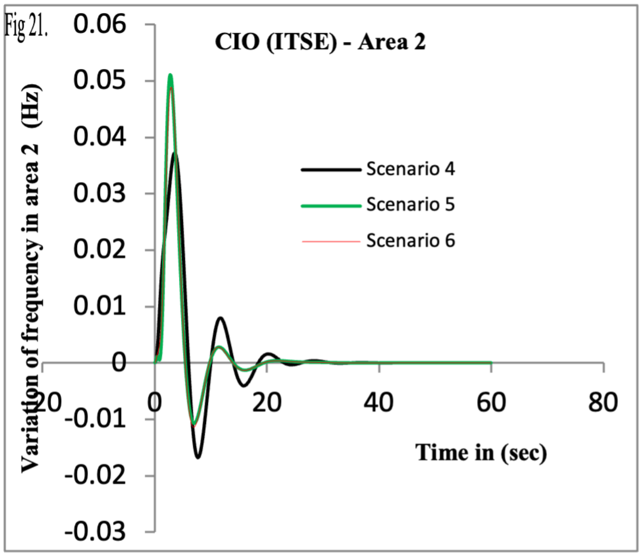

Fig. 22. Cohort Intelligence based ITSE optimised multi micro grid power system responses in area 2: best responses (lower undershoots and overshoots) by S5 and S6 (10 and 50 cohorts).

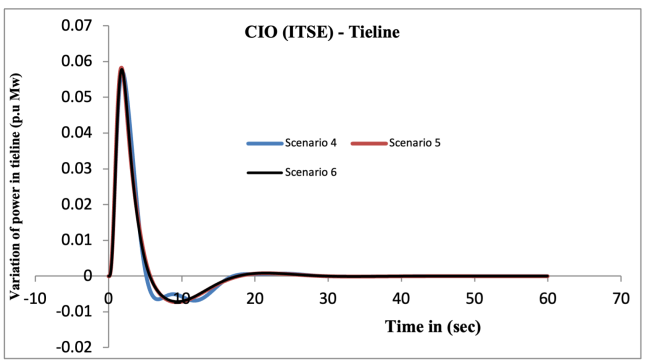

Fig. 23. Cohort Intelligence based ITSE optimised multi micro grid power system responses in tie line: best responses (lower undershoots) by S5 and S6 (10 and 50 cohorts).

teaching learning-based optimization algorithm (Sl-80%, S4-90%) in terms of iterations in Fig. 32. The rate improvement of the cohort intelligence process is compared with the genetic algorithm (Sl-73%, S2-54%, S3-83%, S4-76%, S5-47%, S6-55%) and teaching learning-based optimization algorithm (Sl-70%, S2-72%, S3-76%, S4-94%, S5-63%, S6-23%) in terms of computation time in Fig. 33. From these results, it is evident that the cohort intelligence optimized regulator shows improved results in all the scenarios in terms of the best results with lesser computation, time, and iterations. The evident deficiencies in GA and Teaching Learning Based optimization performances are failures to obtain a good solution and consuming a lot of convergence time and iteration as well. This result could be due to the limitations of GA which include premature convergence, difficult in tuning and difficulty in effectively

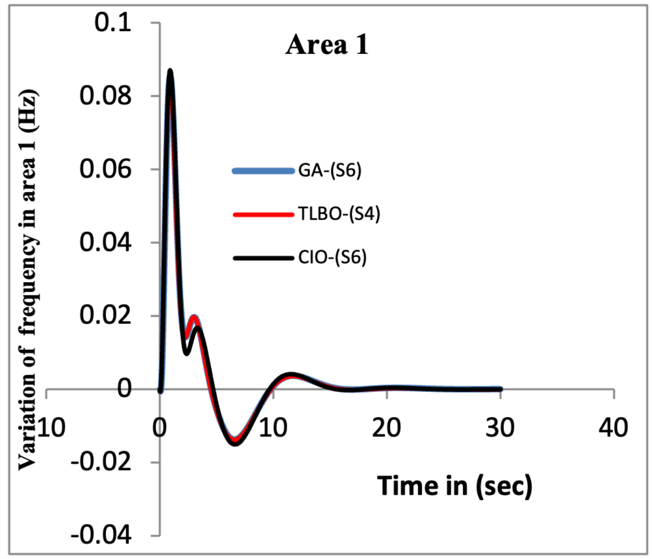

Fig. 24. GA, TLBO and CIO ITSE optimised multi micro grid power system responses in area 1: best response (lower overshoot) by CIO

