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CRAYFISH OPTIMIZATION BASED PID CONTROLLER DESIGN FOR LOAD FREQUENCY CONTROL IN INTERCONNECTED POWER SYSTEMS

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Abstract

This study explores the utilization of the Crayfish Optimization Algorithm (COA) to develop a PID controller aimed at stabilizing frequencies in two-area interconnected power systems. Inspired by crayfish's summer resort behaviour, competition behaviour and foraging behaviour, the proposed work aims to enhance frequency stability amidst varying operational conditions. Through extensive simulations conducted in MATLAB, performance of the proposed design is evaluated and compared with other meta heuristic approaches. Results demonstrate the efficacy and robustness of the COA-based approach, particularly in scenarios involving step load changes, random load fluctuations, and nonlinearities such as governor rate constraint (GRC) and governor deadband (GDB). The controller adeptly minimizes frequency variations, guaranteeing the steady and dependable functioning of the interconnected power system. Furthermore, comparative analyses highlight the superiority of the COA-based PID controller over other metaheuristic approaches. This study provides significant insights into the utilization of COA for power system control applications, paving the way for enhanced stability and efficiency in modern power grids.

Keywords: Crayfish Optimization Algorithm (COA), Frequency Stability, Interconnected Power Systems

1.Introduction

Power system stability has consistently presented challenges for engineers, scientists, and researchers. Operating within a dynamic environment characterized by fluctuating loads and generator outputs, power systems face constant change. With interconnected power systems growing in size, undergoing structural changes, and becoming more complex, frequency control has emerged as a crucial component of ensuring stability. Load Frequency Control (LFC), a key function of Automatic Generation Control (AGC), plays a crucial role in regulating power system frequency and remains a significant control challenge in electric power system design and operation [1]. Voltage and frequency are the two main parameters which require continuous monitoring and control. While voltage mainly depends on reactive power; frequency depends on the amount of mechanical power being developed and electrical power being consumed [2][3]. When the total amount of electricity generated differs from the overall demand, synchronous generators adjust their speed, leading to fluctuations in the

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system frequency. This delicate balance ensures that power supply matches demand, maintaining the stability of the electrical grid. Deviations from normal frequency levels can directly influence the operational efficiency and dependability of the power system. In addition, these occurrences have the potential to harm equipment, impair load performance, overload transmission lines, and ultimately induce instability in the power system. Maintaining frequency and power interchanges between the neighbouring control areas at the schedule value are the two main control objectives of the LFC [4][5].

Several works have been reported in the field of LFC in power systems with single area [6], multi area [7][8], deregulated power systems including many other [9-11]. Wide range of controllers have been investigated ranging from classical controls to intelligent controls. Intelligent control methods have disadvantages due to the high computational load, difficulty of implementation, and the need for expert knowledge. Recent contributions in the field have focused on robust controls [12] [13], sliding mode control [14][15], optimal control [16][17], model predictive control (MPC)[18][19], active disturbance rejection control (ADRC)[20][21], and event triggered control [22][23]. However, the use of proportional integral (PI), proportional integral derivative (PID) controls have always attracted the researchers because its simplicity and easy application. It is seen that the studies on the LFC of power systems are mainly conducted with PI/PID controllers. Numerous optimization approaches have been reported for fine adjustment of the parameters of PI and PID controllers, aiming to stabilize frequency deviations effectively under load disturbances. In recent times, many optimization techniques have been reported after being inspired from the behaviour of animals in nature such as Artificial Bee Colony Algorithm (ABC) [24], Ant Colony Optimization (ACO) [25], Bacteria Foraging Optimization Algorithm (BFOA) [26], Cuckoo Search Optimization (CS) [27], Particle Swarm Optimization (PSO) [28], Salp Swarm Algorithm (SSA) [29][30], Whale Optimization Algorithm (WOA) [31], Firefly Optimization Algorithm [32] including many others. Evolutionary algorithms inspired from evolution mechanism of nature such as Genetic Algorithm (GA)[33], Differential Evolution (DE) [34] are present in literature. Human inspired optimization algorithms inspired by human behaviour such as Teaching Learning (TL) is reported in [35]. It is important to note that no specific algorithm can effectively tackle all problems. While an algorithm may excel in addressing one specific problem, its effectiveness might diminish when applied to others.

