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IIoT-based Automatic FOPID Tuning for AVR Systems Using a Customized Chaotic Whale Optimization

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Abstract

This paper presents a new trend toward Artificial Intelligent Engineering by replacing a stand-alone control with remotely real-time control for users by using the Industrial Internet of Things to enhance AVR system tunning. The AVR is optimized by a new version of the Proportional-Integral-Derivative (PID) controller called FOPID which used the Fractional-Order calculus. The PID control is same FOPID while using external parameter that provide new and good performance extension. The five parameters of controller are tuned by a new version of the most popular metaheuristic algorithm which is Whale Optimization Algorithm (WOA). The usage of classical Whale algorithm is a clear algorithm but non-effective for tuning Fractional order controller in a wide range of optimization issues. Therefore, a Customized Chaotic-WOA (CCWOA) is proposed that is developed by mathematical equations and applied chaotic logistic map, which improves the algorithm convergence rate and precision by permitting it to minimize local minima stagnation. The performance of the proposed algorithm is evaluated with unimodal and multimodal benchmark functions. There are 13 benchmark functions with different characteristics are presented. On the other hand, the efficiency and superiority of the proposed algorithm with some recent algorithms and compare the response of the proposed controller with the classical PID to Justify the reason for switching from PID to FOPID Controller. Additionally, the optimal solutions of the comparison analysis are displayed. Numerical results and robustness analysis verify that CCWOA based on FOPID has effective tuning capability to enhance the step response of the AVR system compared to various existing algorithms.

Keywords: Customized Chaotic Whale Optimization Algorithm (CCWOA), Industrial Internet of Things (IIoT), Artificial Intelligent Engineering (AIE) and FOPID controller.

1. Introduction

Electricity is produced from a variety of natural resources through electrical power-producing systems. The generators built into these systems transform mechanical energy into electrical energy. The systems tend to oscillate at equilibrium during the conversion process due to vibrations in the moving components, load fluctuations, and different external disturbances [1]. To avoid this, exciters are frequently used to feed the synchronous generators. The exciters will regulate the generators' input to maintain a constant output voltage [2]. In this procedure, the exciter's input signal level is maintained using Automatic Voltage Regulator (AVR) systems in the control loop [3], which enables the generator to maintain a consistent output voltage power at the terminals. PID controllers are used as the fundamental control element in most control schemes. Current industrial controllers still employ PID controllers due to their simple design, simple implementation, and resilience under a variety of operating conditions [4,5].

Today, most research focus on improving PID controller performance by using novel mathematical concepts. PID is a commonly used controller in systems, and the value of PID gain parameters (k_p , k_i and k_d) must be set. This is no ordinary or easy task. In 1999, Podlubny firstly proposed the FOPID controller. It is an extension of the conventional fractional calculus-based PID controller. The Fractional-Order PID controller (FOPID), which is considered as a development of the traditional PID has two additional fractional degrees parameters (λ, μ) [6]. λ is cited as integration order and μ is refers to an differentiation order. These additional parameters will benefit FOPID controllers even more [7]. For an optimal tuning, all of these parameters should be carefully tuned. The usage of FOPID controllers was popular in some applications such as DC motors, control of water flow, AVR..etc.

In the literature, a variety of objective functions were used to adjust the FOPID/PID controllers' settings. λ , μ are parameters of the FOPID controller for the step-down converter. for the use of metaheuristic algorithms to set the PID controller parameters even though there is no operation [8]. There's various popular metaheuristic algorithm used in most literature, whale optimization (WOA) in [9,10], firefly algorithm (FA) in [11], particle swarm optimization (PSO) in [12,13], Salp algorithm [14,15], bacterial foraging optimization (BFO) [16] and genetic algorithm (GA) in [17]. Several studies used axiomatical tuning methods based on superior algorithms, and to analysis these tuning several methods are used. These methods are the integrals absolute error (IAE)[18], integral square error (ISE)[19], integral time absolute error (ITAE)[20], integral time squared error (ITSE)[21], and time domain suggested by Zwe-Lee Gaing ZLG, which is a defined performance measure [22].

Many researchers focus on Artificial Intelligent Engineering (AIE) which is based on implementing an optimization system and communicating these systems to each other using IIoT [23] to be controlled remotely. In [24] researcher proposed a real-time optimization model that applied to the AVR System by using a new version of Harris Hawk Algorithm (EHHOA) based on IIoT. In [25] there's an introduction to the architecture of tunning cascade control system using particle swarm optimization using the internet of things (IoT) environment. Another important aspect that introduces a new trend of using new controller rather than conventional PID and tunning via optimization algorithm in [] researcher use standard WOA to tune PID and PID-Acceleration (PIDA) parameter on AVR system.

In light of the discussion above, this paper presents three novel contributions presented as follow:

- Developing the standard whale optimization algorithm using mathematical equations and a chaotic logistic map was applied to improve the convergence of standard algorithm.
- Introducing the proposed stand-alone tunning model using CCWOA and FOPID controller on AVR system.
- Introducing a novel IIoT architecture model to replace the traditional strategy of tunning to FOPID parameters for AVR system with real-time optimization which make the results available and enable remotely control to users.
- Indicating clearly that the dynamic response of FOPID parameters optimization using proposed model by a comparison with classical PID and comparative analysis with some recent algorithms

This paper has been divided into the following parts: Section 2 examines the preliminary information on the FOPID and WOA algorithm and essential operators. Section 3shows the integration of the proposed algorithm CCWOA based on FOPID for the AVR system also the proposed architecture model using IIoT. Section 4 shows the Computational experiments using benchmark functions and includes result analysis. Finally, the conclusion and suggested future directions are shown in section5.

2. Materials and methods

This section provides the principle of information about FOPID control, the mechanism of the standard Whale Optimization Algorithm and the main concept of the IIoT layer.

2.1 Fundamentals of the FOPID controller

Five parameters are used to define FOPID controller: proportional gain, integral gain, differential gain, order of integral and order of derivative (k_p, k_i, k_d , λ , μ). FOPID controller transfer function [27] is represented as follows:

$$G_{FOPID}(s) = K_p + K_i S^{-\lambda} + K_d S^{\mu} \qquad (1)$$

, where $\lambda, \mu > 0$. The graphical illustration of the FOPID controller is represented in Figure 1, where the *x*-axis integral order is fractional while the y-axis represents the integral order of the derivative order representing the degree. The coordinates of the controllers are represented as follow: PID (λ, μ) = (1,1), PD (λ, μ) = (0,1), PI (λ, μ) = (1,0) , and P (λ, μ) = (0,0). all these classic PID controller types and FOPID controller's customs are in the situation. This figure is between the FOPID controller and the traditional

PID controller. FOPID controller, full-order PID controller point-to-point expands to the plane. This extension depends on the controller design. real-life transactions by adding more flexibility. provides accurate control [28].

