

A Comparative Study among Different Algorithms Investigating Optimum Design of PID Controller in Automatic Voltage Regulator

Romany G. George

*Dept. of Electrical Power and
Machines, Faculty of Engineering
Ain Shams University
Cairo 11517, Egypt.*

masteng_romanger@yahoo.com

Hany M. Hasanien

*Dept. of Electrical Power and
Machines, Faculty of Engineering
Ain Shams University
Cairo 11517, Egypt.*

hanymhasanien@gmail.com

Mohamed AL. Badr

*Dept. of Electrical Power and
Machines, Faculty of Engineering
Ain Shams University
Cairo 11517, Egypt.*

hanymhasanien@gmail.com

Mohammed A. Elgendy

*School of Engineering
Newcastle University
Newcastle upon Tyne,
NE1 7RU, UK*

mohammed.elgendy@ncl.ac.uk

Abstract— Proportional-integral-derivative (PID) controller is the most widely applicable controller in industrial control applications. Tuning of PID controller parameters manually requires experience in control tuning and may lead to inaccurate and poor performance. This paper explains in details how to employ whale optimization algorithm (WOA) and water cycle algorithm (WCA) to obtain the optimum PID controller parameters of an automatic voltage regulator (AVR) to enhance the terminal voltage of a synchronous generator. The saturation effect on AVR control system is taken into account in system simulation in order to represent a realistic AVR control system. A comparison is performed between these proposed algorithms and the genetic algorithm (GA) showing that the WCA offers a more satisfactory performance and faster convergence compared to the WOA, and GA.

Keywords— Automatic voltage regulator (AVR), PID controller, Whale optimization algorithm (WOA), Water cycle algorithm (WCA).

I. INTRODUCTION

Numerous control methods have been used to improve the transient responses and to reduce the steady-state errors of different industrial processes. Proportional-integral-derivative (PID) controller is considered the most prevalent in industrial applications due to its robustness and simple structure [1]-[2]. However, proper tuning of PID controller parameters is quite challenging in many cases in particular with high order and nonlinear systems.

Several techniques have been proposed for tuning the PID controller parameters [3]-[8]. Ziegler-Nichols method [3] is the most commonly used but it may not be applicable for some practical systems as it forces the process into a condition of marginal stability during controller tuning which may cause unstable operations. Artificial intelligence (AI) techniques such as fuzzy logic control, neural-fuzzy system, and neural network techniques have also been suggested for fine-tuning of PID controller parameters [5]-[6]. The fuzzy logic system, however, requires training of membership function which is difficult to estimate and may not scale well to large or complex problems. Time-consuming and hardly tuning of PID controller parameters are obvious deficiencies of the artificial

neural network. Another approach has been recommended for proper tuning of PID parameters is lambda tuning method [7]. However, this approach is not beneficial for obtaining a fast response. Furthermore, the interval polynomial stability criterion and Lyapunov theorem have been introduced for designing PID controller parameters [8]. This method manifests complex analysis.

One of the applications that require special care in PID controller design is the automatic voltage regulator (AVR) of the synchronous generator [9]-[10]. In order to keep the terminal voltage of the synchronous generator constant at different load conditions and to supply the necessary reactive power by regulating the voltage of exciter, an optimized PID controller design is necessary. For this application, different meta-heuristic techniques have recently been employed in optimizing the PID controller design. These techniques include Simulated Annealing [11], Genetic Algorithm (GA) [12], Particle swarm optimization (PSO) [13], Taguchi Combined Genetic Algorithm [14], Modified PSO [15], and Harmony Search Algorithm [16].

This paper investigates the use of two meta-heuristic algorithms for tuning the PID controller parameters of the AVR system in order to enhance the terminal voltage response of the synchronous generator; whale optimization algorithm (WOA) and water cycle algorithm (WCA). These algorithms have been applied to solve many optimization problems concerned with electric power systems and machines [17]-[19]. A simulation model of the system including saturation effects is developed using Matlab/Simulink. In order to show the effectiveness of these algorithms, results are compared with that of the GA and the performance of three algorithms, when used for PID controller tuning of the AVR system is analyzed.

II. AVR SYSTEM MODELING

The function of the AVR is to maintain the terminal voltage of the synchronous generator constant in spite of load variation. The AVR control system comprises main four components: amplifier, exciter or excitation system, generator, and a feedback sensor. Modeling of AVR system requires these components to be linearized to obtain transfer function.

