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Improved Invasive weed optimization Algorithm (IWO) Based on Chaos Theory for Optimal design of PID controller

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Abstract

Weed is a phenomenon which is looks for optimality and finds the best environment for life and quickly adapts itself to environmental conditions and resists changes. Considering these features, a powerful optimization algorithm is developed in this study. The invasive weed optimization algorithm (IWO) is a population-based evolutionary optimization method inspired by the behavior of weed colonies. In this paper, the IWO algorithm is based on chaos theory. Among parameters of weed optimization algorithm, standard deviation affects the performance of the algorithm significantly. Therefore, chaotic maps are used in the standard deviation parameter. Performance of the chaotic invasive weed development method is investigated on five benchmark functions, using logistic chaotic mapping. Additionally, the problem of setting the PID controller parameters for a DC motor using the proposed method is discussed. The statistical results on optimization problems show that the improved chaotic weed algorithm has gained fast convergence rate and high accuracy.

Keywords: Improved chaotic Invasive weed optimization, PID controller, DC motor

1. Introduction

In recent years, complex and various optimization problems have been solved using mathematical tools which are inspired by nature. In such cases, traditional methods require special information and often come up with undesirable responses. Therefore, population-based and iteration-based methods are introduced [1]. The meta-heuristic techniques are known as optimization methods used to solve many optimization problems. For example, genetic algorithm, firstly introduced by Holland in 1975, is a standard engineering optimization tool. Other meta-heuristic optimization algorithms such as ant colony optimization [2], particle swarm optimization [3], and artificial bee colony algorithm [4] were also introduced after introduction of genetic algorithm.

Over the past years, optimization algorithms have been introduced based on ecological phenomena among which cellular genetic algorithm [5] and an empirical evolutionary algorithm, which is based on group flexibility, can be mentioned [6]. In this algorithm, evaluations and rankings are performed separately on the basis of two flexible and non-flexible groups in parallel. Best members in both groups are selected as parents. Number of flexible members of a sigmoid-type relationship is limited by the growth of a natural ecological population in a limited space.

Weed algorithms are inspired by the growth process of weeds in nature. This method was presented by Mehrrabian and Lucas in 2006 [1]. Naturally, weeds are heavily grown and this severe growth is a serious threat to useful plants. An important characteristic of weeds is their stability and high adaptability in nature which is the optimization basis of IWO algorithm.

Weed meta-heuristic algorithm is a new and powerful optimization method that finds the global optimum of a mathematical function through imitating compatibility and randomness of weed colonies. This algorithm can be used as a basic design for effective optimization approaches [7].

IWO has been improved in previous studies among which the followings such as "a Cooperative co-evolutionary invasive weed optimization applied to Nash equilibrium search in electricity markets [8]", differential IWO [9], discrete IWO [10], combined weed colony optimization with differential evolution algorithm [11], IWO for optimal Multi-objective algorithm [12], modified IWO [13,14], IWO based on non-dominated sorting [15], combined particle swarm optimization and weed optimization algorithm [16], combined weed optimization and firefly algorithm [17] have gained popularity.

Furthermore, IWO has been successfully applied to a variety of optimization problems including optimization of antenna design [18], telecommunication design optimization [19], DC motor control optimization [20], data clustering [21], chase Index [22], robot path optimization [23], work shop scheduling [24], and economic load distribution [25].

Various studies have been conducted on chaotic invasive weed optimization [26-29]. In [26], chaotic invasive weed optimization has been proposed for parameters estimation of chaotic systems. The proposed method has shown good capability. However, in this paper, some new seeds are generated chaotically distributed adjacent to flowering weed, using a chaotic map. Formulation of this process is not well defined in this paper. In addition to that, chaos is not used in sigma equation. In [27], invasive weed optimization based on chaos has been proposed for solving power flow problems with non-smooth generator fuel cost functions. The chaotic map is used in the equation which instead of normal distribution updates the positions. Although in this way the ability to escape from local optima is improved, but it reduces exploitation ability of the algorithm. In addition, upon using this method, the maps are in the range of [0 1], but the range of normal distribution is larger than chaotic maps. Moreover the negative numbers are also included. Consequently, it can be concluded that the normal distribution can provide better exploitation compared to normal chaotic maps.

In [28], the chaotic invasive weed optimization is utilized for optimization of a fuzzy controller. This controller is used for the purpose of solving the problem of damping the power system oscillations. Chaotic local search has been used in invasive weed optimization. In [29], a modified chaotic invasive weed optimization is used to optimize PID controller parameters of the biped robot. The Chebyshev map is used as the first term of standard deviation formula. These papers have not considered the concept of "moving towards the best position". However in this paper, this concept is considered and the chaotic map is used as the second term of the standard deviation formula. It will be shown that our proposed method achieves good results in terms of convergence speed and accuracy.

The invasive weed algorithm is appropriate in terms of global search. However, this algorithm has poor exploitation ability. Additionally, the best member of the population is not used. Random parameters of the weed algorithm degrade its performance and consequently allocation of the appropriate global coverage to the entire search space would be impossible, and there is no specific strategy for improvement of extraction process is introduced. Additionally, implementation of the algorithm does not change significantly until the termination condition is met. The balance between exploration and exploitation of the algorithm has not been considered. This would affect the accuracy and the speed of the algorithm negatively. This algorithm has some other shortcomings too. Take early integration, being trapped in local optimums, and low population diversity as examples.

Purpose of this paper is to provide an improved weed algorithm based on chaotic theory. The chaos theory examines the behavior of certain systems that are highly sensitive to their initial conditions. Chaotic searches have access to most situations of a given region. They increase the diversity in the location of the population. Therefore, more parts of the search space will be explored and consequently the answers will have the necessary dispersion across all regions. Therefore, it is concluded that this approach is an efficient one in finding optimal solutions. As a result, the first plan is likely to use an initial chaotic population randomly instead of producing the primary population of weeds. So the diversity of the population is likely to get better. It is also ensured that our population members cover the entire search area. In the second plan, an equation is applied to move the current grass towards the best one. So, the standard deviation parameter for which a large value is selected at the beginning of the algorithm and a small value is selected for it at the end of the algorithm changes with chaotic maps. This parameter affects the variation rate of weed position. At the beginning of the process, it is necessary to select a large value to focus on more exploration. But at the end of the run where the optimal global answer is approached, it is necessary to select a small value for this parameter to focus on extraction. Therefore, by setting this parameter, exploration and exploitation would be balanced.

In order to validate the proposed method, this algorithm is firstly evaluated on benchmark functions. Secondly, the problem of setting optimal PID controller coefficients of a DC motor system is investigated. Robust performance of this controller on the one hand and its simplicity in design of PID parameters on the other hand, has made it widely acceptable in the industry. Despite simple structure and robustness of the PID controller, it is time-consuming to set its parameters through trial and error. Therefore, one way to use the intelligent optimization algorithm is to overcome this problem. In order to validate the proposed method for setting the PID controller coefficients, the results are compared to similar IWO algorithms and chaotic IWO in the primary population.

The rest of this paper is organized as follows. Section 2 describes the basic concepts of IWO. Next in section 3 the improved chaotic IWO algorithm is introduced. The benchmark functions and simulation results are presented in section four. In fifth section, optimal design of the PID controller problem with weed is expressed. Simulation results of optimal design of the PID controller are presented in Section 6. Finally, Section 7 concludes the paper.