This article employs the Crayfish Optimization Algorithm (COA) to finely adjust the parameters of the PID controller for optimal performance. The COA stands out as a unique meta-heuristic optimization method inspired by crayfish behaviours observed in their summer habitat, competition patterns, and foraging habits [36]. These behaviours are intricately segmented into distinct stages within the algorithm to strike a balance between exploration and exploitation. The initial phase reflects the exploratory tendencies of crayfish during their summer residency, while the subsequent competition and foraging stages emphasize the exploitation aspect of COA. Temperature plays a critical role in regulating the algorithm's exploration and exploitation dynamics. During high temperatures, crayfish tend to seek refuge in caves for summer retreat or engage in competitive interactions for territory. Conversely, optimal temperature conditions stimulate a variety of foraging behaviours in crayfish,

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influenced by the size of available food. Research in the field has indicated that employing COA to tackle load frequency challenges in interconnected power systems is still a relatively new concept within the academic community. The proposed methodology is subjected to validation tests involving step and random step load disturbances, encompassing nonlinearities such as GRC and GDB present in power systems. In addition, the proposed design is compared with other recent meta heuristic optimization algorithm like GWO, SSA, TL, and WOA.

The remaining article is structured as follows: Section 2 presents the interconnected power system, detailing system modelling and the selection process for the cost function. In section 3, COA is described with three different stages namely exploitation, exploration and foraging. Section 4 comprehensively discusses the results obtained using simulation. Finally, the article concludes with Section 5, offering insights into potential avenues for future research.

2. Two area load frequency control

An interlinked power network comprises of multiple areas as illustrated in Figure 1, each with its generators, loads, and control mechanisms. These areas are linked through transmission lines, facilitating the exchange of power to meet varying demands. Coordinating governors and control strategies across interconnected areas becomes essential to ensure overall system stability and reliability amidst dynamic load fluctuations and disturbances. Interconnected system requires proper management and its secure operation is indeed a challenging problem. The stable operation of interconnected systems hinges on two fundamental principles: first, ensuring frequency stability, and second, maintaining the tie line power between neighbouring areas at scheduled values. The area variables include: $\Delta f_i(t)$, representing the change in frequency (Hz); $\Delta P_{g_i}(t)$, indicating the change in power output (p.u.); $\Delta X_{g_i}(t)$, denoting the change in governor valve position (p.u.); R_i, which is the speed regulation coefficient of the governor (Hz/p.u.); and T_{T_i}, T_{G_i} and T_{P_i}, representing the time constants of the turbine, governor, and load in seconds, respectively

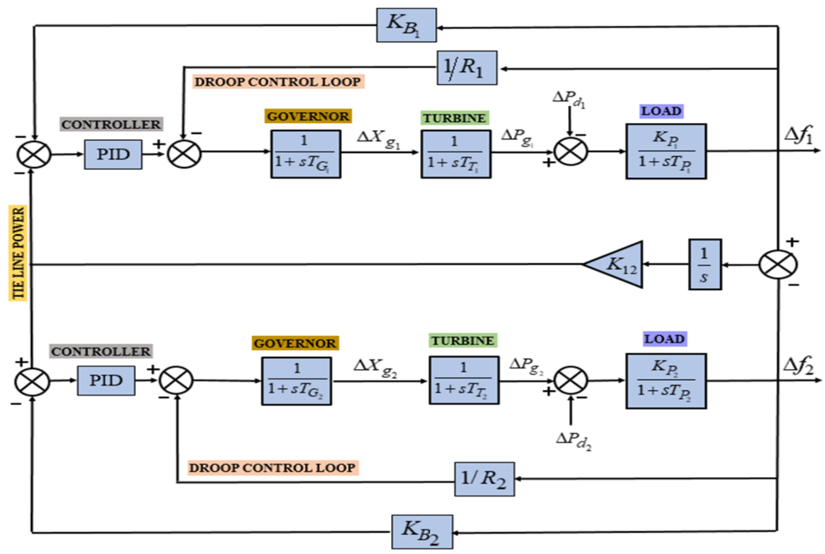

Figure 1. Interconnected power system model

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Traditional LFC relies on tie-line bias control, wherein each area endeavours to minimize the area control error (ACE) towards zero. This control mechanism generates a signal comprising the deviation in tie-line flow added to the frequency deviation, weighted by a bias factor. The ACE expressions for area 1 and area 2 are provided as follows:

$$\left.\begin{aligned} ACE_1 &= K_{B_1}\Delta f_1 + \Delta P_{tie,12} \\ ACE_2 &= K_{B_2}\Delta f_2 + \Delta P_{tie,21} \end{aligned}\right\} \tag{1}$$

The frequency bias factor K_{B_1} and K_{B_2} in (1) regulate the level of interaction among areas during a load disturbance event. The cost function aims to optimize the parameter tuning of the PID controller and is given by,

$$\int_0^t t.\left(ACE_1 + ACE_2\right)^2 dt \tag{2}$$

3. Crayfish Optimization Algorithm

The Crayfish Optimization Algorithm in Figure 2 involves the process of searching for the maximum or minimum value of the function $f(x)$ within a continuous search space. The parameter x represent the solution within the search space. The optimization algorithm undergoes multiple iterations to find the optimal solution $x_{best}\{x_1, x_2, x_3, ..., x_D\}$. D is the suitable dimension of the solution which in general is user defined. After every iteration, a new solution $x_{new}\{x_1, x_2, x_3, ..., x_D\}$ is obtained. If the solution x_{new} is superior to the current solution x_{best}, then x_{best} is updated to x_{new}. Subsequently, these iterations persist until the identified solution satisfies predetermined criteria, culminating in what is termed as the optimal solution. However, if all solutions cluster closely around a specific region, there's a risk of the algorithm converging on a local optimum, hindering the attainment of a superior solution. Moreover, excessive update formula values may cause solutions to stray beyond the designated search scope, diminishing the algorithm's optimization performance. Local optimization refers to minimizing (or maximizing) solutions within a confined range rather than the entirety of the region.

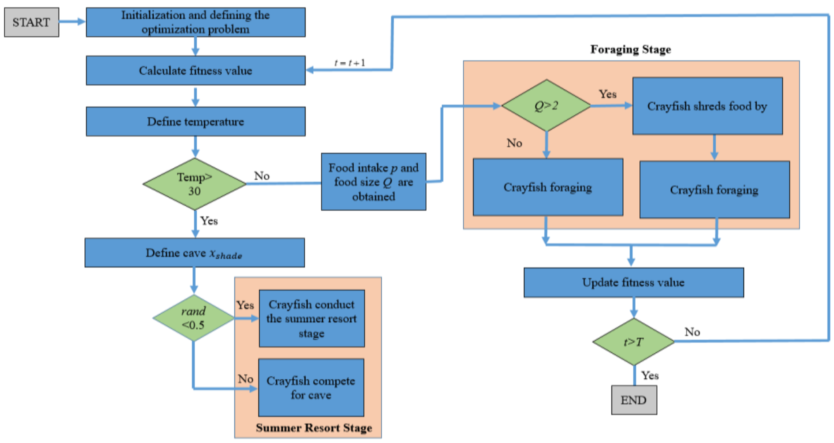

Figure 2. Crayfish optimization algorithm flowchart

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Metaheuristic optimization algorithms enhance the likelihood of discovering the global optimum for a given problem. Consequently, these algorithms possess the capability to identify the global optimal solution independently of initial conditions and solution domains, showcasing robustness.