An efficacious and robust response of AVR system requires a controller introduced into the main component of AVR system consequently, applying a PID controller to AVR system can enhance the dynamic performance of AVR system and exclude the steady-state error.

The transfer function of the AVR components and their typical ranges are indexed in Table (I). The block diagram of the linearized AVR system with PID controller is depicted in Fig. 1. As shown, the terminal voltage of synchronous generator (V_g) is measured through feedback sensor and compared to a reference voltage (V_{ref}) resulting in error voltage (V_e) which is fed to the PID controller to improve dynamic response and eliminate the steady-state error. The output of PID controller is then applied to the exciter which in turn varies the excitation voltage and consequently the synchronous generator terminal voltage.

Nonlinearity in AVR system

The AVR previously illustrated neglects nonlinearity due to magnetic saturation effect both in synchronous generator and exciter. To improve the accuracy of the model, this nonlinearity should be considered. The magnetic circuit of the exciter includes an air path and an iron path. It is the iron path saturation that needs to be taken into account where the relation between the magnetomotive force (MMF) and magnetic flux (Φ) is non-linear depending on synchronous generator loading. The nonlinearity in AVR system due to magnetic saturation in excitation system is consider in this paper by introducing a saturation factor (S_E) combined with the DC-exciter in the AVR linearized model. The additional block diagram shown in Fig. 2 has been added to the exciter model expressing the saturation characteristic of the exciter in AVR control system [20].

The relation between the open circuit voltage of synchronous generator $V_{go/c}$ or E_f and the exciter V_R input voltage is first-order transfer function and can be given as follows:

$$E_f = (V_R - E_f \times S_E) / (K_E + T_E \cdot s) \quad (1)$$

where S_E is a nonlinear function of E_f where $S_E = f(E_f)$ that can be approximated exponentially as follows

$$S_E = A_{ex} e^{B_{ex} E_f} \quad (2)$$

where A_{ex} and B_{ex} are constants constituted by the heavily saturated region of the characteristic curve of the exciter, T_E is the exciter time constant, and K_E is the exciter gain.

To achieve an acceptable transient response, the system must be stabilized in such a way that reduces the transient (high-frequency) gain. This can be accomplished by introducing a feedback stabilization element with time constant T_F and gain K_F as shown in Fig. 3 [20]. Typical values of those parameters are $T_F=0.35-1$ s and $K_F=0.01-0.1$. The overall block diagram of the AVR system with PID controller considering the saturation characteristic is depicted in Fig. 3.

III. OPTIMIZATION METHODS

The WOA and WCA algorithms adopted in this paper search globally inside the search space to select the optimum

values of PID controller parameters $[K_p, K_D, K_i]$. The automatic AVR depicted in Fig. 3 is modeled in MATLAB-Simulink. An M-file MATLAB code is used to initialize the design variables, calculate the desired fitness function, run the optimization algorithm and run the Simulink model in each iteration. The same fitness function is used for all the algorithms. This fitness function ($F.F$) is the trapezoidal integral of the square error between the change in the reference voltage of the synchronous generator (ΔV_{ref}) and the generator's response to it (ΔV_g) as illustrated in (3).

$$F.F = \text{Trapz}(t_{out}, (dE).^2) \quad (3)$$

where $dE = \Delta V_{ref} - \Delta V_g$, t_{out} is MATLAB simulation time.

Table I. Transfer function of AVR system

Components	Transfer function	Parameters range
Amplifier	$K_A/(1+T_A S)$	$10 < K_A < 400$, $0.02 < T_A < 1$ s
Exciter	$K_E/(1+T_E S)$	$1 < K_E < 400$, $0.4 < T_E < 1$ s
Generator	$K_G/(1+T_G S)$	$7 < K_G < 1$, $1 < T_G < 2$ s from full load to no load
Sensor	$K_S/(1+T_S S)$	$0.001 < T_S < 0.06$ s