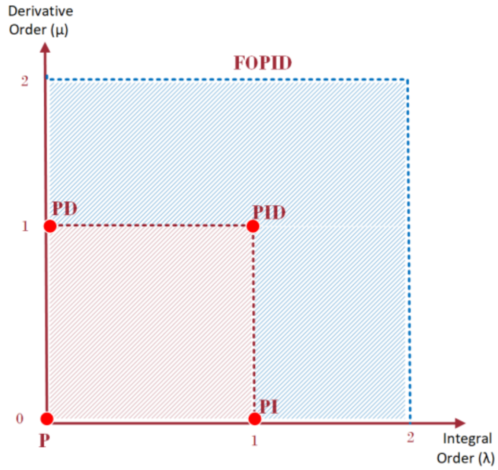

Fig. 1: The graphical representation of the FOPID controller

2.1.1Approximate value of fractional derivative

In practical application, must be calculated numerical solutions of fractional systems and fractional in the time domain. It is difficult to implement operators directly. Approximate approaches are used to resolve this problem. Oustaloup's [29] approximation approach is the most well-known. Oustaloup's approximate is a method which uses an iterative pole and zero distribution. The value of the transfer function is described as:

$$s^{\sigma} \cong \Re \prod_{n=-O}^{O} \frac{1+\frac{s}{\omega_{i,n}}}{1+\frac{s}{\omega_{j,n}}} \quad , \sigma>0 \qquad (2)$$

s^{σ} is fractional order in Laplace transform variables where $\sigma \in -\lambda, \mu$ and O is the order of approximation. If $\Re$ is the transient gain. It is a gain value that allows it to have $\omega_{i,n}$ and $\omega_{j,n}$ if is given as follows:

$$\omega_{i,n} = \omega_b \left(\frac{\omega_h}{\omega_b}\right)^{\frac{n+O+(1-\sigma)/2}{2O+1}} \qquad (3)$$

$$\omega_{j,n} = \omega_b \left(\frac{\omega_h}{\omega_b}\right)^{\frac{n+O+(1+\sigma)/2}{2O+1}} \qquad (4)$$

In Equation 3, 4 ω_b and ω_h are the approximate value and the upper and lower frequency limits of $\omega_b.\omega_h = 1$, $K = \omega_b^{\sigma}$ were descried in [30],[31] and [32].

2.2 The overview of standard Whale Optimization Algorithm (WOA)

The whale optimization algorithm (WOA), a well-known optimization algorithm, was influenced by the bubble net's hunting method even though it was developed as a metaheuristic algorithm. The algorithm describes the specific hunting behaviour of humpback whales; whales follow the typical bubbles, causing a circular-shaped path that is created while encircling the prey during hunting. The three stages of the WOA mathematical model include encircling prey, bubble-net attacking, and searching for prey. The stage of encircling prey and bubble-net is considered as exploitation, while random searching is considered as exploration.

2.2.1 Encircling prey

In nature when hunting, humpback whales locate their prey and totally surround them. There is assumption that the current best search agent is the targeted prey, and that humpback whales iteratively shift their position towards the best search agent. The methodology of this action is provided by the equations below.

$$\vec{W} = \left| \vec{C}.\overrightarrow{X^n}(t) - \vec{X}(t) \right|, \qquad (5)$$

$$\vec{X}(t+1) = \overrightarrow{X^n}(t) - \vec{A}.\vec{W}, \qquad (6)$$

Where $\vec{X^n}(t)$ represents the whale's previous best position at iteration t. $\vec{X}(t+1)$ is the whale's current position, $\vec{W}$ s the distance vector between whale and the prey. The parameters of $\vec{A}$ and $\vec{F}$ are refer to coefficient vectors can be represented as follows:

$$\vec{A} = 2\vec{a}.\vec{r} - \vec{a}, \qquad (7)$$

$$\vec{F} = 2.\vec{r} \qquad (8)$$

, where components of $\vec{a}$ are decreased linearly from 2 to 0 during the iterations, and r is random vectors in [0,1] and can be descried as follow:

$$\vec{a} = 2 - \frac{2t}{MaxIter} \qquad (9)$$

, where MaxIter refers to the maximum number of total iterations.

2.2.2Bubble-net attacking method (exploitation phase)

There's a description to mathematically model the bubble-net behaviour of the humpback whales, two methods are built as follows:

2.2.2.1 Shrinking Encircling Mechanism:

This action is accomplished by decreasing the value of $\vec{a}$ Note that the fluctuation range of $\vec{A}$ is also reduced by $\vec{a}$, To put it another way, $\vec{A}$ is a random value in the interval [-a, a] where, through iterations, and is reduced from 2 to set random values for $\vec{A}$ in [-1,1], the new position of a search agent can be established somewhere between the agent's original position and position of the current best agent.

2.2.2.2 Spiral updating position:

This approach first calculates the distance between the whale located at (X, Y) and the prey located at (X^n,Y^n). Then, a spiral equation is created between the position of the whale and the prey to imitate the helix-shaped movement of the humpback whales:

$$\vec{X}(t+1) = \vec{W}^{'} e^{bl} \cos(2\pi l) + \vec{X}^{n}(t) \qquad \rightarrow \quad (10)$$

Where $\vec{W}^{'} = \left| \vec{X}^{n}(t) - \vec{X}(t) \right|$ and indicates the distance of the ith whale and the prey (best approach so far obtained), t is a random number between [-1,1] and b is a constant for the logarithmic spiral shape. Note that humpback whales swim in a shrinking circle and simultaneously along a spiral-shaped track around the prey. To model this simultaneous behaviour, there’s assumption to probability of choosing 50 % , to update the position of the whales during optimization, choose between either the spiral model or the diminishing encircling technique. The concept of mathematics is as follows:

$$\vec{X}(t+1) = \begin{cases} \vec{X}^{n}(t) - \vec{A}\vec{\mathrm{W}} & \mathrm{P} < 0.5 \\ \vec{W}^{'} e^{bt} \cos(2\pi l) + \vec{X}^{n}(t) & \mathrm{P} \geq 0.5 \end{cases} \qquad \rightarrow (11)$$

, where p is refer to a random number in range [0,1].

2.2.2.3Search for prey (exploration phase)

The same approach may be used to search for prey (exploration), based on the variation of the $\vec{A}$ vector. $\vec{A}$ value range is between 1 and -1 forcibly displacing the search agent from a reference whale. In contrast to the exploitation phase, there’s an update to the position of a search agent according to a random selection search agent during the exploration phase rather than the best search agent. This mechanism and $\left|\vec{A}\right| > 1$ indicate the exploration and permit a global search of the WOA algorithm.

The mathematical model is as follows:

$$\vec{D} = \left| \vec{C}\vec{\mathrm{X}}_{\mathrm{rand}} - \vec{X} \right| \qquad \rightarrow \quad (12)$$

$$\vec{X}(t+1) = \vec{\mathrm{X}}_{\mathrm{rand}} - \vec{A}\vec{D} \qquad \rightarrow \quad (13)$$

Where $\vec{X}_{rand}$ is refer to the random whale or random position vector. The fitness function's computing complexity is O(ND), where N is the population size of the whales and D is the dimension of the search agents.

3. The proposed CCWOA-FOPID for the AVR system

In this section the mechanism of the proposed algorithm CCWOA will be described, also there is a comparison between some significant advantages and disadvantages of the proposed algorithm. In order to make a fair and real comparison with the previous algorithms, the fitness function and constraint will be described in the second subs section. Finally, the integration of the proposed model for the AVR system will be shown.