The crayfish colony x is defined at the beginning of the algorithm. The variable x_i denotes the position of the i^{th} crayfish, representing a solution $x_i = \{x_{i,1}, x_{i,2}, x_{i,3}, \ldots.., x_{i,\mathrm{D}}\}$ in a problem space of dimension *D*. The fitness value, denoted by $f(x_i)$ is determined by the function $f(x)$ guiding the exploration and exploitation behaviour of the crayfish. In this algorithm, outside temperature serves as a regulating factor, representing the environmental conditions experienced by individual crayfish. When temperature is excessively high, COA transitions into the summer resort or competition stage. During the summer resort stage, new solutions are updated based on individual positions x_i and the cave position x_{shade}. Conversely, suitable temperature conditions prompt COA to enter the foraging stage, where the optimal solution represents the location of food. The size of the food is determined by the difference between the current solution $fitness_i$ and the optimal solution $fitness_{food}$. In favourable conditions, crayfish generate new solutions based on their position x_i, food intake constant *P*, and food position x_{food}. If the food is too large, crayfish employ their claws to tear it apart, alternating between feeding with the second and third walking feet. The alternating feeding behaviour of crayfish is simulated using sine and cosine functions. Each stages of the COA is discussed in sequence.

3.1 Initialization

The optimization process begins with the initialization of the COA algorithm, involving the random generation of a set of candidate solutions within the search space. These candidate solutions are determined by the population size N and the dimension D, both specified by the user. This initialization is represented in Equation (3).

$$x = [x_1, x_2, x_3, \ldots.., x_N] = \begin{bmatrix} x_{1,1} & \cdots & x_{1,j} & \cdots & x_{1,D} \\ \mathrm{M} & \cdots & \mathrm{M} & \cdots & \mathrm{M} \\ x_{i,1} & \cdots & x_{i,j} & \cdots & x_{i,D} \\ \mathrm{M} & \cdots & \mathrm{M} & \cdots & \mathrm{M} \\ x_{N,i} & \cdots & x_{N,j} & \cdots & x_{N,D} \end{bmatrix} \tag{3}$$

3.2 Defining Temperature

Changes in temperature directly influence the behaviour of crayfish, prompting them to transition between stages. Temperature is defined in (4). When temperature exceeds 30°C, COA enters either the competition stage or the summer resort stage. In this stage, two crayfish engage in a competitive struggle for territory. In favourable temperature conditions conducive to foraging, COA transitions into the foraging stage, where crayfish actively seek out food. If the food is too large, crayfish utilize their claws to break it down for consumption. However,

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when the food is suitable for consumption, crayfish alternate between using their second and third walking feet to eat.

$$temp = rand * 15 + 20 \tag{4}$$

3.3 Summer Resort Exploration

When the temperature surpasses 30°C, signalling extremely high conditions, crayfish seek refuge in caves for a summer retreat. The cave, represented as x_{shade}, is given by:

$$x_{shade} = \frac{\left(x_G + x_L\right)}{2} \tag{5}$$

where x_G denotes the best position achieved up to the current iteration and x_L represent the optimal position of the current population. The competition among crayfish for caves is a random event. If the random value, $rand < 0.5$, crayfish will enter the cave using:

$$x_{i,j}^{t+1} = x_{i,j}^{t} + C_2 \times rand \times \left(x_{shade} - x_{i,j}^{t}\right) \tag{6}$$

where t represent the current iteration, $t+1$ represent the next iteration, and C_2 denotes the decreasing curve $C_2 = 2 - \left(t / T\right)$ where T denotes the maximum number of iterations. During the summer resort phase, crayfish strive to move toward the cave, representing the optimal solution. At this stage, they gradually advance closer to the cave, bringing the individuals nearer to the optimal solution. This process enhances the exploitation ability of COA, facilitating faster convergence of the algorithm.

3.4 Exploitation Stage

When the temperature exceeds 30° C and $rand \geq 0.5$, other crayfish also express interest in the cave and fight to have the control over the cave through (7),

$$x_{i,j}^{t+1} = x_{i,j}^{t} - x_{z,j}^{t} + x_{shade} \tag{7}$$

where z represents any random crayfish as shown in (8),

$$z = round\left(rand \times \left(N - 1\right)\right) + 1 \tag{8}$$

During the competition stage, crayfish participate in competitive interactions, with each crayfish x_i adjusting its position based on the position of another crayfish x_z. This adjustment broadens the search range of the COA, improving the algorithm's exploration ability.