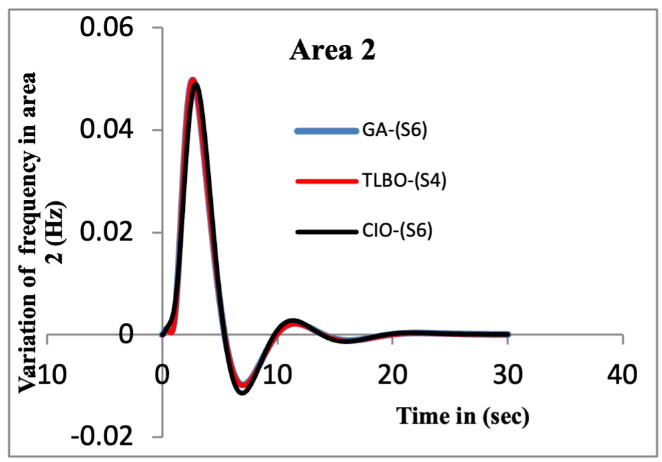

Fig. 25. GA, TLBO and CIO ITSE optimised multi micro grid power system responses in area 2: best response (lower overshoot) by CIO

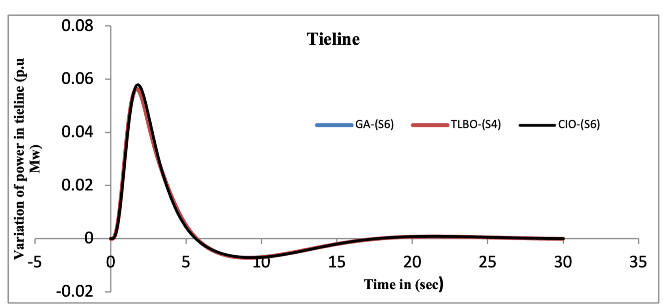

Fig. 26. GA, TLBO and CIO ITSE optimised multi micro grid power system responses in tie line: best response (under and overshoots) by all

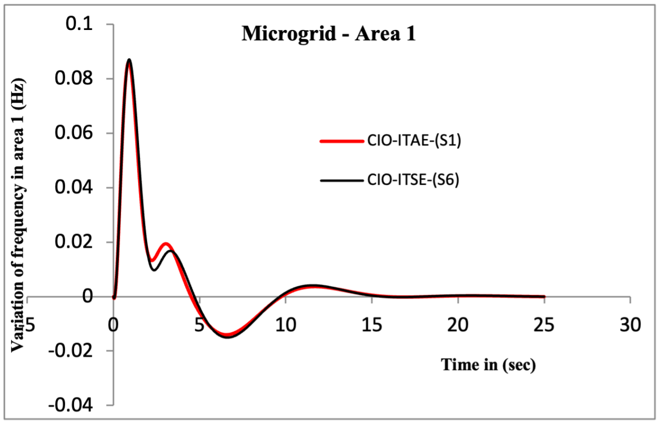

Fig. 27. Best of Best comparative transient response in area 1 of microgrid system: best response (lower undershoot and overshoot) by CIO-ITAE.

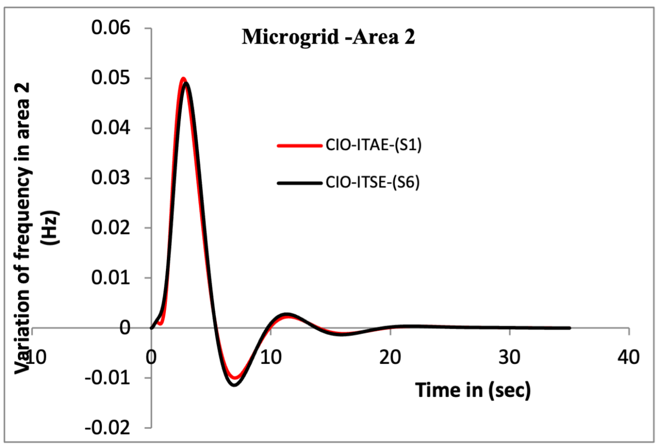

Fig. 28. Best of Best comparative transient response in area 2 of microgrid system: best response (lower undershoot, overshoot and settling time) by CIO-ITAE.

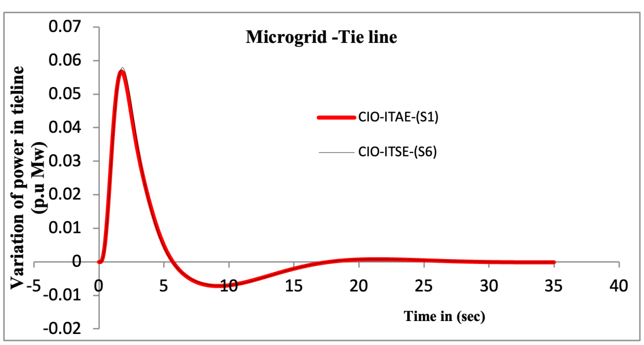

Fig. 29. Best of Best comparative transient response in tie line of microgrid system: best response (lower overshoot) by CIO-ITAE.