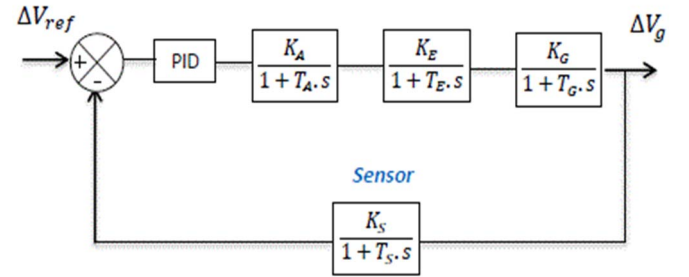


Fig. 1. Block diagram of AVR linearized model

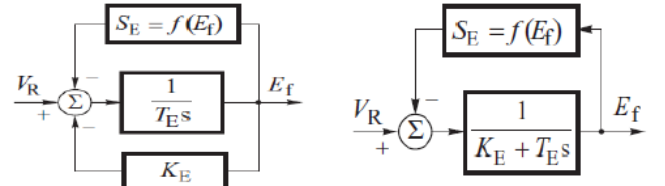


Fig. 2. Block diagram representing saturation

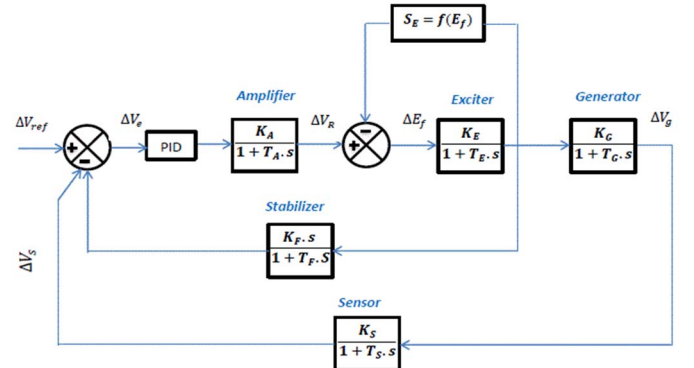


Fig. 3. Block diagram of AVR system controller combining saturation effect

A. Whale Optimization Algorithm

Whale optimization algorithm is a swarm intelligence technique proposed by Seyedali Mirjalili et al. [21], which imitates the mechanism accompanied with humpback whales for hunting their prey, namely bubble-net hunting strategy [22]-[23]. Humpback whales are considered predator creatures. The unique features of humpback whales are their hunting strategies for small fishes near the surface of the sea. In this mechanism, the humpback whales generate very discriminative bubbles with circular or “9” shaped path [24]. Implementing optimization algorithm assigned to humpback whales’ foraging method is represented by modeling the following three mechanisms: encircling prey, spiral-bubble net feeding method, and search for prey.

a) Encircling prey

The humpback whale can determine the region where prey is located and encircle them. Because WOA cannot identify the location of the prey in advance, the WOA supposes that the optimum global solution obtained so far is the objective prey or nearby. On the other hands, the other candidates (whales) seek to update their positions towards prey (best search agent). This behavior is mathematically modeled as follows:

$$\vec{D} = |\vec{C} \cdot \vec{X}^*(t) - \vec{X}(t)| \quad (4)$$

$$\vec{X}(t+1) = \vec{X}^*(t) - \vec{A} \cdot \vec{D} \quad (5)$$

where t represents the current iteration, \vec{A} and \vec{C} are coefficient vectors, X^* indicates the position vector of the best solution, and \vec{X} refers to the position vector of a solution, and $||$ is the absolute value. The vectors \vec{A} and \vec{C} are estimated as follows:

$$\vec{A} = 2\vec{a} \cdot \vec{r} - \vec{a} \quad (6)$$

$$\vec{C} = 2 \cdot \vec{r} \quad (7)$$

where \vec{a} is directly decreased from 2 to 0 throughout the course of iterations and \vec{r} is a random vector from [0,1]. Therefore, Eqn. (5) can update the positions of any search agent in peripheral of the optimum solution thereby simulating encircling the prey.

b) Bubble net hunting strategy

The mathematical formula which expresses the bubble net hunting strategy whereas the humpback whales attack their prey can be formulated by considering two approaches: firstly, shrinking encircling mechanism where the position vector \vec{A} can be varied to achieve different closed position around the optimal search agent by varying the numerical value of a , thereby shrinking the positions of search agents towards the optimal solution is fulfilled. The second step for imitating the bubble net hunting strategy is proposed by spiral updating position mechanism where the WOA calculates the difference in position between the prey and other search agents, and then an equation is introduced into WOA functioning the spiral movement of humpback whales around their prey. This mechanism is mathematically represented as follows:

$$\vec{X}(t+1) = \vec{D} \cdot e^{bl} \cdot \cos(2\pi l) + \vec{X}^*(t) \quad (8)$$

where $\vec{D} = |\vec{X}^*(t) - \vec{X}(t)|$ is the distance between the prey (best solution) and the i th whale, b is constant for defining the

shape of the logarithmic spiral, l is a random number in the range [-1, 1].