3.5 Foraging Stage

When $temp \leq 30$, crayfish are in optimal conditions for feeding. During this period, the crayfish start to move towards the food. It evaluates the size of the food, and if it's too large, the crayfish will employ its claws to break it down. Then, it consumes the food by alternating between its second and third walking feet. The location of the food is denoted by x_{food} and is defined as: $x_{food} = x_G$. Food size Q is defined as:

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$$Q = C_3 \times rand \times \left(fitness_i / fitness_{food} \right) \tag{9}$$

where food factor C_3 represent the maximum food size, and its value remains constant. $fitness_i$ denotes the i^{th} crayfish fitness value, and $fitness_{food}$ denotes the fitness value of the food location. Crayfish determine the size of the food based on the maximum food size. When $Q > 0.5(C_3 + 1)$, it indicates that the food is too large. In such cases, crayfish will tear the food using their first claw foot through (10),

$$x_{food} = \exp(-1/Q) \times x_{food} \tag{10}$$

As the food is shredded into smaller pieces, the crayfish will use their second and third claws alternately to pick up the food and bring it to their mouths through (11). To simulate this alternating process, a combination of sine and cosine functions is utilized.

$$x_{i,j}^{t+1} = \left(x_{i,j}^{t} - x_{food} \right) \times p + p \times rand \times x_{i,j}^{t} \tag{11}$$

In the foraging stage, crayfish employ different feeding methods based on the size of the food Q, and food x_{food} represents the optimal solution. Crayfish will approach the food only when the size of the food Q is suitable for foraging. When Q is too large, indicating a significant disparity between the crayfish and the optimal solution, x_{food} should be reduced and brought closer to the food. This helps control the randomness of the food intake enhancement algorithm for crayfish. Through the foraging stage, COA progressively approaches the optimal solution, enhancing the algorithm's exploitation capabilities and ensuring good convergence ability.

4. Case Studies

The system parameter values for interlinked power network model are shown below in Table 1. In the scenario of simulation, the population size of $N = 10$; dimension $D = 6$; upper and lower bound is within a specified range of $[0, 20]$; and total of 30 iteration is considered.

Table 1. System parameter values [14]

Area	T_{P_i}	K_{P_i}	T_{T_i}	T_{G_i}	R_i	K_{B_i}	GDB	GRC $(\pm\hat{\delta})$
1	20	120	0.3	0.08	2.4	0.41	± 1 sec.	0.1 p.u./min
2	25	112.5	0.33	0.072	2.7	0.37	± 1 sec.	0.1 p.u./min

Case 1: Step Load Disturbance

Change in load demand under normal operating condition of power system is a critical concern in system stability. In this case, the system stability is validated under step load disturbance of 0.02 p.u. and 0.015 p.u. in area 1 and 2 respectively at $t = 0$ second. The two objectives of the LFC i.e. frequency and tie line power stabilization are achieved with acceptable fluctuations (see Figure 3 and 4). The performance of the system optimization algorithm can be visually

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tracked through the convergence curve of the cost function, as depicted in Figure 5. This curve offers a clear insight into the algorithm's progression over iterations. Initially, the curve starts at a higher error value, highlighting a considerable disparity between the current and optimal solutions. However, as the crayfish optimization algorithm advances, the error diminishes. This reduction is evident in the convergence curve, which should ideally exhibit a declining trend. Such a trend signifies the algorithm's efficacy in minimizing errors and approaching the optimal solution. Alongside these assessments, the system's performance is also gauged by monitoring the ACE (see Figure 6). The ACE serves as a crucial metric in this context, representing the difference between the actual frequency and the scheduled frequency, adjusted for tie line deviations. Monitoring and minimizing the ACE are essential for maintaining system stability and ensuring efficient load distribution across areas.