3.1 The Mechanism of the Proposed CCWOA Algorithm

In this study, there's a proposed modification of standard WOA to enhance the selection of parameters A and l. So, the exploration and exploitation stages of WOA will be affected by this enhancement. The experimental investigation is presented in the next section to validate this adjustment. As opposed to being completely random, l is determined by the following equation:

$$l = (a' - 1) * a'' + 1 \qquad (14)$$

, where a' exponentially reduces from − 1.26 to 1.73 through the following equation .. and a'' is a random number with range [0,1]

$$a' = 2 * \left(e^{-\left(1+\frac{t}{MacIter}\right)} - 1 \right) \qquad (15)$$

Thus, the range of the variable l is [-1.73,1]. The next step in the enhancement of WOA is improving the value of the variable in equations 14 and 15 hence, rather than changing linearly, it is modifying exponentially from 2.7 to 1. The new a is described as follows:

$$a = e^{\left(1-\frac{t}{MaxIter}\right)} \qquad (16)$$

Chaos technique is a random phenomenon that emerges in almost non-linear and deterministic systems, is extremely sensitive to beginning values. Numerous chaotic logistic maps [33], including Sine, Circle, Piecewise, Logistic, etc., have been described in the literature. Here, a chaotic sequence is generated using the logistic map as follows:

$$O^{l+1} = CO^l(1-O^l) \qquad (17)$$

The initial parameter can be specified using the default settings: $c = 3, O^l = rand[0,1]$ and $C_1 \notin \{0.25, 0.5, 0.75\}$. Chaotic can be implanted in WOA as follows:

$$C_l = (1-\beta)*T + \mu C_i' \qquad (18)$$

where C_l denotes the optimum solution and T denotes the goal position and could be calculated using the formula:

$$\beta = \frac{MaXIter - CurIter + 1}{MaXIter} \qquad (19)$$

, where $MaxIter$ refers to the maximum number of iterations in the process and $CurrIter$ is the current iteration. In Table 1 there is describe some significant advantages and disadvantages of the proposed CCWOA. All of these steps produced a new algorithm enhanced from the original WOA called CCWOA, figure 2 introduces the flowchart of the proposed algorithm.

Table 1: proposed algorithm advantages and disadvantages

Advantages	**Disadvantages**
Has a fast convergence curve rate.	Have a higher computational complexity than standard WOA algorithm
Good accuracy in computing and can be robust	Must have setting the Initial value
have a higher chance of achieving the global optimum and more efficiency	Have a weak capability of searching locally.
Can be effective in solving issues where finding accurate mathematical models is challenging.	Acquires a high-dimensional issue
can be used for significant problems.	Have a complex theoretical analysis

The steps of the CCWOA can be represented as follows:

- **Step 1**: Initialize parameters of WOA, whale population (N) and the dimension of search agent (D)

- **Step 2**: Start assessing each whale's fitness function in the population.

- **Step 3**: Select the lowest fitness function value and assign X^*

- **Step 4**: Enhance parameters and update position for various cases.

- **Step 5**: Select a random search agent and Evaluation of the fitness function values.

- **Step 6**: Update X when found the best solution

- **Step 7**: Apply a Chaotic logistic map

- **Step 8**: Keep going from Step 2 until the end of the criteria is met.

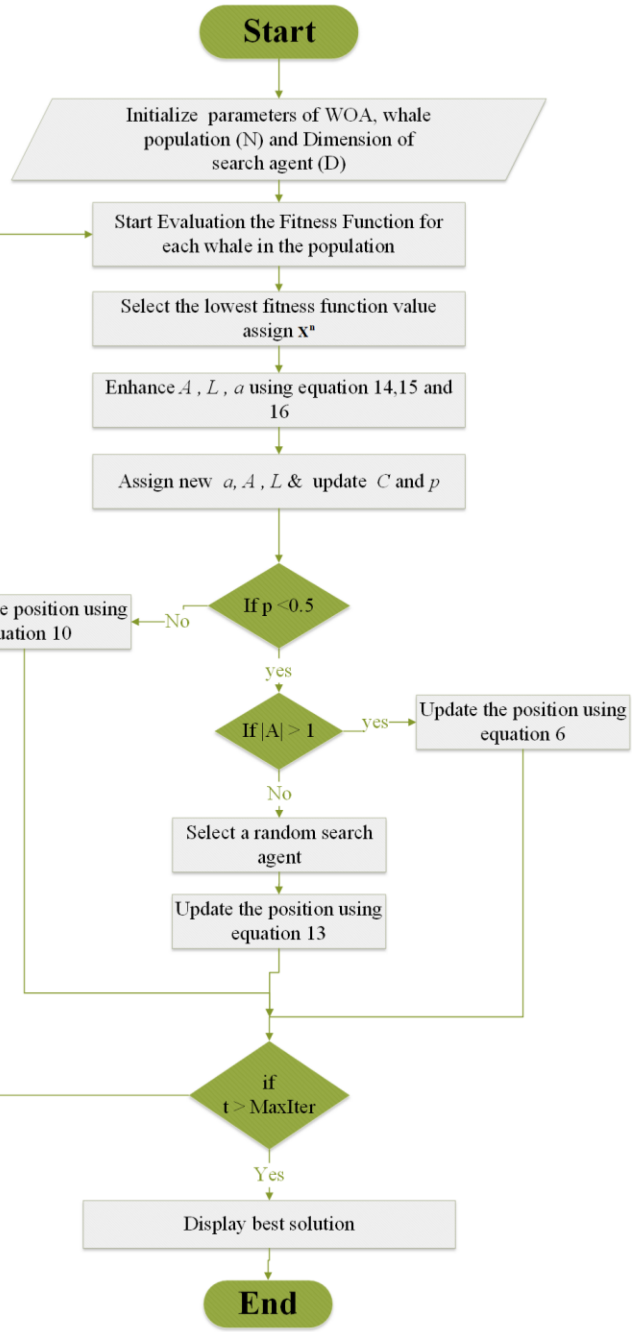

Fig. 2: CCWOA proposed algorithm flow chart diagram

3.2 The objective function and constraints

In this study, the same objective function, ITAE, is utilized to compare the algorithms in a fair and accurate manner. As stated below, the ITAE's prime objective is:

$$ITAE = \int_0^{t_s} t.|e(t)|.dt \qquad (20)$$

, where e(t) represents the error of the control signal that can be calculated with the difference between the output and the reference value. t_s is the simulation time, which is 2.2 s. in this work. When the ITAE goal function is reduced, the AVR control system's transient sensitivity is improved in terms of maximum overshoot, settling time, and rising time. The domain of the FOPID controller parameter is $K_p \in [0.001, 20]$, $K_i \in [0.001, 20]$, $K_p \in [0.001, 20], \lambda \in [0, 2.0]$ and $\mu \in [0, 2.0]$.