c) Search for prey (exploration phase):

In order to identify new promising regions around the search space randomly (i.e. exploration phase), the coefficient vector \vec{A} enlarged to be in the interval $[-1, 1]$. This strategy enables the WOA to search away from reference whale. Moreover, the position of search agent is updated depending on the randomly chosen search agent rather than the optimal search agent. These two mechanisms are represented mathematically as follows:

$$\vec{D} = |\vec{C} \cdot \vec{X}_{rand} - \vec{X}(t)| \quad (9)$$

$$\vec{X}(t+1) = \vec{X}_{rand} - \vec{A} \cdot \vec{D} \quad (10)$$

where \vec{X}_{rand} represents a random position vector chosen from the current population. The flow chart of whale optimization algorithm is depicted in Fig. 4.

B. Water Cycle Algorithm

Water cycle algorithm is an optimization technique proposed by Eskandar et al. [25], which has been applied to solve several optimization engineering problems. This algorithm imitates the natural cycle process of water and how river and streams eventually end up in the sea. Water cycle algorithm supposes that there is a precipitation source where the best individual raindrops (optimum) are considered as the sea, a number of good raindrops are chosen as a river, and the result raindrops are chosen as a stream flows to either rivers or the sea.

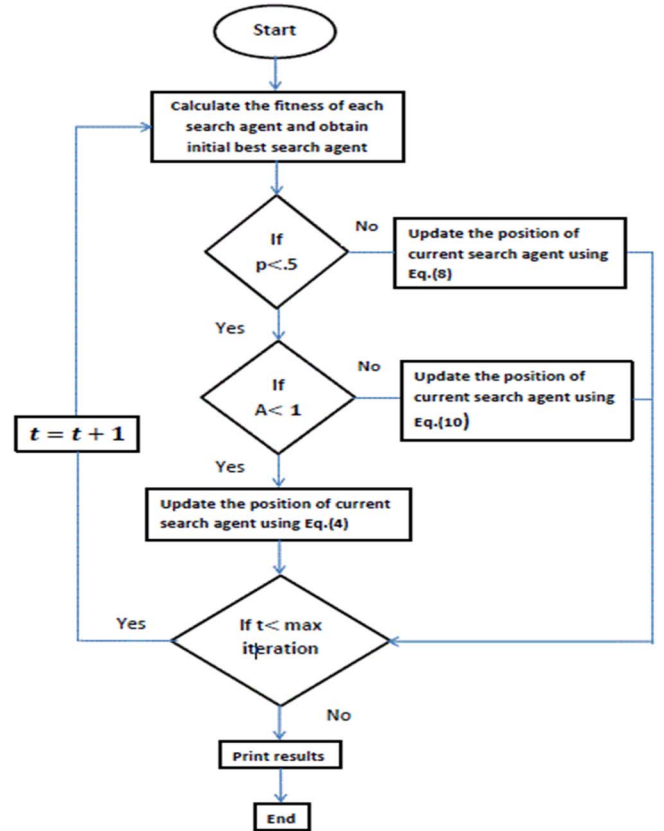


Fig. 4. WOA flow chart

a) Generation of initial populations

Solving optimization problems based on a meta-heuristic algorithm requires that the problem variables' values constituted as an array. Similarly, WCA calls these variables as raindrop for a single solution, but for optimization problem with a number of variables N_{var} , this array is defined as follows:

$$\text{Raindrop} = [X_1, X_2, X_3, \dots, X_n] \quad (11)$$

Water cycle algorithm starts optimization with a number of candidate raindrops with size $N_{pop} \times N_{var}$ where N_{pop} is the number of population. This can be expressed as follows:

$$\text{Population of raindrops} = \begin{bmatrix} \text{Raindrop}_1 \\ \text{Raindrop}_2 \\ \text{Raindrop}_3 \\ \vdots \\ \text{Raindrop}_{N_{POP}} \end{bmatrix} \quad (12)$$

The cost function of a raindrop can be obtained from the following relation:

$$C_i = \text{Cost}_i = f(x_1^i, x_2^i, \dots, x_{N_{var}}^i) \quad i=1, 2, 3, \dots, N_{pop} \quad (13)$$