2. Basic Concepts of Invasive Weed Algorithm

Invasive weed meta-heuristic algorithm is a population-based optimization algorithm that finds the general optimum of a mathematical function through imitating compatibility and randomness of weeds colony.

Weeds are powerful herbs that their offensive growth habits are a serious threat to crops. They have shown to be very resistant and adaptable to environmental changes. Therefore, considering their characteristics, a powerful optimization algorithm is obtained. This algorithm tries to imitate resistance, adaptability, and randomness of a weed community in a sample.

This method is inspired by a phenomenon in agriculture called colonies of invasive weeds. According to a common definition, weed is a plant that grows unintentionally. Although weeds may have many uses and benefits in some regions, if the same plant grows in a region that interferes with human' needs and activities, it is called a weed. In [1], a simple numerical optimization algorithm has been proposed, which is based on colonized weed called the "The Invasive Weed Optimization Algorithm''. This algorithm is simple but effective in convergence to optimal solutions using basic features such as seeding, growth, and competition in a weed colony.

To simulate the habitat behavior of weeds, some basic features of the process are considered as follows:

1) Primary population initialization: A limited number of seeds are distributed in the search space.
2) Reproduction: Each seed grows into a flowering plant and produces seeds that depend on their fitness value. The number of grains of grasses decreases linearly from S_{max} to S_{min} as follows:

$$n(\mathrm{w}_i) = \frac{S_{\max}(\max \quad fit \quad - \quad fit(\mathrm{w}_i)) + S_{\min}(\mathrm{fit}(\mathrm{w}_i) - \min \quad fit)}{\max \quad fit \quad - \min \quad fit} \tag{1}$$

3) Spectral Spread: The seeds produced by the group in the normal distribution with a mean planting position and standard deviation (SD) are produced by the following equation:

$$\sigma_t = \left(\frac{T-t}{T}\right)^n (\sigma_{initial} - \sigma_{final}) + \sigma_{final} \tag{2}$$

   Where T is the number of maximum iterations, σ_t is the current standard deviation, n is the nonlinear modulation index [1].
   This conversion assures that fall of a grain in the range decreases nonlinearly at each step, leading to more fit plants and eliminating inappropriate plants, and Shows the transfer mode from r to selection of K.
4) Competitive deprivation: If the numbers of grasses exceed the maximum numbers of grasses in the colony (Pmax), the grass with worst fitness is removed from the colony so that a constant numbers of herbs are remained in the colony.
5) This process continues until the maximum number of iterations is reached, and then the minimum colony cost function of the grasses is stored.

Parameters of the invasive weed algorithm and the problem are presented in Table 1.

Table1. The invasive weed algorithm and problem parameters

Problem Definition Parameters	
Number of decision variables	nVar
Upper limit of the decision variables	VarMin
Parameters of invasive weed algorithm	
Maximum number of repetitions (T)	MaxIt
Initial population	NPop0
Maximum population	Pmax
Minimum number of seeds	Smin
Maximum number of seeds	Smax
Decreasing power of standard deviation (n)	Exponent
Basic standard deviation	Sigma_initial
the final Standard deviation	Sigma_final

In Figure 1, a typical invasive weed algorithm flowchart is shown.

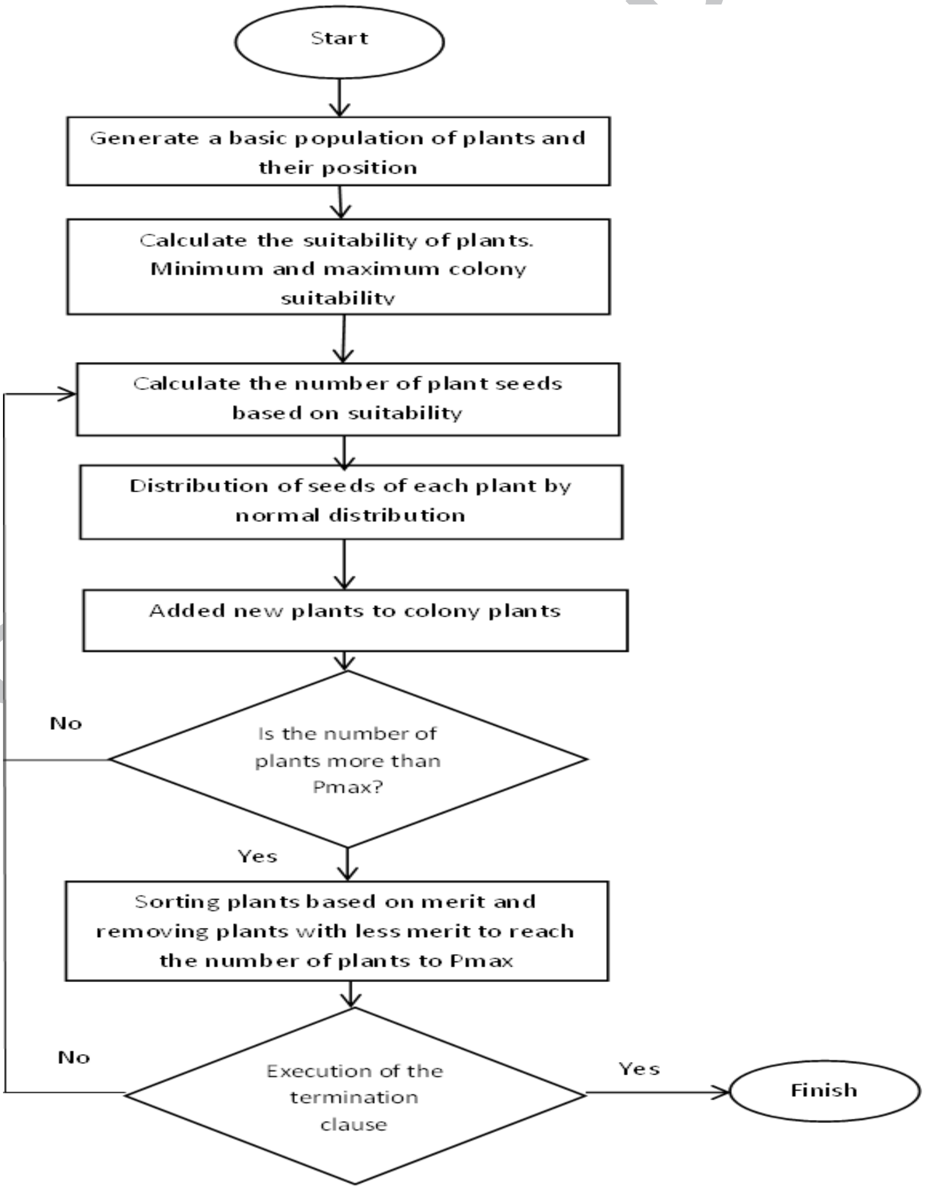


Figure 1. Flowchart of the IWO algorithm

3. Improved Chaotic Invasive Weed Optimization Algorithm

Optimization algorithms based on chaos theory use stochastic search methods. These algorithms are different from evolving competitive algorithms and intelligent population-based algorithms.