3.3 The proposed model for CCWOA-FOPID in the AVR system

The proposed CCWOA algorithm can be used to determine the perfect values for FOPID controller parameters to enhance the closed-loop response of the AVR system in terms of the transient response criteria because it has enhanced exploitation and exploration capabilities in comparison to the original WOA algorithm (maximum overshoot, settling time, and rise time). The proposed CCWOA-FOPID controller approach for the AVR system is depicted as a block diagram and is shown in Figure 3. The parameters are first coded to an initial population as $P = \{K_p, K_i, K_d, \lambda, \mu\}$ and each parameter is assigned with a real number to start optimization of the five FOPID controller settings using the suggested CCWOA. Then, to reduce the value of an objective function, the parameters are enhanced by going through the steps of CCWOA. The amplifier (G_a), exciter (G_e), generator (G_g), and sensor(G_s), are the four major parts of a straightforward AVR system. A first-order system with a time constant and a gain is used to represent the transfer function of each component. The transfer functions' related gain and time-constant typical ranges are further described in Table 2.

Table 2: Mathematical description of the AVR component

Component	Transfer Function	The Gain Range	Time - constant
G_a	$\frac{K_a}{1+\tau_a s}$	$10 < K_a < 400$	$0.02 < \tau_a < 0.1$
G_e	$\frac{K_e}{1+\tau_e s}$	$1 < K_e < 400$	$0.5 < \tau_e < 1.0$
G_g	$\frac{K_g}{1+\tau_g s}$	$0.7 < K_g < 1.0$	$1.0 < \tau_g < 2.0$
G_s	$\frac{K_s}{1+\tau_s s}$	$K_s = 1$	$0.001 < \tau_s < 0.06$

The AVR's transfer function with a FOPID controller and its output reference is shown as follows:

$$G_{AVR} = \frac{output}{reference \text{ value}} = \frac{0.1s+10}{0.0014s^4+0.044s^3+0.554s^2+1.51s+11} \qquad (21)$$

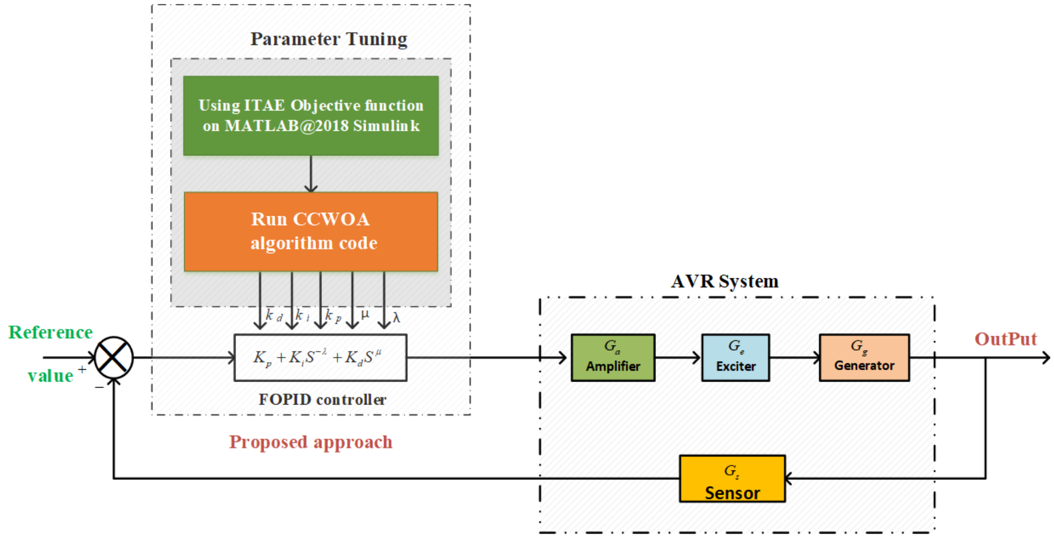

Fig. 3: AVR system control with CCWOA-FOPID

3.4. The proposed CCWOA-FOPID Architecture for IIoT

The proposed architecture will be based on integrating the proposed CCWOA-FOPID to optimize the AVR system automatically based on IIoT. Figure 4 describes IIoT architectures levels that can implement real-time FOPID optimization in which users can control and notify with feedback from system operation through the IIoT layers which consist of the application layer, middleware layer, network layer and perception layer. The IIoT layers services are developed by using a microcontroller (CC3200) which includes features of data security, data management and scheduling. The flow process from the application layer to the perception layer is considered controlling or optimizing. In contrast process from the perception layer to the application, a layer is notifying and sensing.

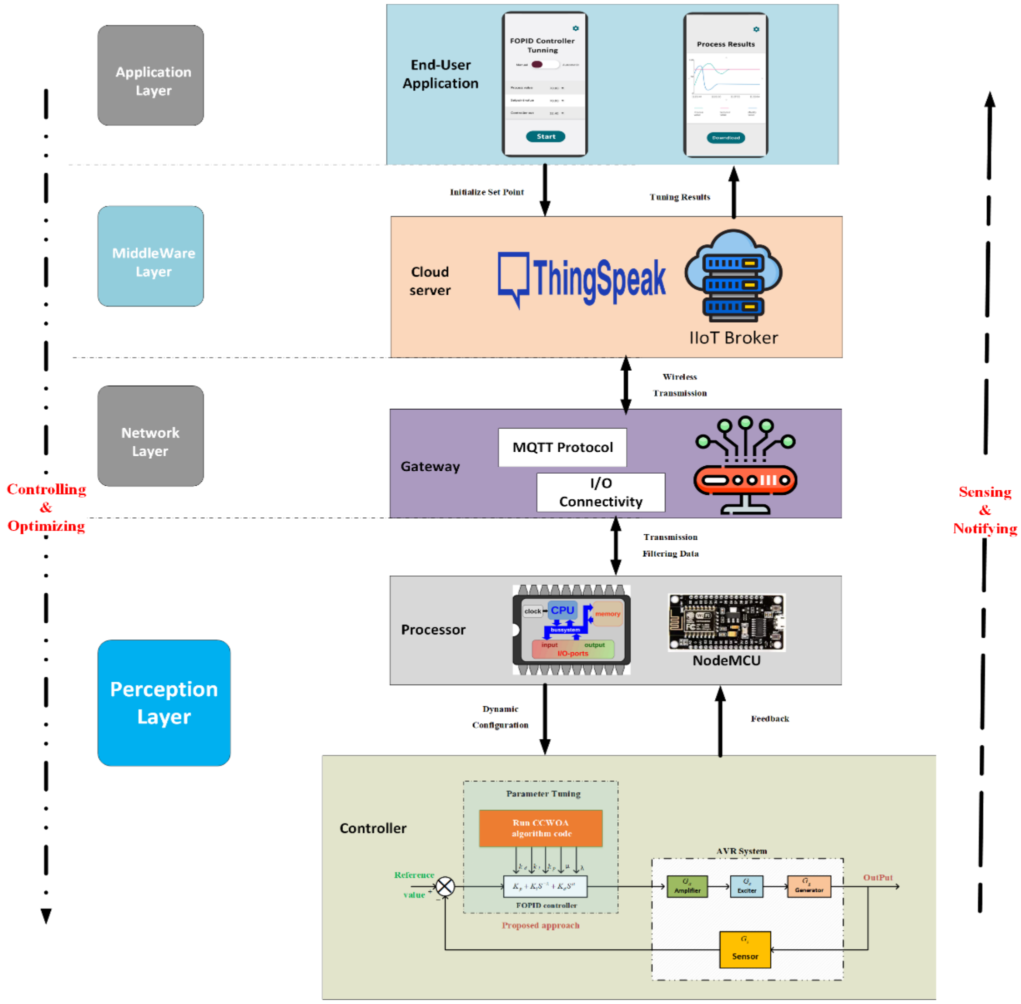

Fig 4: The proposed CCWOA-FOPID Architecture using IIoT

User devices: this block contains the main user devices, where actually status and analytics are observed through the software and application. In addition, the user can control and optimize the system and determine the setpoint and values, such as a smartphone, or laptop. etc.