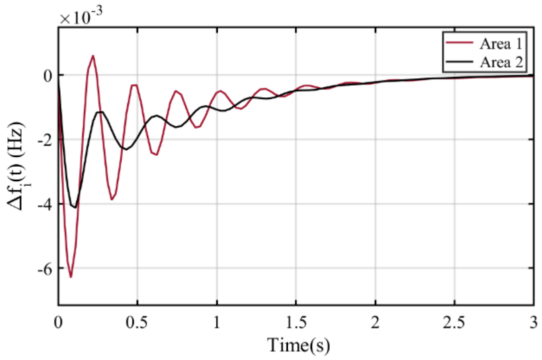

Figure 3. Frequency deviation of two area

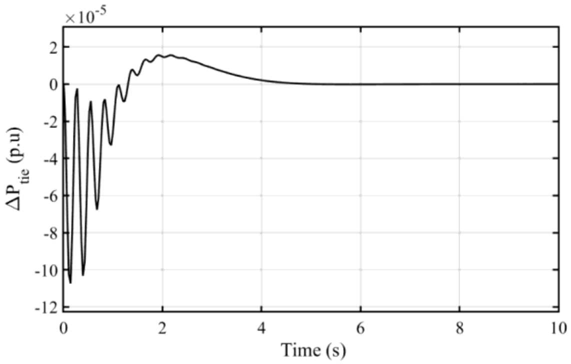

Figure 4. Tieline power deviation

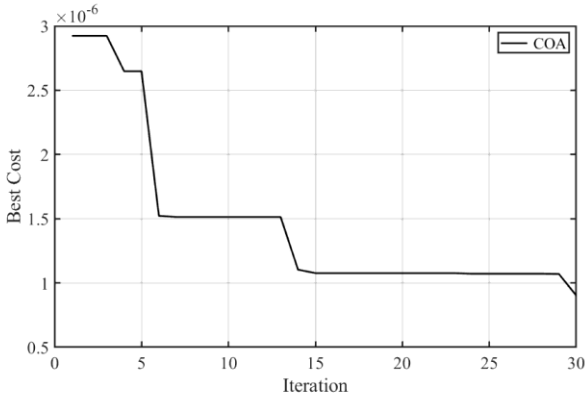

Figure 5. Best Cost vs. Iteration for TLBO

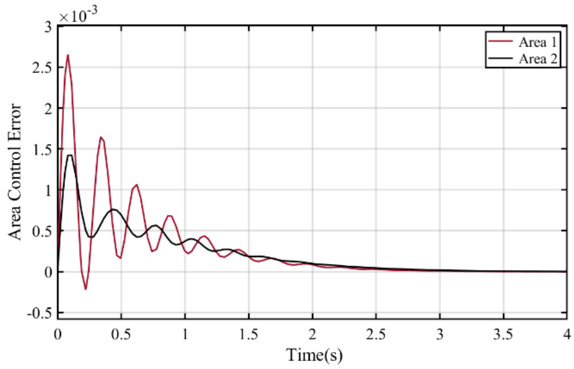

Figure 6. Area control error of two area

Case 2: Validation under random load disturbance

In this case, the proposed design is validated with random changes in load demand in two areas (see Figure 7). The physical significance of random load disturbances lies in their representation of real-world uncertainties. These disturbances can arise due to various factors such as sudden changes in consumer behaviour, unexpected equipment failures, or external events like weather fluctuations affecting demand patterns. Validating a proposed design with

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these disturbances is essential to ensure system robustness, evaluate dynamic behaviour, optimize performance, and enhance stakeholder confidence and acceptance (see Figure 8).