Due to non-repetitive nature of chaos theory, it performs the global searches at a faster pace than accidental searches that are related to probabilities. In addition, diversity of the population would be better. It is also ensured that our member's population covers the entire search area. Therefore, optimal or close to optimal responses will be among the population.

One of the well-known chaotic maps is the logistic chaotic map. This function is a second order polynomial. This map is defined as follows:

$$\begin{aligned} & x_{j+1} = a x_j (1 - \mathrm{x}_j) \\ & for \quad 0 < a \leq 4 \quad j = 0,1,2,\ldots \quad x_j \in [0,1] \end{aligned} \tag{3}$$

Where x_0 is initial value of the function and x_n is value of the function after n^{th} iteration. To make this equation show a chaotic behavior, λ should be set to 4. The initial conditions should be within the range of (1, 0). Such that $x_0 \neq \{0, 0.25, 0.5, 0.75\}$.

The second scheme to improve the invasive weed method is to use chaotic mapping to update standard deviation formula. It can be the following equation.

$$\sigma(t) = (\frac{T - t}{T})^n (\sigma_{initial} - \sigma_{final}) + \sigma_{final} \times z(t) \tag{4}$$

Where z(t) can be equivalent to chaotic mapping in the t^{th} iteration.

In this method, best weed can be used to move the remaining weeds to the best position. Therefore, another equation is proposed:

$$x_i^{t+1} = \sigma(t) \times x_i^t + (\mathrm{x}_{\mathrm{best}} - \mathrm{x}_i^t) \tag{5}$$

In which x_i^{t+1} is the new weed position in t^{th} iteration. $\mathrm{x}_{\mathrm{best}}$ is the best weed found in the whole population. The new position in (5) is updated using previous position and the difference between previous position and the best position in the standard deviation. Then, these new situations are also evaluated in the algorithm.

This equation improves local and global search algorithms, because the standard deviation plays the role of equilibrium in local and global searches. Flowchart of The proposed method is shown in Figure 2.

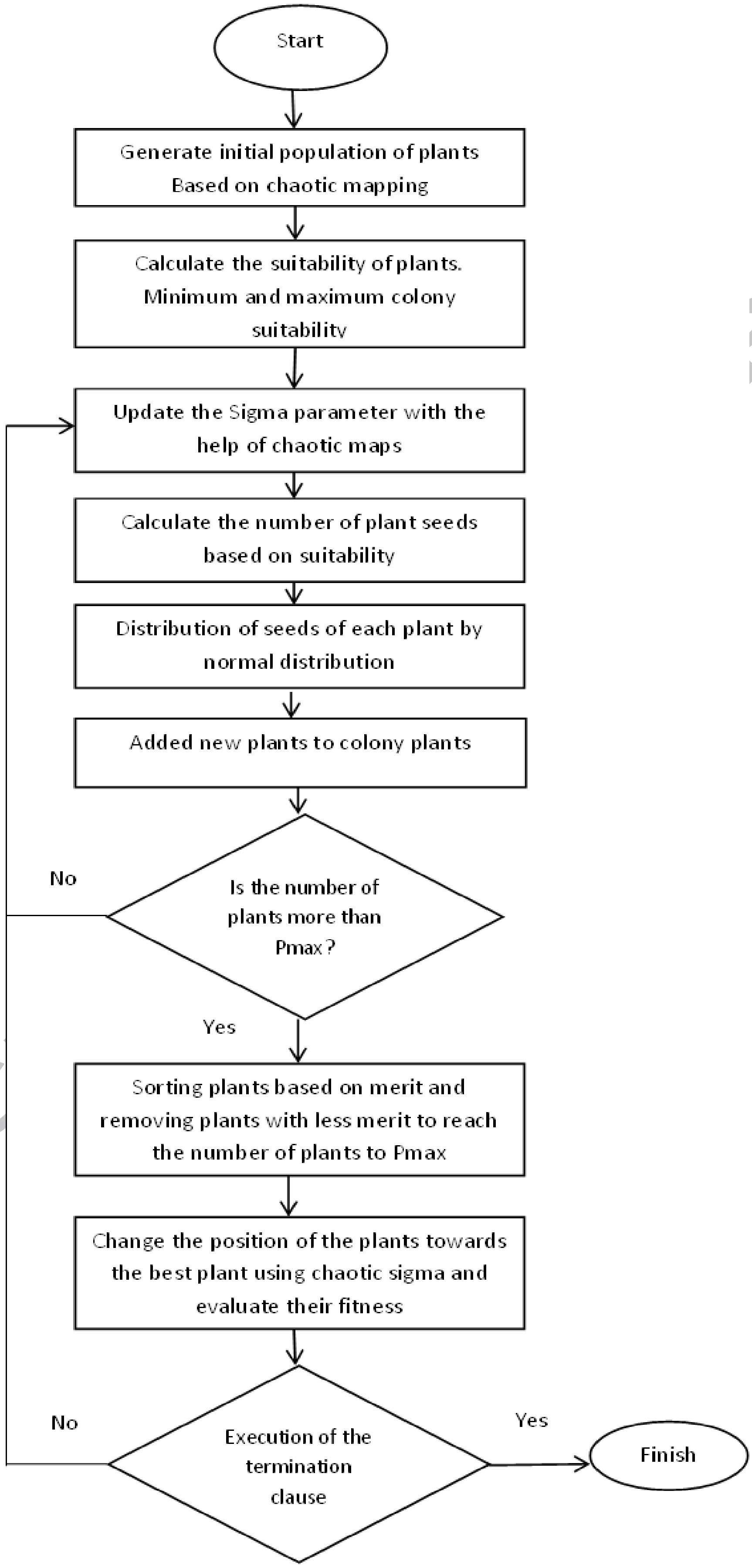


Fig. 2- Flowchart of Improved IWO algorithm based on chaos theory

4. Simulation Study on Benchmark Functions

In this section, some simulation studies are conducted to demonstrate suitability of the proposed optimization algorithm. In the first step, ability of the algorithm to find minimum of three benchmark functions, which is often presented in the research, is shown. These functions are Sphere, Griewank and Rastrigin, EASOM and EF10. In order to show that the proposed algorithm converges to the global response, the results are compared with the standard weed algorithm and chaotic weed with the randomized primitive population.

4-1- Convergence of Optimized Chaos Invasive Weed Optimization Algorithm

These studies have focused on demonstrating capability of the improved chaos IWO algorithm in the global minimum positioning of continuous functions. 'Sphere', 'Griewank' and 'Rastrigin' are three examples of benchmark functions. Their features are shown in Figure 3.

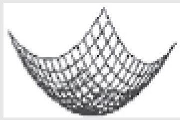
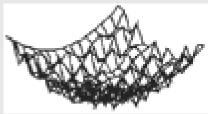
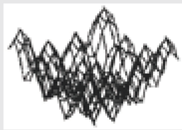
Name	Formula	Sketch in 2D
Sphere	$f(x) = \sum_{i=1}^{n} x_i^2$	
Griewank	$f(x) = \frac{1}{4000}\sum_{i=1}^{n} x_i^2 - \prod_{i=1}^{n} \cos\left(\frac{x_i}{\sqrt{i}}\right) + 1$	
Rastrigin	$f(x) = \sum_{i=1}^{n} (x_i^2 - 10\cos(2\pi x_i) + 10)$	

Fig. 3 - Sphere, Griewank, Rastrigin Benchmark functions.