Firstly, N_{POP} raindrops are generated, and then a number of N_{sr} is created which expresses the minimum of N_{POP} as the sea and rivers. The minimum value of raindrop is considered as the sea. So N_{sr} is the summation of the number of rivers and only the sea.

$$N_{sr} = \text{number of rivers} + 1 \quad (14)$$

The rest of raindrops which flow to a river or directly to the sea can be estimated as follows:

$$N_{Raindrops} = N_{POP} - N_{sr} \quad (15)$$

In order to assign raindrops to rivers and sea based on the intensity of flow, the following equation is given by:

$$NS_n = \text{round} \left\{ \left| \frac{\text{Cost}_n}{\sum_{i=1}^{N_{sr}} \text{Cost}_i} \right| \times N_{Raindrops} \right\}, \quad n=1, 2, \dots, N_{sr} \quad (16)$$

where NS_n indicates the number of streams which flow to specific rivers or sea.

The purpose of WCA is to imitate how rivers and streams flow into the sea. This necessitates identifying the distance between river or stream and the sea in advance and then updates this position accordingly. This scenario can be represented as follows: streams and rivers are connected to each other by a path; a randomly chosen distance given by the following relation:

$$X \in (0, c \times d), \quad c > 1 \quad (17)$$

where d is the distance between a stream and a river

The new positions for stream and river can be calculated as follows:

$$X_{Stream}^{i+1} = X_{Stream}^i + \text{rand} \times C \times (X_{River}^i - X_{Stream}^i) \quad (18)$$

$$X_{River}^{i+1} = X_{River}^i + \text{rand} \times C \times (X_{Sea}^i - X_{River}^i) \quad (19)$$

where C is a numerical value between 1 and 2. The best value of c is chosen as 2, and rand is a randomly distributed value between 0 and 1. If the solution introduced by a stream is

more efficient than a river, their corresponding positions should be exchanged. Similarly, this mechanism should also be applied if the solution encountered by a river is better than the sea.

b) Avoiding local optima

In order to avoid local optimal solutions and accelerates convergence rate, WCA supposes that evaporation process exists whenever streams and rivers flow into the sea. This can be examined by investigating the following condition: If $|X_{Sea}^i - X_{River}^i| < d_{max}$ $i = 1, 2, 3, \dots, N_{sr} - 1$, where d_{max} is a value close to zero. The value of d_{max} is decreased corresponding to the following relation:

$$d_{max}^{i+1} = d_{max}^i - \frac{d_{max}^i}{\text{max iteration}} \quad (20)$$

c) Raining process

Subsequent to verified evaporation condition, a raining process is initiated, where raindrops fall to the earth. Consequently, new streams are formed in various locations. The locations for these new streams can be identified by the following equation:

$$X_{Stream}^{new} = LB + \text{rand} \times (UB - LB) \quad (21)$$

where LB and UB are the lower and upper bounds given by the problem, respectively. According to these new raindrops, the best ones are chosen as river while the rest are considered new streams flow to the river or directly to the sea.

With regard to those new streams directly flow into the sea, reinforcing the convergence rate and computational processes are accomplished using Eq. (22).

$$X_{Stream}^{new} = X_{Sea} + \sqrt{\mu} \times \text{randn}(1, N_{var}) \quad (22)$$

where μ is defined as the range of searching region near the sea and randn is distributed random number. The flow chart of WCA is depicted in Fig. 5.

IV. SIMULATION RESULTS

In this section, simulation results of the AVR system described in Section II with different PID tuning algorithms is discussed. The gains of the amplifier, exciter, synchronous generator, feedback sensor, and stabilizer are $K_A=10$, $K_E=1$, $K_G=1$, $K_F=0.05$, and $K_R=1$, respectively. The time constants of these components are $T_A=0.1$, $T_E=0.4$, $T_G=1$, $T_F=1$, and $T_R=0.05$. The saturation factor is set as $S_E = A_{ex} e^{B_{ex} E_f}$, where $A_{ex}=0.05$ and $B_{ex}=8$. The transfer function of the stabilizer is $(K_f s / T_f s + 1)$ with gain and time constant of 0.05 and 1, respectively. A step reference input signal of amplitude 0.1pu is applied to the AVR system. The simulation time is set at 10s and the sampling time is 0.0001s. With these parameters, the output response of AVR control system without PID controller and with PID controller tuned by WOA, WCA, and GA is investigated. Genetic algorithm MATLAB-toolbox is used to implement the GA optimization tool [26]. As shown in Fig. 6, without PID controller, the output voltage of the synchronous generator has about 18% steady-state error and therefore the use of PID controller is necessary to eliminate the error. On the other hand, utilizing

WCA, WOA, and GA proved to enhance the output response of terminal voltage of the synchronous generator. The steady-state error introduced by these algorithms is almost equal and infinitesimal. The values of the steady-state error with WCA, WOA and GA are 0.031%, 0.046, and 0.048%, respectively.