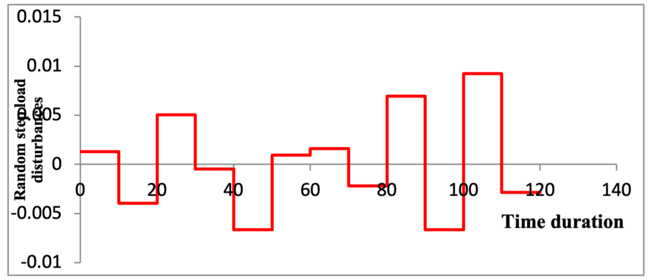

Fig. 30. Random step load perturbation input for microgrid system

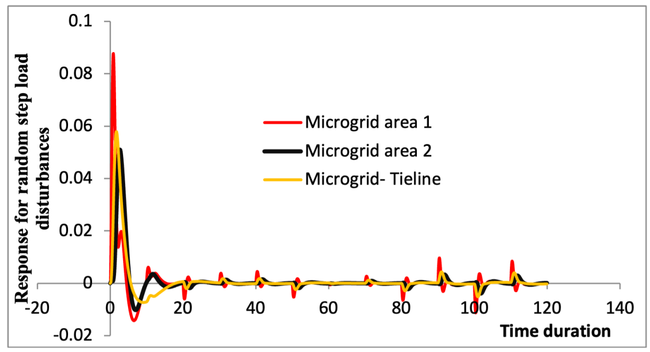

Fig. 31. Microgrid system response for random step load perturbation

handling complex objective functions. TLBO is also prone to premature convergence and lack of effective balance between local and global optima/search regions. In summary, this section presents the results and associated discussions of the attainment of the stated objectives of this study: LFC gain parameter optimization, comparative performance analysis of optimization algorithms and validating the effectiveness of the best performing algorithm under a perturbation step input scenario.

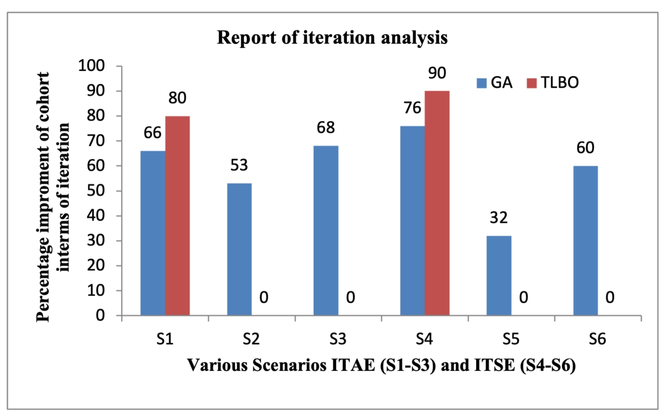

Fig. 32. % improvements in CIO iterations over GA and TLBO in respective scenarios.

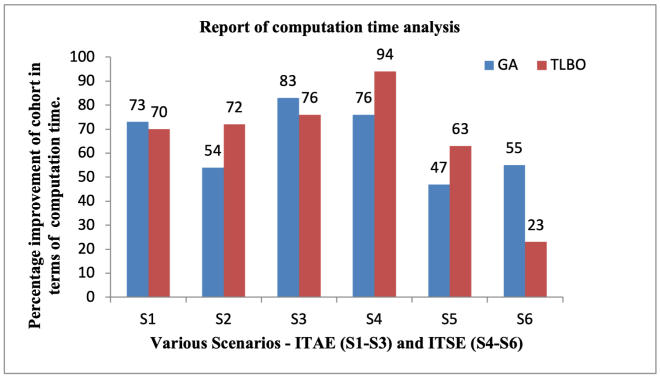

Fig. 33. % improvements in CIO computation time over GA and TLBO in respective scenarios.