A. The Sphere Function

Numeric values for a given implementation to minimize the Sphere function of dimension d = 2 are given in Table 2. The parameters are adjusted according to the results of [1]. Modulation index and initial value of the standard deviation are within the two parameters that have the maximum effect in IWO algorithm. According to the results obtained from [1], the modulation index which is greater than 2 gets better results. In this article, a value of 4 is selected that can change the parameter to get the standard deviation value faster. Initial value of the standard deviation parameter also affects the search algorithm. If its value is selected large, it may act weakly in convergence towards a global optimum and reach this point in more repetitions. In [1], the authors have concluded that the initial value less than 1 in the convergence process is more effective. So the initial value of 0.75 is used in this research.

Table 1. Setting parameters for minimizing Sphere function

value	Quantity	Symbol
10	Initial population	N_0
100	Maximum number of repeat	it_{max}
2	Dimensions of the problem	dim
15	Maximum plant population	p_{max}
5	Maximum number of seeds	s_{max}
0	Minimum number of seeds	s_{min}
4	Nonlinear modulation index	n
0.75	Initial standard deviation	$\sigma_{initial}$
1e-6	Final standard deviation	σ_{final}
$-40 < x_{ini} < 30$	Initial search range	x_{ini}

Final value of the standard deviation parameter is also chosen according to [1] (equal to 1e-06). According to the results obtained in [1], selecting a smaller value would lead to a better effect on final accuracy.

While moving towards the best position, the following equation is taken into practice:

$$X_i^{t+1} = \sigma(\mathrm{t}) * X_i^t + \sigma(\mathrm{t}) * \mathrm{rand}(1, \mathrm{nVar}) .* (\mathrm{Gbest} - \mathrm{X}_i^t) \qquad (6)$$

A Sigma coefficient plays the role of moving towards the best location by being multiplied to each position. In functions which best parameter value is zero, the Sigma coefficient contributes greatly to quick convergence before previous position value. So, it should be noted that for cases where the best value is not zero, parameter sigma should not be put before current position X_i^t.

After an iteration, the final value of the fitness function for the Sphere function with the proposed method would be equal to f(x0) = 0, for $x_0 = [-1.2476\mathrm{e}-214, 1.4705\mathrm{e}-213]$. According to accuracy of MATLAB software, this point shows that the value of the cost function is zero. It is known that optimal value of the function at point [0,0] in the x-y plane is zero. Table 2 shows the results for chaotic weed with primary population and improved chaotic weed algorithm. These are obtained after implementing a conventional weed algorithm for 30 times.

Figure 4 depicts the curve of the best cost function obtained from the proposed algorithm in terms of number of iterations.

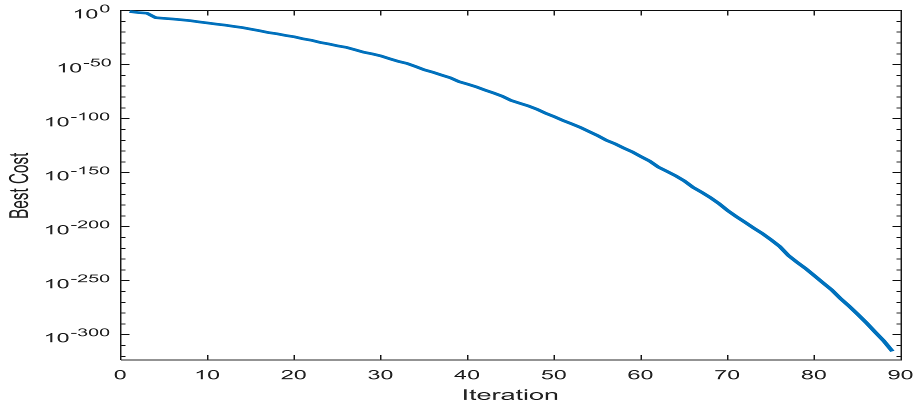


Fig. 4 - Convergence of the proposed IWO to the optimal value of the Sphere function.

Considering fig. 4, it is found that in the 90th iteration, the best cost function is zero.

Table 2. Results of minimizing Sphere function with 30 runs using three variants of IWO algorithms.

Proposed chaotic invasive weed algorithm	Chaotic invasive weed algorithm 1	Ordinary invasive weed algorithm	Performances
0	1.4717e-14	3.6064e-14	mean
0	5.1054e-16	2.9971e-15	best
0	4.7038e-14	1.5761e-13	worst

It is found that the best mean Obtained, after running the Sphere function for thirty times with the proposed CIWO2 algorithm.

B- Rastrigin Function

In order to demonstrate the ability of IWO to minimize various functions, another challenge of optimization problem is addressing the minimization of the Rastrigin function. Figure 5 shows the design of the Rastrigin function with dimension of 2 (d=2). Figure 5 shows that the Rastrigin function has some local minimums. The valleys are similar to the Griewank function. But this function has only one global minimum that occurs at point [0, 0] in the x-y curve; as shown by the vertical line in the curve, value of the function is zero. In each local minimum other than the global minimum, value of the Rastrigin function is greater than zero. The farther the local minimum from the basis, the larger is the value of function at that point. Since the local minimum numbers of the Rastrigin function with low dimension make it difficult to find a global answer using gradient methods, it is regularly used in research for examination of evolution algorithms,

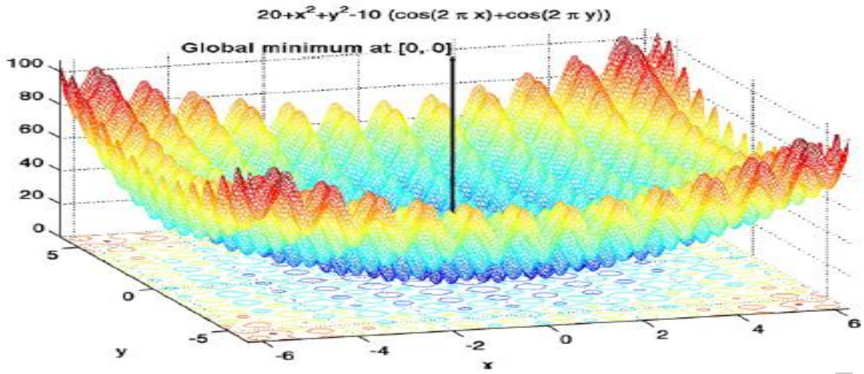


Fig. 5 - The Rastrigin function.

Table 3 shows how to set the parameters of the problem of minimizing the Rastrigin function.

Table 3- Setting parameters for minimizing Rastrigin function

value	Quantity	Symbol
10	Initial population	N_0
500	Maximum number of repeat	it_{max}
2	Dimensions of the problem	dim
30	Maximum plant population	p_{max}
5	Maximum number of seeds	s_{max}
0	Minimum number of seeds	s_{min}
4	Nonlinear modulation index	n
0.75	Initial standard deviation	$\sigma_{initial}$
1e-06	Final standard deviation	σ_{final}
$-20 < x_{ini} < 20$	Initial search range	x_{ini}

Implementation of the improved Chaos IWO algorithm for minimizing this function is presented in Table 4.