Cloud server: in this level, all data will be stored from the application area and IIoT implantation process. Also, it serves the data with users' request, such as thing-speak, Microsoft azure, amazon web services…etc.

Gateway: It prepares data for transmission to the cloud server and adds value to the system using various protocols such as the message queue telemetry transport (MQTT) protocol.

Processors: It controls all sensors and actuators and supplies them with the necessary electrical power. All programming languages will be implemented using an embedded microcontroller (CC3200-Wifi).

Controller: This block will contain all of the sensor and physical hardware that are linked together and are implemented and performed using the IIoT process's received values.

4. Simulation results and Discussion

In this part, a number of test experiments are carried out to evaluate the effectiveness of the proposed algorithm CCWOA/FOPID. The CCWOA were developed using MATLAB / Simulink ® 2013b software, which was also used to model response of the system, frequency response, and robustness analysis. These simulations are performed on a personal computer with CPU Intel (R) Corei7 (R) of 1.35 GHz and RAM is 6 GB.

4.1 Benchmark and analysis of the proposed CCWOA

The performance of the CCWOA is investigated to solve the unimodal and multimodal benchmark functions. In this paper, 13 benchmark functions [34,35] with different characteristics are presented. The functions from f1 to f7 are shown in Table 3 that presented in [36]. These are unimodal test functions that require only exploitation to converge to the unique global optimum. Table 4 include Multimodal test functions from f8 to f13 applied in order to avoid local optima and achieve the global one, several (local and global) optima are presented, with an emphasis on a balance between exploitation and exploration. The CCWOA algorithm is compared to some of the best algorithms in the literature, such as GA, PSO, and standard WOA for results verification. Algorithms are compared equally using the same criteria in order to assess their performance, and more than 40 runs with separate population initializations for all test functions indicated in Tables 3, 4, and Table 5 presents the experimental observations of the average and standard deviation values for each algorithm. Figure 5 presents the convergence curves of the algorithm for each benchmark function.

Table 3: Unimodal test functions.

Test function	Range	f_{opt}
$f_1(X)=\sum_{i=1}^{n} x_i^2$	[-100,100]	**0**
$f_2(X)=\sum_{i=1}^{n}\lvert x_i\rvert+\prod_{i=1}^{d}\lvert x_i\rvert$	[-10,10]	**0**
$f_3(X)=\sum_{i=1}^{n}\left(\sum_{j=1}^{i} x_j\right)^2$	[-100,100]	**0**
$f_4(X)=\max_i \lvert x_i\rvert,\quad 1\le i\le d$	[-100,100]	**0**
$f_5(X)=\sum_{i=1}^{n-1}\left[100\left(x_{i+1}-x_i^2\right)^2+\left(x_i-1\right)^2\right]$	[-30,30]	**0.86**
$f_6(X)=\sum_{i=1}^{n}\left([x_i+0.5]\right)^2$	[-100,100]	**1.25**
$f_7(X)=\sum_{i=1}^{n} i x_i^4+rand(0,1)$	[-1.28,1.28]	**0.002**

Table 4: Multimodal test functions.

Test function	Range	f_{opt}
$f_8(X)=\sum_{i=1}^{n}-x_i\sin\left(\sqrt{\lvert x_i\rvert}\right)$	[-500,500]	**-4.2**
$f_9(X)=\sum_{i=1}^{n}\left[x_i^2-10\cos(2\pi x_i)+10\right]$	[-5.12,5.12]	**0**
$f_{10}(X)=-20\exp\left(-0.2\sqrt{\frac{1}{d}\sum_{i=1}^{n}x_i^2}\right)-\exp\left(\frac{1}{d}\sum_{i=1}^{n}\cos(2\pi x_i)\right)+20+e$	[-32,32]	**8.8**
$f_{11}(X)=\frac{1}{400}\sum_{i=1}^{n}x_i^2-\Pi_{i=1}^{d}\cos\left(\frac{x_i}{\sqrt{(i)}}\right)+1$	[-600,600]	**0**
$f_{11}(X)=\frac{\pi}{d}10\sin^2(\pi y_1)+\sum_{i=1}^{n-1}(y_i-1)^2\left[1+10\sin^2\left(\pi y_{i+1}\right)\right]+\left(yd-1\right)^2+\sum_{i=1}^{n}u(x_i,10,100,4)+y_i$ $=1+\frac{x_i+1}{4},u(x_i,a,k,n)=\begin{cases}k(x_i-a)^n & x_i>a\\ 0 & -a<x_i<a\\ k(-x_i-a)^n & x_i<-a\end{cases}$	[-50,50]	**4.7**
$f_{13}(X)=\left\{0.1\sin^2(3\pi y_1)+\sum_{i=1}^{n}(x_i-1)^2\left[1+\sin^2(3\pi x_i+1)\right]+(x_n-1)^2\left[1+\sin^2(2\pi x_n)\right]\right\}+\sum_{i=1}^{n}u(x_i,5,100,4)$	[-50,50]	**1.3498e-32**

The convergence diagram shown in Figure 4 and the results in Table 5 clearly show that the CCWOA algorithm is the best algorithm for test functions with the lowest statical analysis of variation . The CCWOA result of the analysis shows WOA, PSO, and GA in producing optimal values for unimodal functions from F1 to F7 with the lowest standard deviation and average values. The results are competitive compared to WOA in F5, and even though PSO exceeded it in F6, it is still second. CCWOA provides efficient exploitation, which contributes to its quick convergence to the best solution.

On the other hand, show that multimodal functions with greater dimensions such as F8, F9, F10, F11, F12, and F13, CCWOA quickly converged to the best solution, followed in the second stage with WOA, PSO performs relatively poorly for the remaining four functions, while having stronger convergence for F12 and F13. With estimated average and standard deviation values when compared to PSO, CCWOA is placed second for functions F12 and F13.

The results show CCWOA has the best average rank for all tests. Thus, the performance of CCOWA is better than various algorithms.