V. Conclusions

In this paper, we have systematically assessed the effectiveness of numerical optimization algorithms, including GA, TLBO, and CIO techniques, in the context of a two-area multi-power microgrid framework. By varying the sizes of initial optimization solution vectors, we optimized the performance of our proposed microgrid power scheme using ITAE and ITSE objective functions across all optimization algorithms. Our comparative optimization results analysis clearly demonstrates the superior performance of the Cohort Intelligence Optimization (CIO) algorithm when coupled with a PID controller, especially in the presence of a one-percent step load disturbance, surpassing the performance of GA and TLBO algorithms. Furthermore, we subjected the CIO-optimized PID LFC to a rigorous test by applying random step load perturbations, confirming the robustness and effectiveness of our proposed PID regulator in real-world scenarios of hybrid (conventional and non-conventional) energy source microgrids. These results consistently indicate that the CIO-ITAE optimized PID LFC not only excels in dynamic performance with step load disturbances but also exhibits remarkable robustness, ease of implementation, and cost-effectiveness. Robustness is very important considering the dynamic conditions of supply and demand in a multi source microgrid. The cohort intelligence-optimized PID LFC controller excels in minimizing computation time (up to 76% and 94% lesser than GA and TLBO respectively) and exhibits superior robust response characteristics. Moreover, the cohort intelligence algorithm requires fewer iterations (upto 66% and 90% lesser than GA and TLBO respectively) and enhances power supply quality within the multi-power micro-grid electrical framework, specifically in terms of effective load frequency control.

This research makes a significant contribution to the field of microgrid control by showcasing the practical advantages of the CIO-optimized PID LFC. This research paves way for faster integration of natural energy sources into the conventional/connected power grids, including those of remote locations. The precision achieved by our solution is balanced with traceability, robustness, and affordability.

The algorithmic parameter tuning was limited in the present study to only three scenarios. Further exploration of tuning parameters, especially in case of the genetic algorithm may yield improved optimal solutions. As we move forward, future research in this area may explore further enhancements and applications of the CIO algorithm and PID control in even more complex microgrid systems. These findings hold promise for improving the stability and efficiency of microgrids in diverse real-world settings.

Appendix

a) Micro grid systems parameter [14]

Solar photovoltaic system gain value (K_{pv}) = 0.0075
Time constant of solar photovoltaic system (T_{pv}) = 0.03 sec
Wind turbine system gain value (K_{wtg}) = 1
Time constant of wind turbine system (T_{wtg}) = 1.5 sec
Diesel Engine system gain value (K_e) = 1
Time constant of diesel engine system (T_e) = 3 sec
Battery energy storage system gain value (K_{bess} = 1)
Time constant of battery energy storage system (T_{bess} = 0.1 sec)
Time constant of mechanical valve actuators = (T_2 = 2 sec & T_3 = 3 sec)
Speed regulation coefficients = R_1 = R_2 = 5 Hz/pu MW
Rotor gain values= K_{p1} = K_{p2} = 60
Time constant of rotor swing = T_{p1} = T_{p2} = 18 sec
Tieline coefficient (T_{12}) = 0.225

b) Soft computing parameters

The soft computing parameters for the algorithms explored in this study are displayed in Table V.

TABLE V
Soft computing parameters

Algorithms	Initial population size (Psize)	Cycle /Iteration (approx)	Others
GA	3 / 10 / 50	600	Design variables = 6
TLBO	3 / 10 / 50	1000	Teaching factor (Te =1 to 2) Unknown variables =6
CIO	3 / 10 / 50	200	Decision variables=6, Saturation = 0.001, reduction factor =0.92

References

[1] O. Elgerd, *Electric Energy Systems Theory–An Introduction*. New Delhi: Tata McGraw Hill, 2000.

[2] H. Bevrani, *Robust Power System Frequency Control*. Berlin: Springer, 2009.

[3] A. Kassem, "Neural predictive controller of a two-area load frequency control for interconnected power system," *Ain Shams Engineering Journal*, vol. 1, no. 1, pp. 49–58, 2010.

[4] K. Jagatheesan, B. Anand, N. Dey, A. Ashour, and V. Balas, "Load frequency control of hydro-hydro system with fuzzy logic controller considering non-linearity," in *Recent Developments and the New Direction in Soft-Computing Foundations and Applications*, (Cham), pp. 307–318, Springer, 2018.

[5] W. Eshetu, P. Sharma, and C. Sharma, "Anfis based load frequency control in an isolated micro grid," in *2018 IEEE International Conference on Industrial Technology (ICIT)*, pp. 1165–1170, IEEE, 2018.

[6] D. Murugesan, K. Jagatheesan, P. Shah, and R. Sekhar, "Fractional order $pi^{\lambda}d^{\mu}$ controller for microgrid power system using cohort intelligence optimization," *Results in Control and Optimization*, p. 100218, 2023.

[7] E.-H. Dulf, "Simplified fractional order controller design algorithm," *Mathematics*, vol. 7, no. 12, p. 1166, 2019.

[8] S. Nangrani and S. Bhat, "Fractional order controller for controlling power system dynamic behavior," *Asian Journal of Control*, vol. 20, no. 1, pp. 403–414, 2018.