The best cost curve in terms of number of repetitions is shown in Figure 6.

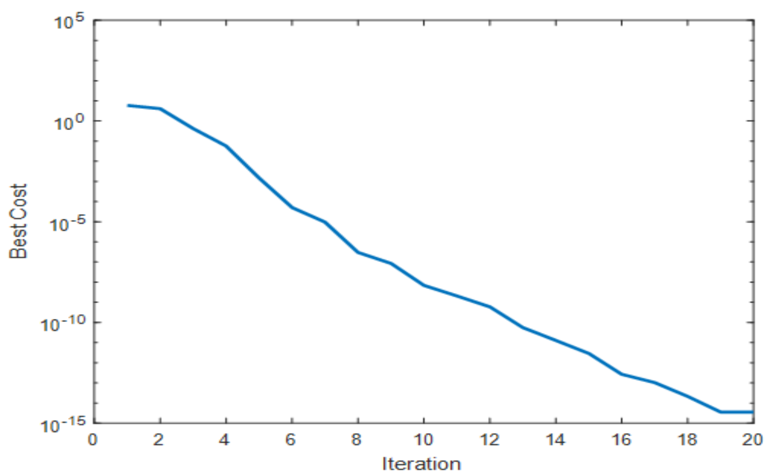


Fig. 6. Convergence of the proposed IWO to the optimal value of the Rastrigin function

In figure 6, it can be seen that function reaches zero after the 20th iteration, which is not shown in the logarithmic graph.

Table 4: The values obtained from the best target function related to the Rastrigin benchmark function with 30 runs performed by three different weed algorithms

Proposed invasive chaotic weed algorithm	Chaotic invasive weed algorithm 1	Ordinary invasive weed algorithm	Performances
0	3.7386e-13	5.1070e-13	mean
0	8.8818e-15	1.0658e-14	best
0	1.4495e-12	3.4905e-12	worst

C-Griewank Function

Finding the minimum Griewank function is a challenge which is the main reason for choosing a well-known benchmark function for optimization algorithms. A Griewank function scheme with dimension of 2 (d = 2) is shown in Figure 7. This figure shows that the function only has one global minimum at [0,0] in the x-y plane and several local minimums.

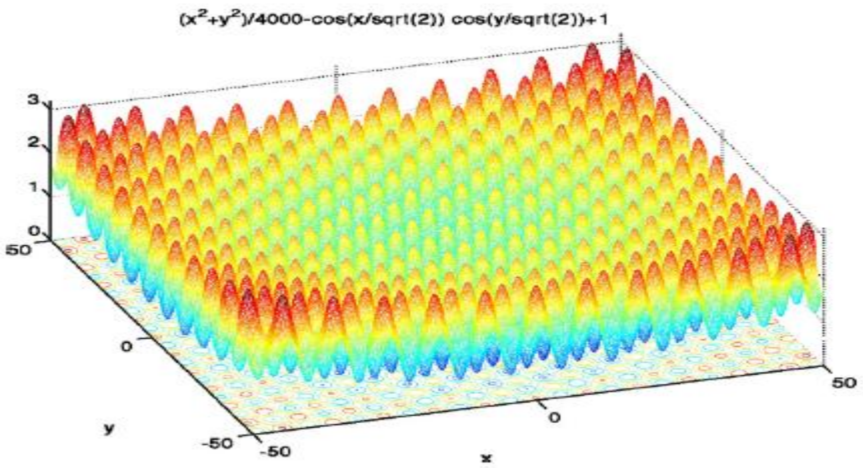


Fig 7. The Griewank function

Table 5 shows how to set the parameters of the problem of minimizing the Griewank function.

Table 5- Setting parameters for minimizing Griewank function

value	Quantity	Symbol
10	Initial population	N_0
500	Maximum number of replays	it_{max}
2	Dimensions of the problem	dim
30	Maximum plant population	p_{max}
5	Maximum number of seeds	s_{max}
0	Minimum number of seeds	s_{min}
4	Nonlinear modulation index	n
0.75	Initial standard deviation	$\sigma_{initial}$
1e-6	Final standard deviation	σ_{final}
$-20 < x_{ini} < 20$	Initial search range	x_{ini}

Implementation of the IWO algorithm for minimization of the Griewank function is specified in Table 6. Figure 8 shows the process of obtaining the optimal solution of the problem. The best cost curve for the Griewank function in terms of number of repetitions with the proposed algorithm is shown in Figure 8.

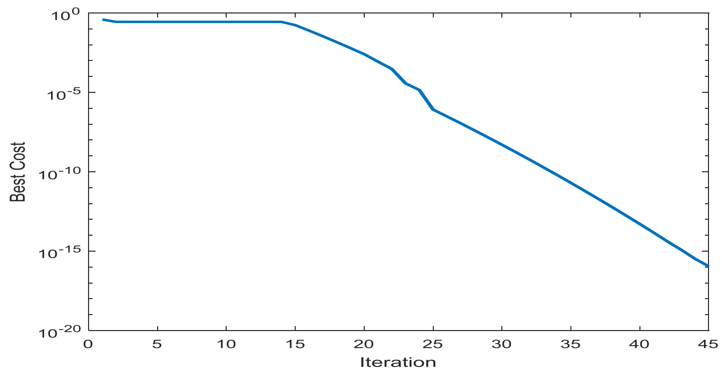


Fig. 8. Convergence of the proposed IWO to the optimal value of the Griewank function

It can be seen that the best cost from 45th iteration is zero..

Table 6: The values obtained from the best target function related to the Griewank benchmark function with 30 runs performed by three different weed algorithms

Proposed chaotic invasive weed algorithm	Chaotic invasive weed Algorithm 1	Ordinary invasive weed Algorithm	Performances
0	0.0081	0.0322	mean
0	1.1102e-16	2.2204e-16	best
0	0.0592	0.1060	worst

According to Table 6, the best average value to find minimum of the Griewank Function is obtained with the proposed algorithm and it equals zero. The mean value, the best and worst solution obtained with proposed method in 30 runs is better than other algorithms.

D-EF10 Function

The EF10 function is a nonlinear, integral function that contains two variables.

$$f\ 10(x, y) = (x^2 + y^2)^{0.25}\{\sin^2[(x^2 + y^2)^{0.1} + 1\} \qquad (7)$$

An expanded EF10 function is proposed to scale the main EF10 equation for any number of arbitrary variables as follows:

$$EF10(x) = \sum_{j=1}^{N}\sum_{i=1}^{N} f\ 10(x_i, x_j) \qquad (8)$$

Similar to Griewank, its global optimum point is zero for all variables.

Table 7 shows how to set the parameters of the minimization problem of the EF10 function.

Table 7- Setting parameters for minimizing EF10 function

value	quantity	symbol
10	Initial population	N_0
800	Maximum number of repeat	it_{max}
10	Dimensions of the problem	dim
30	Maximum plant population	p_{max}
5	Maximum number of seeds	s_{max}
0	Minimum number of seeds	s_{min}
4	Nonlinear modulation index	n
7.5	Initial standard deviation	$\sigma_{initial}$
1e-06	Final standard deviation	σ_{final}
$-20 < x_{ini} < 20$	Initial search range	x_{ini}

Figure 9 shows the best cost curve for number of iterations associated with EF10 function, using the proposed method.