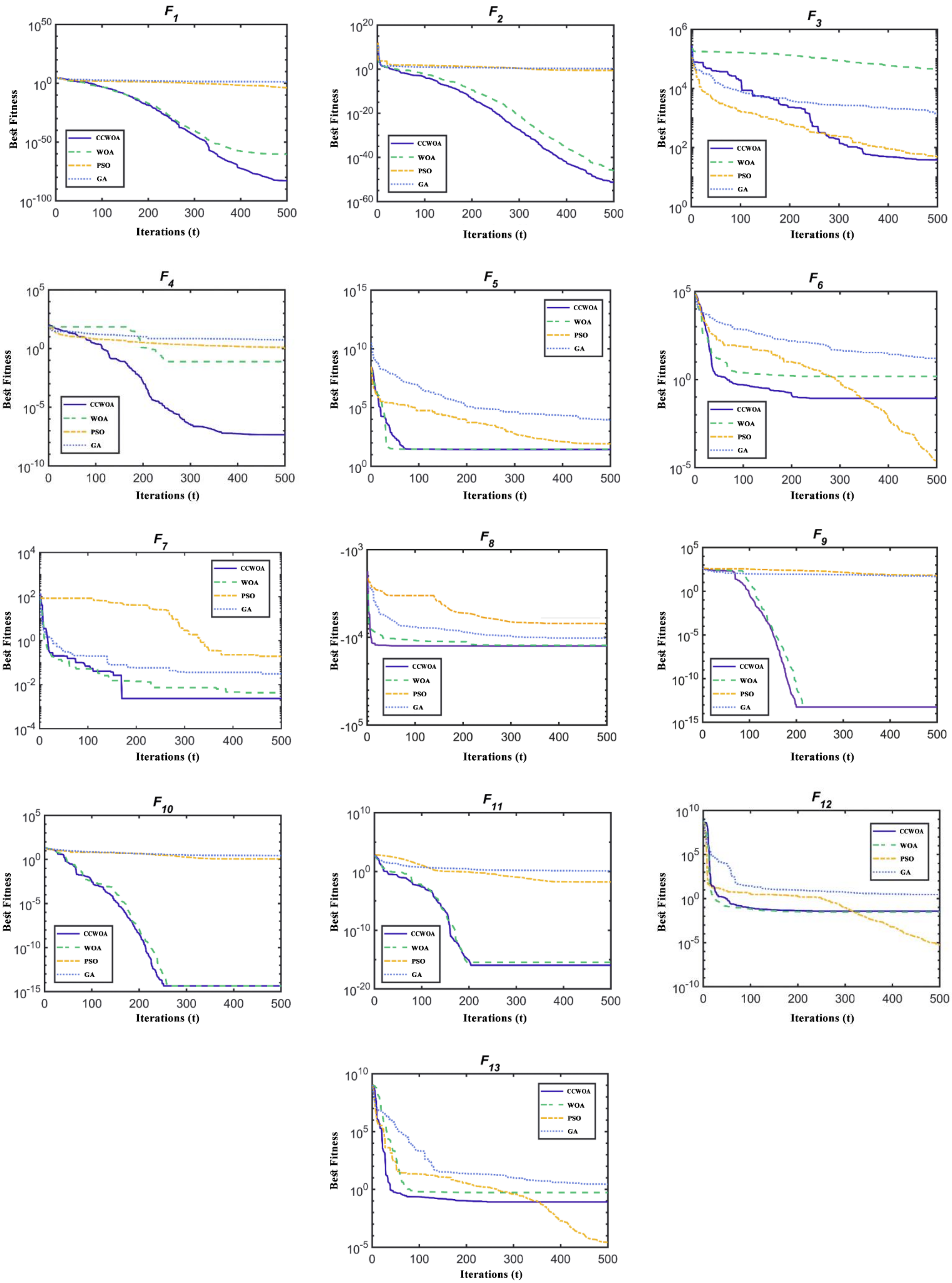
F1
F2
F3
F4
F5
F6
F7
F8
F9
F10
F11
F12
F13
CCWOA
WOA
PSO
GA
Best Fitness
Iterations (t)

Fig. 5 : Benchmarks diagram of Unimodal and Multimodal test function of four algorithms

Table 5. the numerical analysis for the proposed algorithm and comparison algorithms

ID	Algorithm	Best	Worst	Median	Average	STD
F1	**GA**	318.2456	1596.236	3277.126	3377.126	4356.922
	PSO	2122580.2	3303439.2	5118398	51183981	44448371
	WOA	21225803	3136.197	3615.217	3515.217	3694.592
	CCWOA	946.67259	3944.208	3944.208	4320.079	2587.169
F2	**GA**	3122580.2	333439.2	5118398	0	0
	PSO	51225803	31136.197	6615.217	0	0
	WOA	1946.6725	33944.208	6944.208	0	0
	CCWOA	212580.2	3439.2	1183.98	0	0
F3	**GA**	300	300	300	300	3.19E-07
	PSO	2108.9402	22578.087	3992.327	6016.056	5175.158
	WOA	2108.934	553.0946	336.0311	351.9874	60.95221
	CCWOA	300.00026	300.0135	300	300.0009	0.00305
F4	**GA**	400.2762	406.4312	403.7745	403.0263	2.158708
	PSO	407.7791	563.3884	411.8474	445.8044	53.72375
	WOA	407.7791	406.155	405.1933	404.7927	1.218841
	CCWOA	404.19418	408.2303	405.7141	405.2344	1.761902
F5	**GA**	525.869	577.6307	534.326	539.4732	18.60687
	PSO	541.7889	586.5452	552.5374	555.4925	16.46151
	WOA	541.7889	521.8991	511.4803	512.518	5.314397
	CCWOA	523.39745	565.6667	536.3159	536.7357	14.41524
F6	**GA**	604.1243	631.77	610.5965	612.658	9.789651
	PSO	632.4178	669.2541	638.3776	639.1642	12.69702
	WOA	632.4178	600.0397	600.0018	600.0039	0.008619
	CCWOA	606.89526	664.2668	624.1763	623.7979	17.04332
F7	**GA**	750.0333	800.2865	763.4635	764.1849	16.53892
	PSO	772.9736	847.5869	793.4636	792.6721	23.35112
	WOA	772.9736	740.8953	725.2596	726.0932	9.138484
	CCWOA	744.14382	825.2143	772.1789	770.9763	27.35464

F8	**GA**	820.8941	864.6718	828.8537	831.873	12.90815
	PSO	835.4478	894.0145	842.7488	845.4111	15.93723
	WOA	835.4478	822.884	811.4466	812.7699	5.127114
	CCWOA	825.86888	867.6564	831.1175	836.8516	15.70172
F9	**GA**	933.0708	2050.989	1106.709	1227.608	344.9987
	PSO	1068.03	2003.276	1244.185	1324.466	302.6735
	WOA	1068.03	900.9107	900	900.0955	0.245944
	CCWOA	961.34396	1969.029	1110.379	1176.302	284.5671
F10	**GA**	1898.049	2448.151	2062.364	2047.175	221.7145
	PSO	2022.64	2867.226	2242.572	2204.926	396.7856
	WOA	2022.64	2027.393	1501.675	1535.13	251.2706
	CCWOA	1698.2082	2713.746	2149.467	2081.553	392.1674
F11	**GA**	1130.47	1326.676	1142.507	1170.421	57.90485
	PSO	1164.94	1388.425	1230.57	1245.814	79.42272
	WOA	1164.94	1123.327	1106.585	1107.871	5.072009
	CCWOA	1137.9006	1236.306	1163.346	1164.88	34.34812
F12	**GA**	6797.742	62694.31	13409.94	20867.36	18432.64
	PSO	245965.6	13451165	1329347	4009393	4284488
	WOA	245965.6	892221	18180.07	84984.78	207174.6
	CCWOA	9863.9141	61694.72	18109.56	25057.7	19056.18
F13	**GA**	2356.48367	38924.49	9988.713	2.3437	1.0152
	PSO	7102.542	29165.68	6143.643	0.00490	0.0079
	WOA	6450.515	41102.19	11605.69	0.51868	0.3087
	CCWOA	5159.601	44266	10765.25	0.3412	0.24581

4.2 Simulation results for applied CCWOA-FOPID on AVR system

The efficiency and superiority of the proposed CCWOA-FOPID are examined by comparing the WOA-FOPID controller against other techniques identified in the literature that use the same AVR parameter (PSO-FOPID, GA-PID and Ziegler-Nichols (Z-N) method), in addition to the original WOA-FOPID approach. Additionally, the optimal solutions of the comparison analysis are displayed. The following subsections highlight the study's Importance.