To allow comparison of WOA and WCA with GA, the number of search agents, the maximum number of iterations, the number of design variables, upper bound, and lower bounds are kept the same for the three optimization algorithms at 10, 50, 3, 2, and 0, respectively. With WCA, the number of rivers in addition to the sea is set as $N_{sr}=4$ while the operator for evaporation is set as $d_{max}=1e-16$. Because WCA, WOA, and GA are stochastic-dependence solutions, the algorithms are run 30 times. The fitness functions and the proportional, integral, derivatives parameter for WCA, WOA, and GA are shown in Table II. It is clear that the proportional, integral, and derivative gains obtained using the three algorithms are close to each other. It is also clear from Fig. 6 that the proposed WOA and WCA algorithms and also the GA can accurately tune the PID controller so that the generator output voltage can track the reference with negligible steady state error and a shorter rise time. The WCA offers the minimum steady-state error compared to the WOA and GA.

The convergence curves for the proposed algorithms are depicted in Fig. 7, the average best –so-far illustrates the best solution obtained at each iteration over 30 run. As shown, it is evident that WCA has the most efficient convergence rate towards the optimum global solution in comparison with WOA and GA. This is related to the efficient behavior of WCA to balance between exploration and exploitation phases in first iterations. In comparison with WCA, WOA accelerates to its final optimum solution after nearly half iterations where WCA success to find its optimum global solution in early stages. GA is the worst case for finding the optimum global solution and convergence rate this is due to its methodology to find the optimal solution in which the worst solution in each iteration is discarded. The standard deviation, variance, maximum, minimum and average values are also shown in Table III.

V. CONCLUSION

In this paper the WOA and WCA meta-heuristic algorithms were employed in the AVR control system in order to globally search for the optimum design of PID controller parameters to enhance the output voltage of the synchronous generator. The saturation characteristic of the exciter is considered to increase model accuracy. In order to investigate the response of the proposed algorithms, a comparison is performed between the proposed algorithms and genetic algorithm. The proposed methods manifest very competitive and better performances to the genetic algorithm. Moreover, comparing the proposed algorithms to each other resulted in WCA is capable of achieving the minimum steady-state error. The results obtained from convergence curves, standard deviation, and mean value evidence the superiority of WCA over the others. WCA succeeded to find the optimum at very early stages in comparison to the other algorithms. This is attributed to its ability to exploit the search space to introduce very good balance between exploration and exploitation phases over course of iterations.