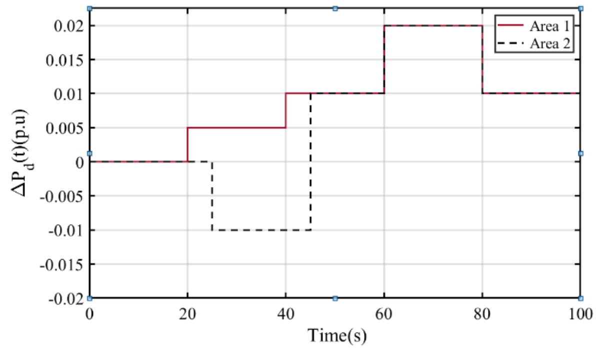

Figure 7. Random step load disturbance

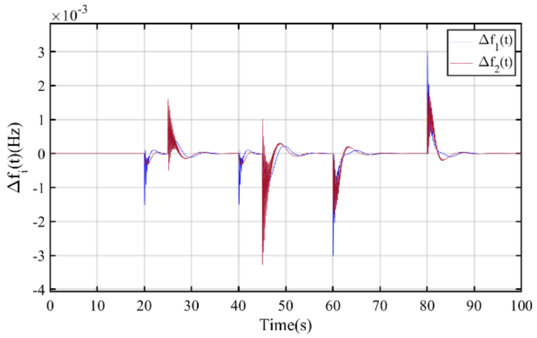

Figure 8. Frequency deviation of two area

Case 3: With GRC and GDB

The generation rate constraint (GRC) and governor deadband (GDB) are crucial parameters that significantly influence the dynamic response, stability, and operational efficiency of power systems (see Figure. 9). GRC limits the rate at which the power generation can change over time. GDB represents the range within which the governor control system does not respond to minor frequency deviations. Validating the proposed design with respect to these parameters is essential to ensure system stability, reliability, compliance, and stakeholder confidence, facilitating optimal performance. Figure. 10 illustrates the frequency deviation with and without GRC and GDB. It is observed that the frequency stabilization achieved using COA is within acceptable limits affirming the resilience of the proposed design.

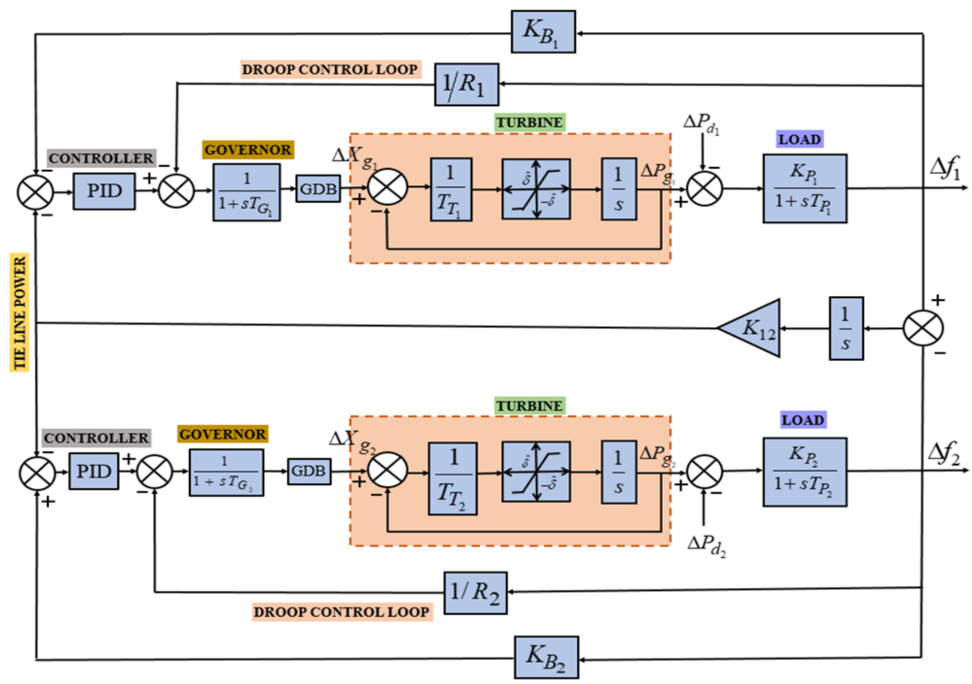

Figure 9. Interconnected power system with GRC and GDB [22]

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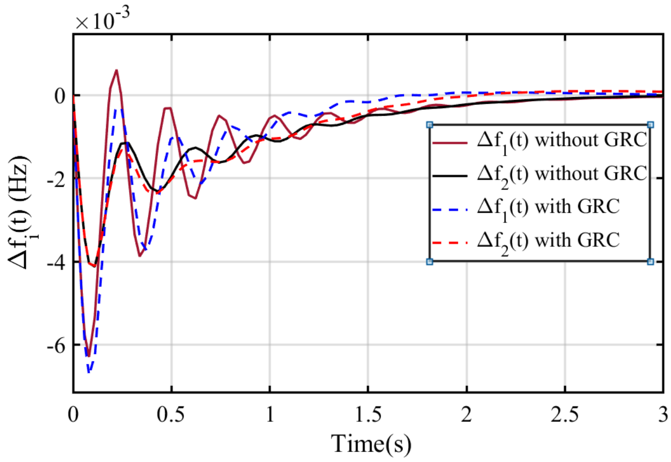