4.2.1 Simulation results of tuning FOPID using the CCWOA on AVR system

The proposed algorithm used the equation to improve the main operators, then used a Chaotic logistic map to enhance the Whale Optimization Algorithm. Figure 6 shows the enhancement convergence rate. However, the proposed algorithm has the limitation of a high computational execution in terms of methodology and application.

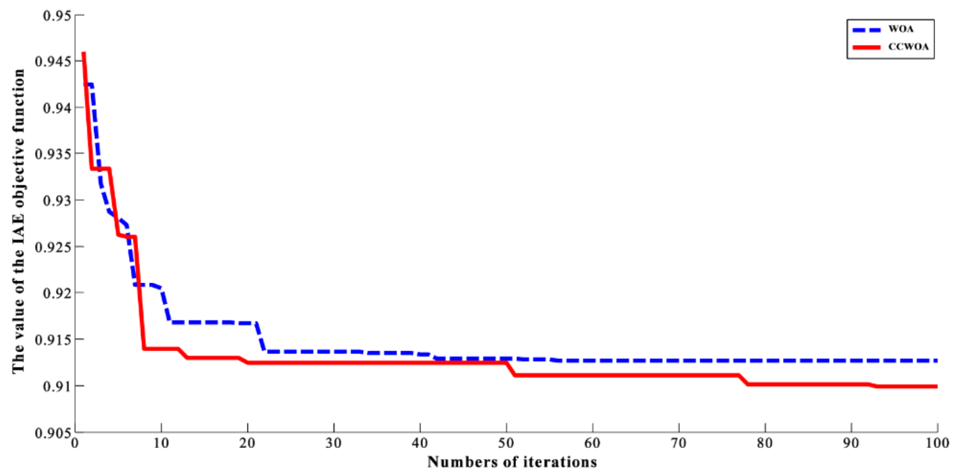

Fig. 6: The convergence rate obtained by the proposed CCWOA and original WOA

The FOPID controller gains are optimized by using the CCWOA to obtain a sufficient response for the tuning parameters of an AVR system. The initialized parameters of the CCWOA algorithm to simulate are shown in Table 6.

Table 6: Values of initialize parameters for CCWOA

Parameter	Value
Population size	40
Maximum iteration	40
Dimension of the optimization problem (D)	3
Initial Chaotic Parameter (C)	4

Figure 7 compares the proposed CCWOA-FOPID controller's periodic responses to those of other well-known and popular algorithms such as (WOA-FOPID, PSO-FOPID, GA-FOPID, and Ziegler-Nichols (Z-N) method). The proposed CCWOA-FOPID controller, in comparison to previous algorithms, has a better step response.

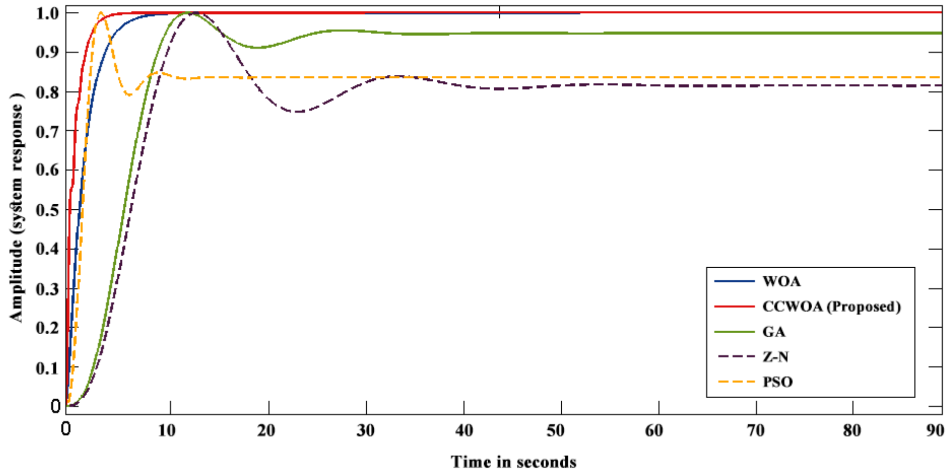

Fig. 7 : Step response of the proposed algorithm and various optimized tuning algorithms of the AVR system

CCWOA and other comparable techniques were executed separately 40 times in order to calculate the results of the performance index statistics for all runs. Furthermore, most studies use the four essential error criteria, integral absolute error (IAE), integral square error (ISE), integral time absolute error (ITAE) and integral time square error, to indicate system performance (ITSE). Table 7 displays the outcomes attained by various algorithms regarding the overall performance of any system in the control unit and the time domain specifications as a statistical measure.

Table 7. Comparative performance of various optimized FOPID controllers through dynamic parameters

Methods / Performance Index			IAE	ITAE	ISE	ITSE
Z-N/FOPID	**K_i**	4.6978	804	21.512e+04	3.767e+05	1770.98
	K_p	1.8098				
	K_d	1.2847				
	λ	1.8755				
	μ	1.3429				
PSO/FOPID	**K_i**	1.4898	100	1.565e+02	1.002+06	54.909
	K_p	1.2453				
	K_d	.98754				
	λ	1.1551				
	μ	0.9929				
GA/FOPID	**K_i**	1.9688	104.46	17.565e+02	6925	89.24
	K_p	.0504				
	K_d	.6300				
	λ	1.0755				
	μ	0.9969				
WOA/FOPID	**K_i**	.77635	16.113	36.02	313.8	17.153
	K_p	.96776				
	K_d	.75356				
	λ	0.9755				
	μ	0.9429				

CCWOA/FOPID	K_i .67635 K_p .06776 K_d .45356 λ 0.8401 μ 0.9112	9.733	17.02	201.8	4.153

It is clear from Table 8 results that the proposed CCWOA algorithm with FOPID achieves the third-best value of overshoot and provides the best dynamic responses when compared to the metaheuristic algorithms PSO, GA, WOA, and Z-N in terms of rising time, settling time, and peak time. CCWOA-FOPID controller is significantly lowered time-domain performance indices' values.