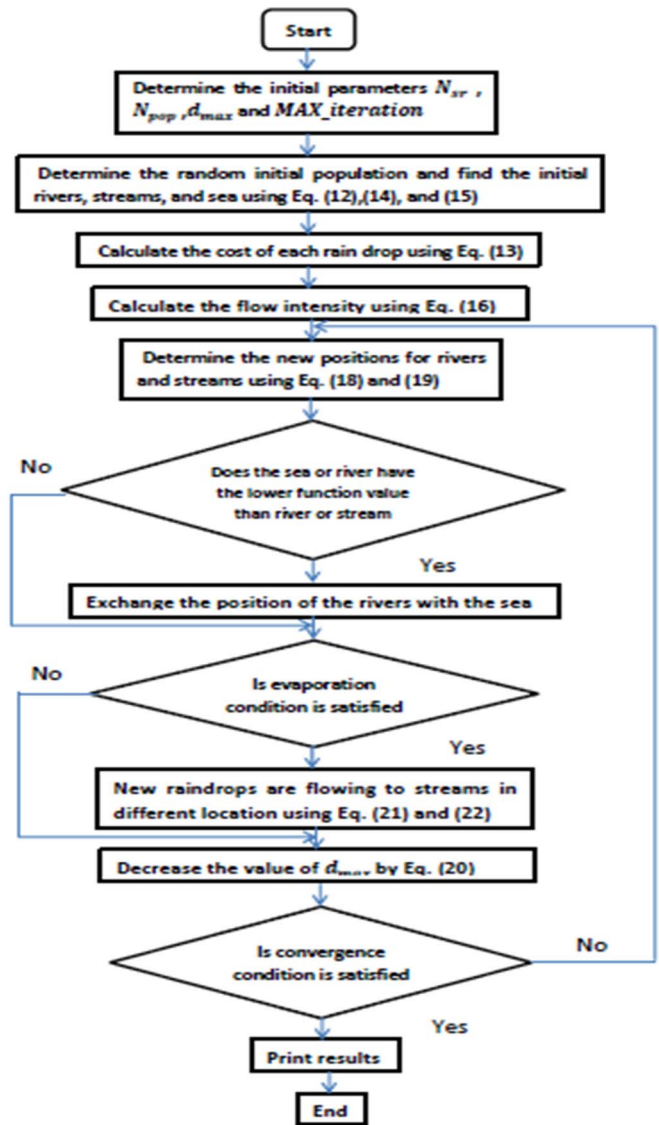


Fig. 5. WOA flow chart

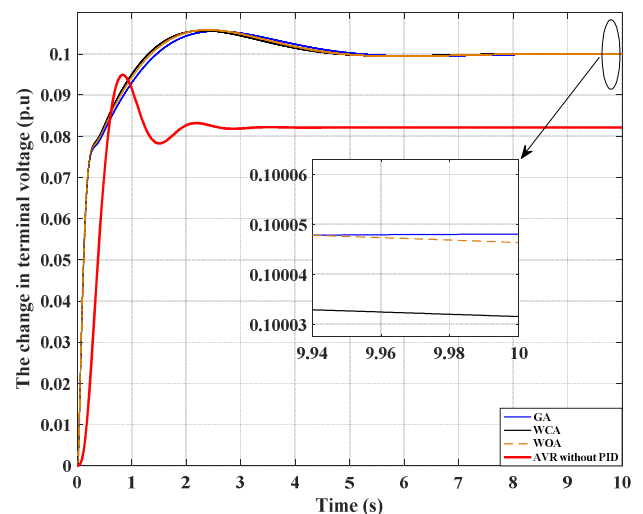


Fig. 6. Terminal voltage response

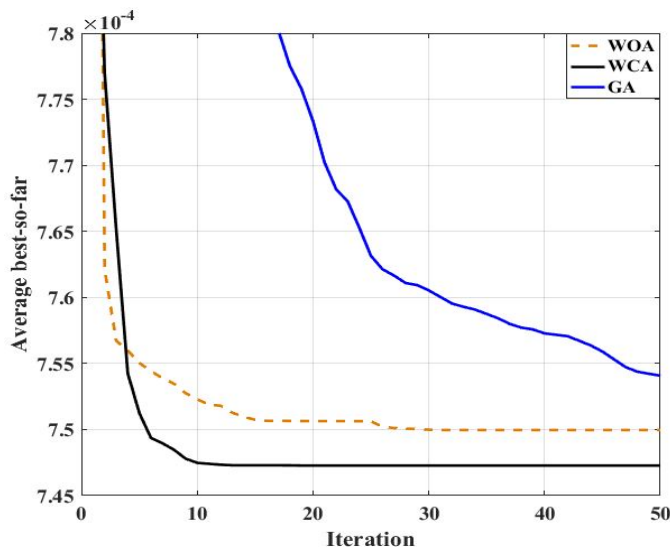


Fig. 7. Convergence curves for GA, WOA and WCA

Table II. Fitness Function values and obtained PID controller parameters

Proposed Algorithm	Fitness function for the proposed algorithm	Kp	Ki	Kd
GA	0.00075408	1.90	1.79	1.42
WCA	0.00074728	2	2	1.33
WOA	0.000749967	1.98	1.98	1.41

Table III. Variance, maximum, minimum, and average values of Fitness Functions

Proposed algorithm	Standard Deviation	Variance	Maximum Value	Minimum Value	Average Value
GA	1.07635E-05	1.15852E-10	0.000797001	0.000747602	0.00075408
WCA	4.87288E-19	2.3745E-37	0.00074728	0.00074728	0.00074728
WOA	6.84961E-06	4.69171E-11	0.00076743	0.00074728	0.000749967

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