[9] M. Zheng, G. Zhang, and T. Huang, "Tuning of fractional complex-order direct current motor controller using frequency domain analysis," *Mathematical Methods in the Applied Sciences*, 2020.

[10] A. V. Tare, J. A. Jacob, V. A. Vyawahare, and V. N. Pande, "Design of novel optimal complex-order controllers for systems with fractional-order dynamics," *International Journal of Dynamics and Control*, vol. 7, no. 1, pp. 355–367, 2019.

[11] M. Shahiri, A. Ranjbar Noei, M. R. Karami, and R. Ghaderi, "Tuning method for fractional complex order controller using standardized k-chart: Application to pemfc control," *Asian Journal of Control*, vol. 18, no. 3, pp. 1102–1118, 2016.

[12] B. Ross, W. Haven, and F. H. NORTHOVER, "A use for a derivative of complex order in the fractional calculus," 1978.

[13] J. A. Jacob, A. V. Tare, V. A. Vyawahare, and V. N. Pande, "A review of time domain, frequency domain and stability analysis of linear complex-order systems," in *2016 IEEE International WIE Conference on Electrical and Computer Engineering (WIECON-ECE)*, pp. 164–169, IEEE, 2016.

[14] A. Mohan, N. Meskin, H. Mehrjerdi, Z. Yue, S. Zhang, W. Xiao, A. Annamraju, S. Nandiraju, L. Bhukya, M. Ramesh, and A. Yadav, "Load frequency control of multi-microgrid system considering renewable energy sources using grey wolf optimization," *Journal: Smart Science*, no. 3, pp. 198–217, 2019.

[15] U. Rout, R. Sahu, and S. Panda, "Design and analysis of differential evolution algorithm based automatic generation control for interconnected power system," *Ain Shams Engineering Journal*, vol. 4, no. 3, pp. 409–421, 2013.

[16] S. Surendiran and S. Thangavel, "Time varying acceleration coefficients with dominant social component particle swarm optimization for interconnected power system," *ARPN Journal of Engineering and Applied Sciences*, vol. 11, no. 3, pp. 1936–1946, 2016.

[17] D. Murugesan, K. Jagatheesan, and D. Boopathi, "Meta-heuristic strategy planned controller for frequency supervision of integrated thermal plant with renewable source," in *2021 IEEE 3rd PhD Colloquium on Ethically Driven Innovation and Technology for Society (PhD EDITS)*, pp. 1–2, IEEE, 2021.

[18] K. Naidu, H. Mokhlis, and A. Bakar, "Multiobjective optimization using weighted sum artificial bee colony algorithm for load frequency control," *International Journal of Electrical Power & Energy Systems*, vol. 55, pp. 657–667, 2014.

[19] R. Ramjug-Ballgobin and C. Ramlukon, "A hybrid metaheuristic optimisation technique for load frequency control," *SN Applied Sciences*, vol. 3, no. 5, pp. 1–14, 2021.

[20] H. Shabani, B. Vahidi, and M. Ebrahimpour, "A robust pid controller based on imperialist competitive algorithm for load-frequency control of power systems," *ISA Transactions*, vol. 52, no. 1, pp. 88–95, 2013.

[21] F. Daneshfar and H. Bevrani, "Multiobjective design of load frequency control using genetic algorithms," *International Journal of Electrical Power & Energy Systems*, vol. 42, no. 1, pp. 257–263, 2012.

[22] R. S and K. A., "Modified genetic algorithm based load frequency controller for interconnected power systems," *Int J Electr Power Eng*, vol. 3, no. 1, pp. 26–30, 2009.

[23] A. Roy, S. Dutta, and P. Roy, "Load frequency control of interconnected power system using teaching learning based optimization," *International Journal of Energy Optimization and Engineering (IJEOE)*, vol. 4, no. 1, pp. 102–117, 2015.

[24] D. Murugesan, K. Jagatheesan, A. Kulkarni, P. Shah, and R. Sekhar, "Comparison of biologically inspired algorithm with socio-inspired technique on load frequency control of multi-source single-area power system," in *Applied Genetic Algorithm and Its Variants: Case Studies and New Developments*, pp. 185–208, Springer Nature Singapore, 2023.

[25] R. Rao, V. Savsani, and D. Vakharia, "Teaching–learning-based optimization: an optimization method for continuous non-linear large scale problems," *Information Sciences*, vol. 183, no. 1, pp. 1–15, 2012.

[26] R. Rao and V. Kalyankar, "Parameter optimization of modern machining processes using teaching–learning based optimization algorithm," *Engineering Applications of Artificial Intelligence*, vol. 26, no. 1, pp. 524–531, 2013.