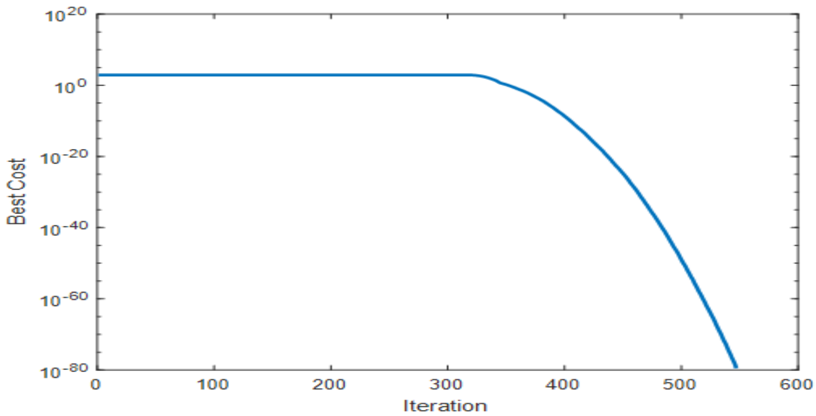


Fig. 9. Convergence of the proposed IWO to the optimal value of the EF10 function

As shown in Fig. 9, after 548th iteration, the best obtained cost function is zero.

Table 8 shows the results of 30 times implementation of the minimization function of EF10 function for three algorithms.

Table 8- Values obtained from the best target function related to the EF10 benchmark function with 30 runs performed by three different weed algorithms

Proposed chaotic invasive weed algorithm	Chaotic invasive weed algorithm 1	Ordinary invasive weed Algorithm	performances
0	0.0689	16.3695	mean
0	0.0575	0.0633	best
0	0.0790	355.7728	worst

According to Table 8, the best mean value obtained from the proposed method is zero. Therefore, efficiency of the proposed method is observed in minimizing the benchmark of EF10 function. The worst results in this table refer to the conventional weed method.

E) EASOM Function

The EASOM function is a nonlinear function with a global minimum in a very thin aperture. The quagmire of this narrow-graft aperture is often a flat function. The EASOM function is defined as:

$$ES\,(\mathrm{x},\mathrm{y}) = -\cos(\mathrm{x})\cos(\mathrm{y})\exp[-(\mathrm{x}-\pi)^2 - (\mathrm{y}-\pi)^2] \qquad (9)$$

The global minimum in the x-y axis is $x, y = \pi$ **,** where value of the target function is 1.

The parameters set for algorithms are shown in Table 9.

In the EASOM function, the error value is defined as follows:

$$EASOMERROR = best\cos t + 1 \qquad (10)$$

In which BestCost is the best cost obtained by the algorithm. Table 10 is depicted based on the error value.

In Fig. 10, the best cost function for the EASOM function is shown using the proposed method.

Table 9- Setting parameters for minimization of EASOM function

value	quantity	symbol
5	Initial population	N_0
200	Maximum number of repeat	it_{max}
10	Dimensions of the problem	dim
10	Maximum plant population	p_{max}
5	Maximum number of seeds	s_{max}
0	Minimum number of seeds	s_{min}
4	Nonlinear modulation index	n
7.5	Initial standard deviation	$\sigma_{initial}$
1e-06	Final standard deviation	σ_{final}
$-10 < x_{ini} < 10$	Initial search range	x_{ini}

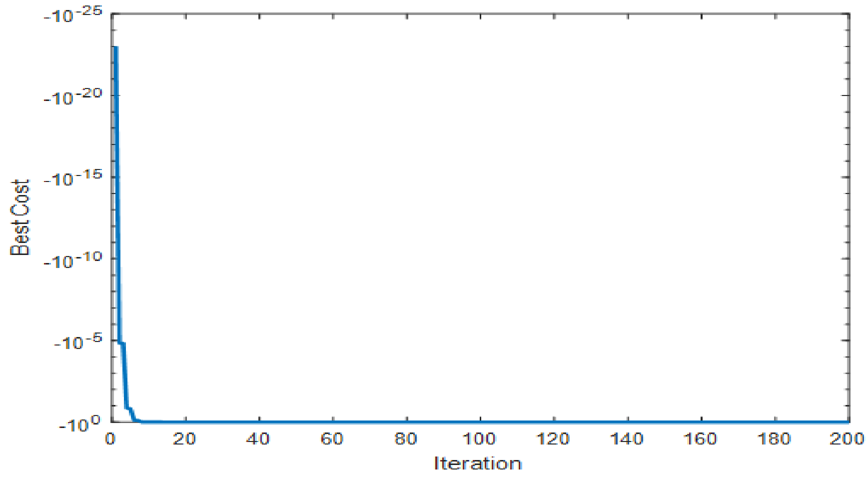


Fig. 10. Convergence of the proposed IWO to optimal value of the EASOM function

In Table 10, results of the 30-times execution of the EASOM benchmark are given.

Table 10- Values obtained from the best target function related to the EASOM benchmark function with 30 runs performed by three different weed algorithms

Proposed invasive chaotic invasive weed algorithm	Chaotic invasive weed algorithm 1	Ordinary invasive weed algorithm	Performances
8.5117e-17	2.0905e-14	5.3754e-14	mean
0	7.7716e-16	2.3315e-15	best
8.8818e-16	8.6264e-14	1.8519e-13	worst

According to Table 10, the mean value obtained by ordinary invasive weed and chaotic weed algorithm 1 are 5.3754e-14 and 2.0905e-14 respectively. While using the proposed method, negative power of 17 was reached. The error is also zero in most executions, since a better average value is obtained. Therefore, effectiveness of the proposed method, in contrast to the other two methods, is proved.

From these results, it can be noted that the aim of this paper is not only limited to improving the exploration ability of chaos. One of the main purposes of this paper is to get fast and good results for simple functions that their best point answer is zero. For these types of problems, a standard deviation is placed at the beginning of the weeds' positions. As a result, equation (5) is updated in a way that a reduction takes place in it as fast as possible. For example, table 4 shows that the proposed approach can achieve a fast result. This is because, the best cost function reaches zero in its 20th iteration.

The modulation index can be a help for rapid reduction of the standard deviation parameter in difficult problems and where the best point is not zero. Chaos theory helps the exploration ability. The standard deviation must not be placed before current position in the position updating equation. In this situation, the main equation of IWO that uses the normal distribution and its multiplied to chaotic standard deviation, helps both exploration and exploitation ability. It also improves the balance between these two abilities. For example, for harder problem cases such as EASOM function, good results can be achieved too.

In order to conclude in this section, it can be stated that the proposed method is very effective in minimizing benchmark functions.

5. Optimal PID Controller Design Problem

The conventional PID controller has been one of the most developed control theories in the world over the past 70 years and it is still commonly used in industrial control systems. PID controller is widely used for industrial applications due to its advantages like simplicity, stability, reliability and convenient adjustment of parameters. Common structure of the PID controller is shown in Fig. 2-6. The standard PID controller calculates the difference e(t) between the reference value and the actual value. Then, the BLDC motor control system is controlled by the signal u (t) and linear combination of the proportional, integral, and derivative components. The PID control rule corresponding to Fig. 11 can be expressed as an interface (11) [26].