Table 8. the time domain specifications of FOPID parameter tunning with various algorithms

Time / Specification domain.	Z-N /FOPID method	PSO/FOPID algorithm	GA/FOPID algorithm	WOA/FOPID algorithm	CCWOA/FOPID (Proposed)
Overshoot (%)	22.7%	19.6%	5.3%	0%	%0
Rise time (s)	6.6s	1.68s	6.72s	4.2s	2.16s
Peak time (s)	14.9s	4.22s	14.3s	12.86s	7.52s
Settling time (s)	30.03s	7.34s	15.38s	5.9s	3.14s
Steady-state error (Ess)	0.185	0.17	0.052	0	0

4.2.2 Robustness analysis of CCWOA-FOPID

The proposed controller CCWOA-FOPID robustness is examined on the AVR system components individually, under different time constants from -50 % to +50% in levels of 25 %. Figures 8-11 show the step responses of the AVR systems for the four varying time constants; from the nominal response, which can be seen the parameters are within a narrow range, as shown in Table 9.

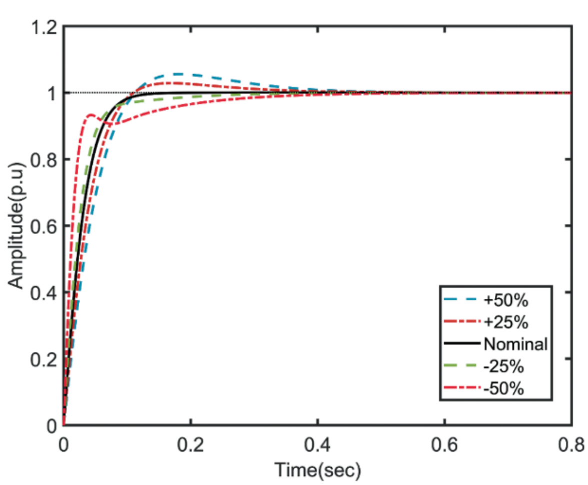

Fig. 8: Diagram of step response for T_A

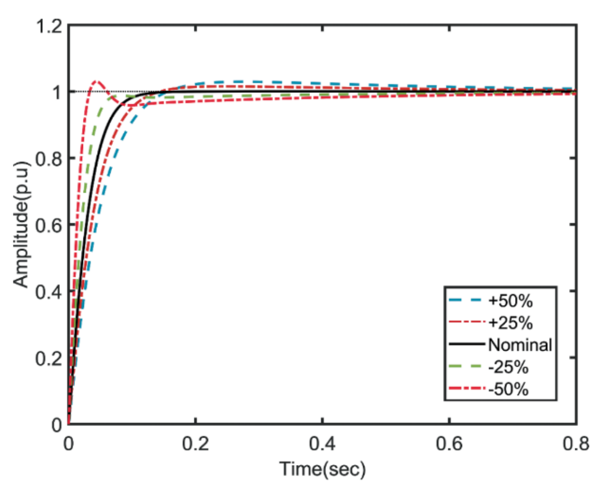

Fig. 9: Diagram of the step response for T_E

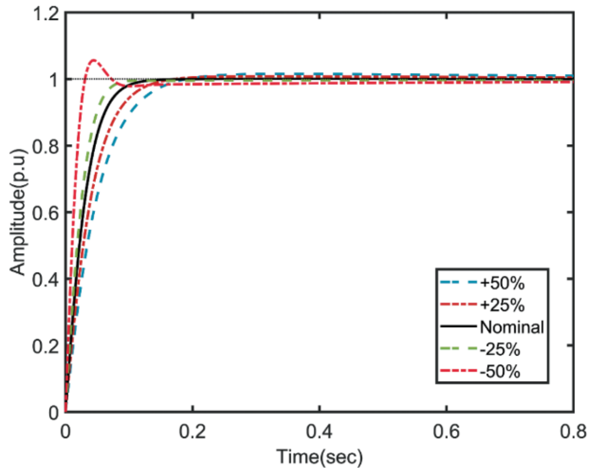

Fig. 10: Diagram of step response for T_G

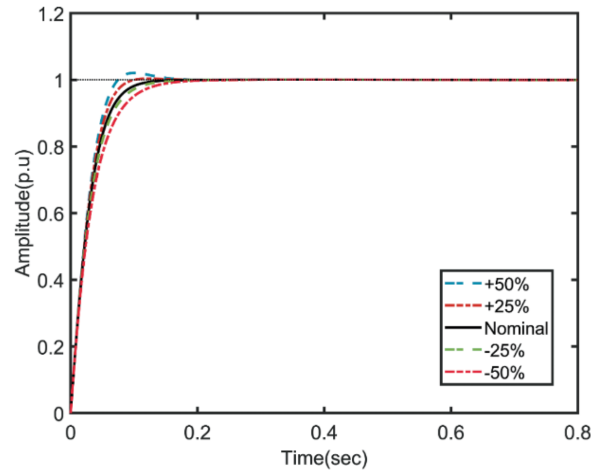

Fig 11: Diagram of step response for Ts

Table 9: Performance analysis for the proposed CCWOA-based FOPID

Time constant Parameters	**Precent of Change ratio**	**Amplitude (p.u)**	**Settling time (t_s)**	**Rise time (t_r)**	**Peak time (t_p)**
τ_a	**+50%**	1.0566	0.3477	0.0862	0.1938
	+25%	1.0176	0.2286	0.0777	0.1554
	-25%	0.9988	0.1987	0.0489	0.7533
	-50%	0.9998	0.2846	0.0326	0.8831
τ_e	**+50%**	1.0182	0.4810	0.0809	0.2734
	+25%	1.0173	0.1290	0.0858	0.2415
	-25%	0.9993	0.0993	0.0395	1.6785
	-50%	1.0289	0.3882	0.0258	0.0422
τ_g	**+50%**	1.0245	0.1655	0.0869	0.3424
	+25%	1.0071	0.1395	0.0380	0.3090
	-25%	0.9870	0.0853	0.0568	0.6429
	-50%	1.0852	0.1261	0.0231	0.0429
τ_s	**+50%**	1.0107	0.1033	0.0471	0.0974
	+25%	1.0134	0.0801	0.0553	0.1213
	-25%	1.0106	0.1172	0.0615	0.3584
	-50%	1.0086	0.1289	0.0713	0.3688

In several ways, the CCWOA algorithm outperforms other algorithms, such as its ability to attain global optima quickly while avoiding a standard developed to the local one. These results occur from the enhancement of operator choice and applying the chaotic map technique with the basic WOA algorithm, which generates fresh solutions in the search region and expands the population. In addition, WOA's exploitation and exploration processes promote it over metaheuristic methods. In terms of decreasing computing time, overshoot, and oscillations, the CCWOA method is useful, highly effective, and suitable for control engineering applications.

6. Conclusions

Today, many industrial processes used PID controller, Therefore, it was inevitable to enhance the performance of PID controllers through the applications of novel mathematical methods. To enhance system tunning, FOPID controller was used fractional-order calculus. The novel approach in this paper was proposed Customized Chaotic WOA to develop a new algorithm called CCWOA for FOPID controller tuning that has been compared with the most popular metaheuristic algorithms in MATLAB Simulink environment. Furthermore, the traditional strategy of tunning the FOPID parameters for AVR system was replaced with IIoT architecture to make the results available and enabled remotely real time control to users. The CCWOA was used to reduce the ITAE objective function and the reference value with the FOPID controller. The FOPID controller parameters were obtained with the least iterations at the end of the optimization process. To illustrate the effectiveness of the proposed CCWOA-FOPID, performance comparisons were done not only with the original WOA-tuned FOPID but also with the most popular algorithm using various analyses.

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