[27] A. Kulkarni, I. Durugkar, and M. Kumar, "Cohort intelligence: a self supervised learning behavior," in *2013 IEEE International Conference on Systems, Man, and Cybernetics*, pp. 1396–1400, IEEE, 2013.

[28] D. Murugesan, P. Shah, K. Jagatheesan, R. Sekhar, and A. Kulkarni, "Cohort intelligence optimization based controller design of isolated and interconnected thermal power system for automatic generation control," in *2022 Second International Conference on Computer Science, Engineering and Applications (ICCSEA)*, pp. 1–6, IEEE, 2022.

[29] D. Murugesan, K. Jagatheesan, A. Kulkarni, and P. Shah, "A socio inspired technique in nuclear power plant for load frequency control by using cohort intelligence optimization-based pid controller," in *Renewable Energy Optimization, Planning and Control: Proceedings of ICRTE 2022*, pp. 1–12, Springer Nature Singapore, 2023.

[30] P. Shah and A. Kulkarni, "Application of variations of cohort intelligence in designing fractional pid controller for various systems," *Socio-cultural Inspired Metaheuristics*, pp. 175–192, 2019.

[31] R. Sekhar and P. Shah, "Predictive modeling of a flexible robotic arm using cohort intelligence socio-inspired optimization," pp. 193–198, 2020.

[32] Y. Chen, "Ubiquitous fractional order controls?," *IFAC Proceedings Volumes*, vol. 39, no. 11, pp. 481–492, 2006.

[33] Z. Li, L. Liu, S. Dehghan, Y. Chen, and D. Xue, "A review and evaluation of numerical tools for fractional calculus and fractional order controls," *International Journal of Control*, vol. 90, no. 6, pp. 1165–1181, 2016.

[34] Y. Chen, I. Petras, and D. Xue, "Fractional order control - A tutorial," in *2009 American Control Conference*, 2009.

[35] C. I. Muresan, I. Birs, C. Ionescu, E. H. Dulf, and R. De Keyser, "A Review of Recent Developments in Autotuning Methods for Fractional-Order Controllers," *Fractal and Fractional*, vol. 6, no. 1, p. 37, 2022.

[36] I. Petraš, "Practical Aspects of Tuning and Implementation of Fractional-Order Controllers," in *Volume 3: 2011 ASME/IEEE International Conference on Mechatronic and Embedded Systems and Applications, Parts A and B*, 2011.

[37] I. Petras, "Tuning and implementation methods for fractional-order controllers," *Fractional Calculus and Applied Analysis*, vol. 15, no. 2, pp. 282–303, 2012.

[38] I. Petras, "Practical aspects for implementation of fractional-order controllers," in *Proceedings of the 2014 15th International Carpathian Control Conference (ICCC)*, 2014.

[39] I. Petras, "Fractional-order nonlinear controllers: Design and implementation notes," in *2016 17th International Carpathian Control Conference (ICCC)*, 2016.

[40] I. Petras, "A note on fractional-order non-linear controller: possible neural network approach to design," in *2016 International Joint Conference on Neural Networks (IJCNN)*, 2016.

[41] A. Soukkou, M. C. Belhour, and S. Leulmi, "Review, Design, Optimization and Stability Analysis of Fractional-Order PID Controller," *International Journal of Intelligent Systems and Applications*, vol. 8, no. 7, pp. 73–96, 2016.

[42] A. Tepljakov, B. B. Alagoz, C. Yeroglu, E. A. Gonzalez, S. H. Hosseinnia, E. Petlenkov, A. Ates, and M. Cech, "Towards Industrialization of FOPID Controllers: A Survey on Milestones of Fractional-Order Control and

Pathways for Future Developments," *IEEE Access*, vol. 9, pp. 21016–21042, 2021.

[43] D. Valério and J. S. da Costa, "Tuning-RULES FOR FRACTIONAL PID CONTROLLERS," *IFAC Proceedings Volumes*, vol. 39, no. 11, pp. 28–33, 2006.

[44] B. M. Vinagre, C. A. Monje, A. J. Calderón, and J. I. Suárez, "Fractional PID Controllers for Industry Application: A Brief Introduction," *Journal of Vibration and Control*, vol. 13, no. 9-10, pp. 1419–1429, 2007.

[45] C. Yeroglu and N. Tan, "Note on fractional-order proportional–integral–differential controller design," *IET Control Theory & Applications*, vol. 5, no. 17, pp. 1978–1989, 2011.