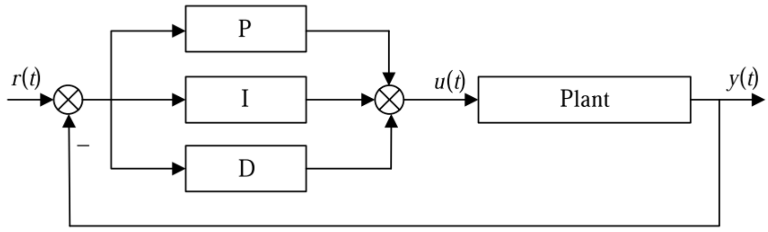


Fig 11. Block diagram of the PID control system

$$u(\mathrm{t}) = \mathrm{K}_P(\mathrm{e}(\mathrm{t}) + \frac{1}{T_I}\int_0^t e(\mathrm{t})\,\mathrm{dt} + \mathrm{T}_D \frac{de(\mathrm{t})}{dt}) \qquad (11)$$

K_P is the proportional constant, T_I is the integral time constant, T_D is the time derivative constant.

PID controllers include various forms such as proportional controller, controller Parabolic-Integrator, Partial-Sequential Controller, and combination of all of the above. The Parallel-Integral is the most commonly used controller in DC motor control systems. The derivative component can effectively reduce the maximum transients and maximize the dynamic deviation, but on the other hand, the controlled system may be easily affected by high frequency disturbances. To eliminate these disturbances, a coefficient is applied to the Derivative filter. Consequently, the system would not be affected by high frequency disturbances.

The objective function in parameter setting of the PID controller is the step response characteristic including, settling time (Ts), maximum overshoot (Mp), steady state Error (Ess). Here, the settling time is more important than other characteristics.

$$z = w_1 Mp + w_2 Ts + w_3 Ess \qquad (12)$$

In equation 12 w_1, w_2, w_3 are massive weights, settling time, and static state error. Lower settling time means less response time to the final value, So that there are more options for its weight. For example $w_1 = 1$, $w_2 = 20$, $w_3 = 10$ can be selected.

Figure 12 shows the block diagram of a CIWO-based PID controller design. In order to verify validity of the proposed method in setting the PID controller coefficients, the results are compared to similar algorithms like PSO, GA, typical IWO algorithm and Chaotic IWO algorithm which the chaotic initial population is used in it.

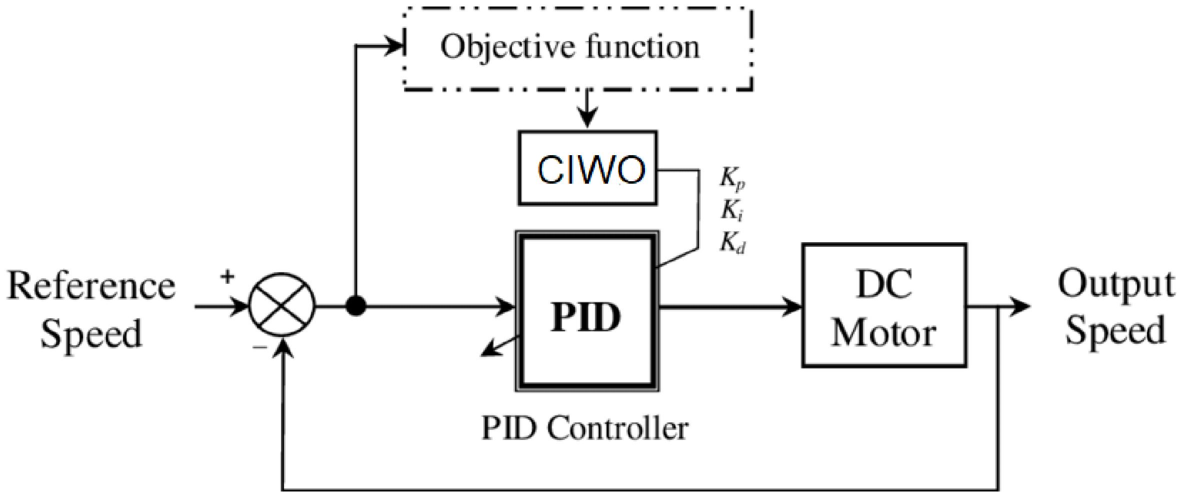


Fig 12. Block diagram of PID controller tuning using proposed chaotic IWO

Consider a loop as large as a population and apply the following equation to a chaotic weed algorithm.

$$X_i^{k+1} = X_i^k + sigma(\mathrm{it}) * \mathrm{rand}(1, \mathrm{nVar}).*(\mathrm{Gbest} - \mathrm{X}_i^k) \quad (13)$$

In the above equation, weeds move towards the best weed with a random coefficient. The sigma parameter changes in each repetition by decreasing the chaos mapping. Table 11 shows how weed parameter algorithms are set in such a way to solve the PID controller parameters.

Table 11: Adjustment of Invasive weed algorithm Parameters for PID Controller Parameter Setting

Value	Quantity	Symbol
20	Initial population	N_0
200	Maximum number of repeat	it_{max}
3	Dimensions of the problem	dim
40	Maximum plant population	p_{max}
5	Maximum number of seeds	s_{max}
0	Minimum number of seeds	s_{min}
4	Nonlinear modulation index	n
7.5	Initial standard deviation	$\sigma_{initial}$
1e-6	Final standard deviation	σ_{final}
$0.01 < x_{ini} < 100$	Initial search range	x_{ini}

Algorithms are executed and then the results are saved. Tables 12 and table 13 show the results of three particular weed algorithms.

Table 12 - Results obtained from best value of the cost function and PID parameters set using the proposed algorithm, weed algorithm and chaotic weed algorithm in the initial population

kd	ki	kp	value of cost function	Algorithm
10.8476	15.7001	34.8105	23.0944	Ordinary invasive weed
5.3771	10.1246	29.4239	15.5553	Chaotic invasive weed 1
4.1272	5.9033	23.569	8.0369	Chaotic invasive weed 2

According to Table 12, the best answer is obtained for the cost function of the proposed chaotic weed algorithm.

Table 13- Results of response characteristics of the step response obtained from PID controller based on weed algorithms

Overshoot	Rise time	Settling time	Mean squared error	Algorithm
5.7644	0.1453	0.690	0.0189	Ordinary invasive weed
3.046	0.1948	0.437	0.023	Chaotic invasive weed 1
1.23	0.222	0.344	0.0121	Chaotic invasive weed 2

According to Table 13, it is shown that in terms of mean square error and the settling time, the best algorithm is the proposed method. This is because of it smaller values. In terms of settling time, the minimum obtained value is related to the proposed chaotic weed algorithm. In terms of Excessive measure, the best value is obtained by the proposed chaotic weed algorithm. According to the results, efficiency of the proposed chaotic weed algorithm in Controlling PID controller parameters is proved.

Figure 13 shows the curve of the best cost function in terms of number of replicas associated with the three weed algorithms.