Figure 10. Frequency deviation with and without GRC and GDB

Case 4: Comparison

In this case, the proposed COA is compared with other meta heuristic optimization algorithm namely, GWO, SSA, TL, and WAO. While COA simulates the cooperative burrowing behaviour of crayfish to achieve optimization, GWO mimics the social hierarchy and hunting strategies of grey wolves, balancing between exploration and exploitation. TLBO models the classroom teaching and learning process to foster collaboration and knowledge exchange among individuals. SSA draws inspiration from the swarming behaviour of marine organisms, emphasizing adaptability and decentralized decision-making. The suggested design demonstrates a reduced frequency deviation peak of approximately 24.4% compared to GWO, 45.5% compared to SSA, 20.5% compared to TL, and 52.2% compared to WOA in area 1 (refer to Figure 11). Likewise, in area 2, the frequency deviation peak is lower by around 20.3% compared to GWO, 12.3% compared to SSA, and 30.6% compared to TL (see Figure 12). However, no significant improvement is noted in area 2 compared to WOA (see Table 2).

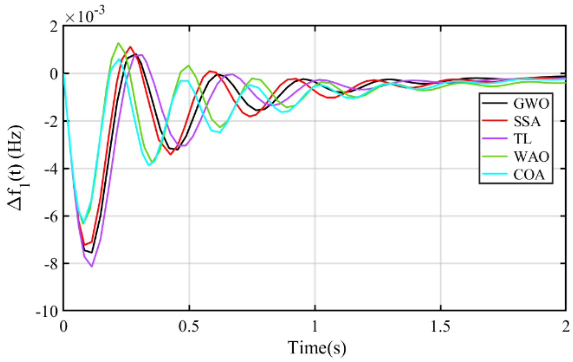

Figure 11. Area 1

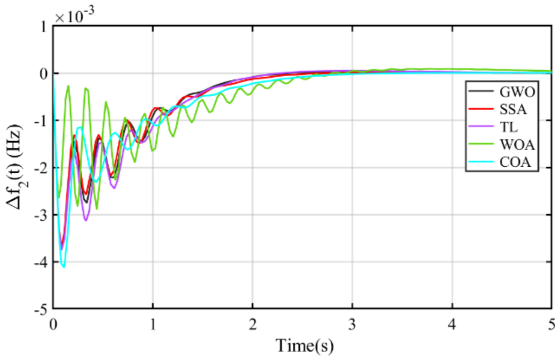

Figure 12. Area 2

Table 2. Peak value comparison

	GWO	SSA	TL	WOA	COA
$\lvert\nabla f_1(t)\rvert$	0.000810	0.001124	0.000770	0.001281	0.000612

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$\left\|\mathrm{V} f_2(t)\right\|$	0.001440	0.001309	0.001654	0.000260	0.001147

5. Conclusion

The utilization of the Crayfish Optimization Algorithm (COA) in designing a PID controller for frequency stabilization in a two area interconnected power system has been thoroughly investigated. Through extensive simulations conducted in MATLAB, the proposed COA-based controller has demonstrated remarkable efficacy and robustness when compared to other metaheuristic approaches. Specifically, its performance has been evaluated under various scenarios, including step load changes, random load fluctuations, and the presence of nonlinearities such GRC and GDB. The results affirm the superiority of the COA-based PID controller, showcasing its ability to effectively stabilize frequency and tie line power within acceptable limits while maintaining robustness and adaptability in challenging operating conditions. This study underscores the potential of COA as a promising optimization tool in power system control applications, offering valuable insights for future research and practical implementations in real-world power systems.

Future work in crayfish optimization may focus on refining its exploration and exploitation capabilities, integrating adaptive mechanisms, and benchmarking against state-of-the-art algorithms to establish its efficacy across various optimization domains.

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