[46] P. Shah, R. Sekhar, I. Iswanto, and M. Shah, "Complex order $PI^{a+jb}D^{c+jd}$ controller design for a fractional order dc motor system," *Advances in Science Technology and Engineering Systems Journal*, vol. 6, pp. 541–551, 03 2021.

[47] R. Sekhar, T. P. Singh, and P. Shah, "ARX/ARMAX modeling and fractional order control of surface roughness in turning nano-composites," in *2019 International Conference on Mechatronics, Robotics and Systems Engineering (MoRSE)*, pp. 97–102, 2019.

[48] B. H. Abdelfettah, L. Mohamed, and D. Abdelbaki, "Synergy between fractional order control and industry 4.0: a bibliometric analysis," *Procedia Computer Science*, vol. 204, pp. 803–810, 2022. International Conference on Industry Sciences and Computer Science Innovation.

[49] P. Shah, D. Sharma, and R. Sekhar, "Analysis of research trends in fractional controller using latent dirichlet allocation," *Engineering Letters*, vol. 29, pp. 109–119, 02 2021.

[50] P. Shah, R. Sekhar, I. Iswanto, and M. Shah, "Complex order pi a+ jb d c+ jd controller design for a fractional order dc motor system," *Advances in Science Technology and Engineering Systems Journal*, vol. 6, pp. 541–551, 03 2021.

[51] P. Shah and R. Sekhar, "Predictive modeling and control of clamp load loss in bolted joints based on fractional calculus," in *Advances in Computing and Network Communications*, (Singapore), pp. 15–32, Springer Singapore, 2021.

[52] R. Sekhar, T. Singh, and P. Shah, "Micro and nano particle composite machining: Fractional order control of surface roughness," 02 2020.

[53] R. Sekhar, T. Singh, and P. Shah, "System identification of tool chip interface friction while machining cnt-mg-al composites," vol. 2317, p. 020019, 02 2021.

[54] R. Bhimte, K. Bhole, P. Shah, and R. Sekhar, "Precise position control of quanser servomotor using fractional order fuzzy pid controller," pp. 58–63, 12 2020.

[55] R. Sekhar, T. P. Singh, and P. Shah, "Machine learning based predictive modeling and control of surface roughness generation while machining micro boron carbide and carbon nanotube particle reinforced Al-Mg matrix composites," *Particulate Science and Technology*, vol. 40, no. 3, pp. 355–372, 2022.

[56] R. Sekhar, T. P. Singh, and P. Shah, "Complex Order $PI^{\alpha+i\beta}D^{\gamma+j\theta}$ Design for Surface Roughness Control in Machining CNT Al-Mg Hybrid Composites," *Advances in Science, Technology and Engineering Systems Journal*, vol. 5, no. 6, pp. 299–306, 2020.

[57] P. Shah and S. Agashe, "Design of controller for a higher order system without using model reduction methods," *Progress in Fractional Differentation and Applications*, vol. 3, pp. 289–3004, 2017.

[58] R. Sekhar, T. Singh, and P. Shah, "Micro and nano particle composite machining: Fractional order control of surface roughness," in *Third International Conference on Powder, Granule and Bulk Solids: Innovations and Applications PGBSIA 2020 February 26-28, 2020*, pp. 35–42, 2020.

[59] P. Shah, R. Sekhar, and S. Agashe, "Application of fractional PID controller to single and multi-variable non-minimum phase systems," *International Journal of Recent Technology and Engineering*, vol. 8, no. 2, pp. 2801–2811, 2019.

[60] P. Shah, D. Sharma, and R. Sekhar, "Analysis of research trends in fractional controller using latent dirichlet allocation.," *Engineering Letters*, vol. 29, no. 1, 2021.

[61] N. Solke, P. Shah, R. Sekhar, and T. Singh, "Machine learning-based predictive modeling and control of lean manufacturing in automotive parts manufacturing industry," *Global Journal of Flexible Systems Management*, vol. 23, no. 1, pp. 89–112, 2022.

[62] S. Li, L. Kang, and X.-M. Zhao, "A survey on evolutionary algorithm based hybrid intelligence in bioinformatics," *BioMed research international*, vol. 2014, 2014.

[63] J. Liepe, P. Kirk, S. Filippi, T. Toni, C. P. Barnes, and M. P. Stumpf, "A framework for parameter estimation and model selection from experimental data in systems biology using approximate bayesian computation," *Nature protocols*, vol. 9, no. 2, pp. 439–456, 2014.

[64] R. Sekhar and P. Shah, "Predictive modeling of a flexible robotic arm using cohort intelligence socio-inspired optimization," in *2020 1st International Conference on Information Technology, Advanced Mechanical and Electrical Engineering (ICITAMEE)*, pp. 193–198, IEEE, 2020.