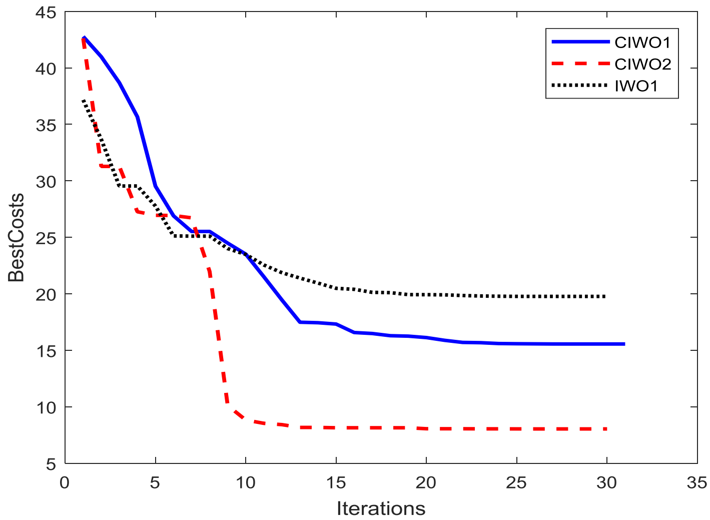


Fig. 13. Convergence of CIWO1, CIWO2 and typical IWO in optimization of PID parameters.

As shown in Fig. 13, the best answer is obtained by the proposed PIDCIWO2 algorithm, which has received a better cost after 11th iteration. But the other algorithms have not reached this value. Figure 14 shows the step response curve obtained from the PID controller optimized by three weed algorithms.

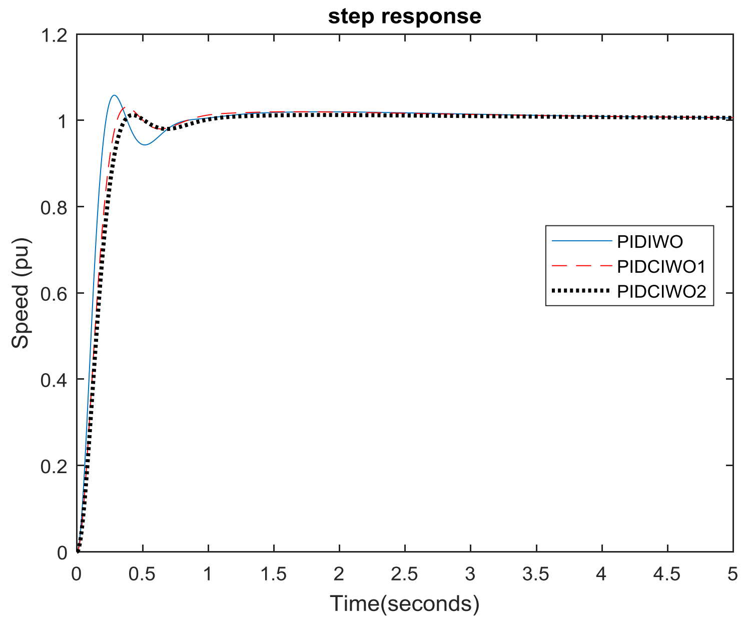


Fig. 14. Step response of system with PID controller using three IWO algorithms

It can be seen that the fastest response is obtained using the proposed CIWO1 algorithm. The highest overshoot is related to PIDIWO. Thus, efficiency of the proposed method is observed in setting optimal parameter of the PID controller.

6- Conclusion

In this paper, an invasive weed-based algorithm based on improved chaotic was proposed which moves the population towards the best weed by adjusting the sigma parameter. The proposed approach first applies the chaotic mappings to the initial population and then to the standard deviation parameter (sigma) algorithm. Chaos has pseudo random properties that are based on nonlinear equations. Its advantage is that it increases the diversity of the population. The standard deviation parameter was applied to the equation which was used for updating the position of weeds to the best position. The reason for using this equation is to receive feedback from the best positioning information in the population. Sigma was configured to make rapid changes over repetitions. The final sigma affects the final accuracy, so its value is likely to be very small.

In order to validate the proposed method, the algorithm was first evaluated for optimization of five benchmark functions. The results showed that, both initial and final sigma are very influential on performance of the algorithm. In simpler cases, it is concluded that low initial sigma is needed, but in more complex issues, sigma is needed in the range of 7 to 10. The modulation index parameter also influences magnitude of the value versus [1]. This is due to the fact that speed of the variation in the standard deviation is greater than the speed value that proposed in [1]. Therefore, it results in better performance. Simulations were performed on Sphere, Rastrigin, Griewank, EF10, EASOM benchmark functions. Based on results of the benchmark functions, the modulation index, and the same initial and final sigma were used to solve the PID controller problem regarding complexity of the problem. The results were compared to the normal weed algorithm and chaotic weed in the initial population. Finally, efficiency results of the proposed method were taken into practice for optimal setting of the PID controller parameters.

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Interest:

The conventional PID control over the past 70 years is one of the most developed control theories in the world, which is still commonly used in industrial control systems.

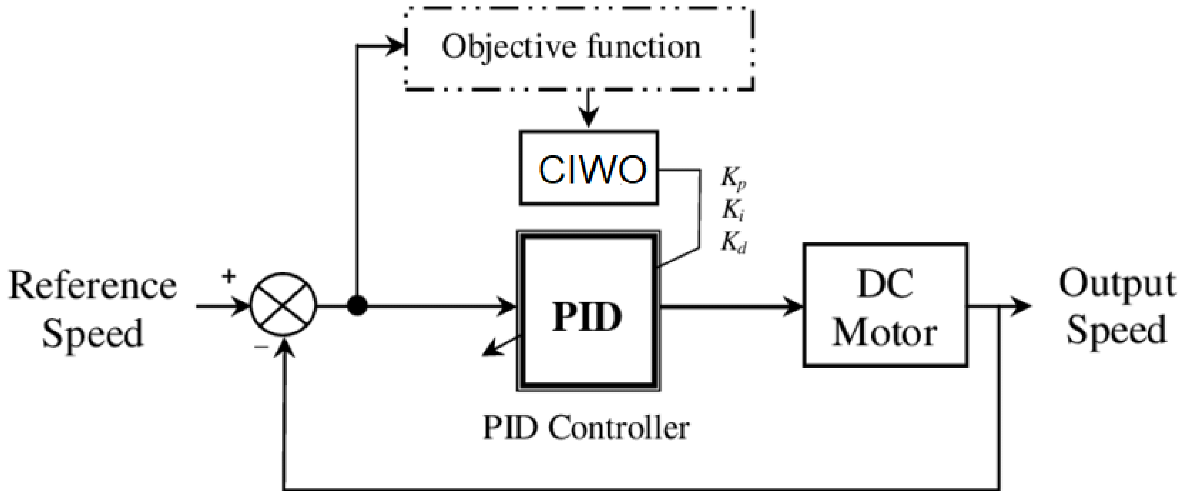
PID controller is widely used for industrial applications due to its advantages like, simplicity, stability, reliability and convenient adjustment of parameters.

Conflict:

Fast optimal setting of the PID controller parameters.

Highlights

- Improved Invasive weed optimization Algorithm (IWO) based on Chaos theory.
- Improved setting the parameters of PID controller uses Chaotic IWO Algorithm.



Block diagram of PID controller tuning using proposed chaotic IWO