[65] A. Sohail, "Genetic algorithms in the fields of artificial intelligence and data sciences," *Annals of Data Science*, vol. 10, no. 4, pp. 1007–1018, 2023.

[66] M. Gen and L. Lin, "Genetic algorithms and their applications," in *Springer handbook of engineering statistics*, pp. 635–674, Springer, 2023.

[67] B. Alhijawi and A. Awajan, "Genetic algorithms: Theory, genetic operators, solutions, and applications," *Evolutionary Intelligence*, pp. 1–12, 2023.

[68] K. Wu, H. Hu, L. Wang, and Y. Gao, "Parametric optimization of an aperiodic metastructure based on genetic algorithm," *International Journal of Mechanical Sciences*, vol. 214, p. 106878, 2022.

[69] D. Murugesan, K. Jagatheesan, A. J. Kulkarni, P. Shah, and R. Sekhar, "Comparison of biologically inspired algorithm with socio-inspired technique on load frequency control of multi-source single-area power system," in *Applied Genetic Algorithm and Its Variants: Case Studies and New Developments*, pp. 185–208, Springer Nature Singapore Singapore, 2023.

[70] M. Dastan, S. Shojaee, S. Hamzehei-Javaran, and V. Goodarzimehr, "Hybrid teaching–learning-based optimization for solving engineering and mathematical problems," *Journal of the Brazilian Society of Mechanical Sciences and Engineering*, vol. 44, no. 9, p. 431, 2022.

[71] K. Y. Gómez Díaz, S. E. De León Aldaco, J. Aguayo Alquicira, M. Ponce-Silva, and V. H. Olivares Peregrino, "Teaching–learning-based optimization algorithm applied in electronic engineering: A survey," *Electronics*, vol. 11, no. 21, p. 3451, 2022.

[72] Y. Xu, Y. Peng, X. Su, Z. Yang, C. Ding, and X. Yang, "Improving teaching–learning-based-optimization algorithm by a distance-fitness learning strategy," *Knowledge-Based Systems*, vol. 257, p. 108271, 2022.

[73] R. Kommadath, D. Maharana, C. Sivadurgaprasad, and P. Kotecha, "Parallel computing strategies for sanitized teaching learning based optimization," *Journal of Computational Science*, vol. 63, p. 101766, 2022.

[74] M. Arashpour, E. M. Golafshani, R. Parthiban, J. Lamborn, A. Kashani, H. Li, and P. Farzanehfar, "Predicting individual learning performance using machine-learning hybridized with the teaching-learning-based optimization," *Computer Applications in Engineering Education*, vol. 31, no. 1, pp. 83–99, 2023.

[75] D. Murugesan, K. Jagatheesan, P. Shah, and R. Sekhar, "Fractional order piλdμ controller for microgrid power system using cohort intelligence optimization," *Results in Control and Optimization*, vol. 11, p. 100218, 2023.

[76] C. Liu, W. Zhang, L. Zeng, B. C. Ooi, J. W. L. Yip, and K. Zheng, "Toward cohort intelligence: A universal cohort representation learning framework for electronic health record analysis," *arXiv preprint arXiv:2304.04468*, 2023.

[77] S. Tutun, A. Tosyali, H. Sangrody, M. Khasawneh, M. Johnson, A. Albizri, and A. Harfouche, "Artificial intelligence in energy industry: forecasting electricity consumption through cohort intelligence & adaptive neural fuzzy inference system," *Journal of Business Analytics*, vol. 6, no. 1, pp. 59–76, 2023.

[78] M. Haghighat, L. Browning, K. Sirinukunwattana, S. Malacrino, N. Khalid Alham, R. Colling, Y. Cui, E. Rakha, F. C. Hamdy, C. Verrill, *et al.*, "Automated quality assessment of large digitised histology cohorts by artificial intelligence," *Scientific Reports*, vol. 12, no. 1, p. 5002, 2022.

[79] M. S. Sapre, A. J. Kulkarni, I. R. Kale, and M. S. Pande, "Application of cohort intelligence algorithm for numerical integration," in *Intelligent Systems and Applications: Select Proceedings of ICISA 2022*, pp. 445–453, Springer, 2023.

[80] T. Muther, F. I. Syed, A. K. Dahaghi, and S. Negahban, "Socio-inspired multi-cohort intelligence and teaching-learning-based optimization for

hydraulic fracturing parameters design in tight formations," *Journal of Energy Resources Technology*, vol. 144, no. 7, p. 073201, 2022.
[81] The MathWorks, Inc., *MATLAB Control Toolbox*. MATLAB Software, 2014. Version R2014a.