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A New Meta-Heuristic Optimization Algorithm Inspired by FIFA World Cup Competitions: Theory and Its Application in PID Designing for AVR System

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Abstract This paper presents a new optimization algorithm based on human society's intelligent contests. FIFA World Cup is an international association football competition competed by the senior men's national teams. This contest is one of the most significant competitions among the humans in which people/teams try hard to overcome the others to earn the victory. In this competition there is only one winner which has the best position rather than the others. This paper introduces a new technique for optimization of mathematic functions based on FIFA World Cup competitions. The main difficulty of the optimization problems is that each type of them can be interpreted in a specific manner. World Cup Optimization (WCO) algorithm has a number of parameters to solve any type of problems due to defined parameters. For analyzing the system performance, it is applied on some benchmark functions. It is also applied on an optimal control problem as a practical case study to find the optimal parameters of PID controller with considering to the nominal operating points (K_g, T_g) changes of the AVR system. The main objective of the proposed system is to minimize the steady-state error and also to improve the transient response of the AVR system by optimal PID controller. Optimal values of the PID controller which are achieved by WCO algorithm are then compared with particle swarm optimization and imperialist competitive algorithm in different situations. Finally for illustrating the system capability against the disturbance, it is applied on a generator with disturbance on it and the results are compared by the other algorithms. The simulation results show the excellence of WCO algorithm performance into the nature base and other competitive algorithms.

Keywords Meta-heuristic algorithm · Optimization · Continuous optimization problems · World Cup Optimization (WCO) · Genetic algorithm · PSO algorithm · ICA · AVR system · Optimal PID control

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1 Introduction

Optimization is the process of finding a solution for minimizing a function considering the problem limitations. The main purpose in the optimization is to nominate the problem variables to minimize or maximize the cost function based on the considered objective. A general definition of the optimization is given below:

$$\begin{aligned} &f_{\min} = \min_{x \in s} f(x), \quad \text{and} \quad f_{\max} = \max_{x \in s} f(x),\\ &\quad x = (i = 1, 2, 3 \ldots l)^T \\ &c_i(x) = 0, \quad i = 1, 2, 3 \ldots M' \quad i = 1, M' \in N \\ &c_i(x) \geq 0, \quad i = M' + 1 \ldots M \quad i = 1, M \in N \end{aligned} \tag{1}$$

where $f(x)$ describes the fitness (cost) function, x is the column vector of the l independent variables and $c_i(x)$ illustrates the class of constraint functions. Constraint equations of the form $c_i(x) = 0$ are entitled equality constraints, and those of the form $c_i(x) \geq 0$ are inequality constraints. $f(x)$ and $c_i(x)$ are specified as the problem functions (Floudas and Pardalos 2014).

By employing the initial optimization techniques like: linear programming (Bazaraa and Jarv 1977), integer programming (Bixby 2012), dynamic programming (Bertsekas 2007) and nonlinear programming (Luenberger and Ye 2008), the problems have been followed to some difficulties. One of the most important difficulties of these methods is their time-wasting; as even with using the new technologies, solving an extensive problem needs several years to solve the problem (Ramezani and Lotfi 2012). This big problem makes the researchers to get new strategies to solve the same problems.

In the recent years meta-heuristic algorithms have been introduced as a proper solver of the optimization problems. A major group of these algorithms have been inspired from the nature, and some others have been inspired from the human treatment like social treatment and political treatment (Atashpaz-Gargari and Lucas 2007).

Nature-based algorithms start with an initial set of variables as population and then conclude to achieve the global minimum or maximum of the objective function. One of the most popular methods in this outline is *genetic algorithm* (GA). Genetic algorithms are inspired from the evolution of the living beings, described by Charles Darwin. They employ operators imitated by natural genetic variation and natural selection (Melanie 1999; Mühlenbein et al. 1991). Another example for the nature-based algorithms is *particle swarm optimization* (PSO) (Kennedy and Eberhart 1995). PSOs are inspired by the team working of the groups like birds and fish. In PSOs, a number of particles are placed into the parameter space of the problem and each particle evaluates the fitness at its current location. Particles then set their movement through the parameter space by merging some aspect of the history between their own cost values with those of members of the swarm and then by moving among the parameter space with a specified velocity by the locations and processed cost values of those other members, along with some random perturbations (Kennedy and Eberhart 2001; Engelbrecht 2005). Among the new meta-heuristic algorithms, the hunting search (HuS) is a new meta-heuristic optimization algorithm which has inspired using the strategy of group hunters in catching their victim (Oftadeh et al. 2010). Cuckoo optimization algorithm (COA) is another new evolutionary optimization algorithm which is inspired by lifestyle of a bird called Cuckoo; in this algorithm, in the final immigrations (iteration) all cuckoo population aggregates the same habitat which is the area's best position (Rajabioun 2011). Therewith, there is a great number of nature-inspired optimization algorithms and also still being done (Riedmiller and Braun 1993; Tsoulos and Lagaris 2006; Colorni et al. 1991; Müeller et al. 2002; Philipse and Maas 2002; Simon 2008).

Recently, besides these nature-inspired algorithms, some other algorithms are developed based on social humanity. These algorithms show better performance in more applications into nature-based algorithms. Cultural evolutionary algorithm (CE) is one of these algorithms. It is developed by Jin and Reynolds (1999). The main idea in cultural algorithms is to nominate beliefs from the derived population and in return implement that knowledge to guide the search.

Imperialist competitive algorithm (ICA) is another social-based evolutionary algorithm which is recently introduced by Atashpaz and Lucas. This algorithm has been recently proposed for utilizing with different optimization problems (Atashpaz-Gargari and Lucas 2007).

ICA has been inspired from the imperialism and imperialistic competitions. In ICA, revolution makes a country to change its socio-political characteristics abruptly. The stop criterion of the ICA has been achieved when there is only one empire.

In this paper, we introduce a new meta-heuristic algorithm in which it is simulated from the FIFA World Cup competitions for reaching the champion cup. In this algorithm each country attempts to conquest the other countries in its continent and also in the other continents to move into the higher stage; just like the real FIFA competition, the country which conquest to the others (the strongest team) forms the best point (solution) of the optimization problem.

2 FIFA World Cup Tournaments

There were various competitions in the nature before the human's creation. But since the human societies were built, a new type of competitions was engendered. This type of intelligent competition among the human societies gets started to a high quality of the competition. Sport competitions are such cases that human societies try hard to win. In the final of these competitions, one person/team becomes champion; in fact, champion states the best contestant in the competition. In the recent years natural-based methods for optimization of systems and different affairs are presented. The modeled competition-based optimization algorithms are basically based on environmental and animal competitions. After FIFA was established in 1904, it tried to address a cosmopolitan football tournament among nations outside the Olympic framework in Switzerland in 1906. These were primeval days for international football, and the official history of FIFA illustrates the contest as having been a failure (FIFA.com).

In 1914, FIFA passed to legalize the Olympic competition as a *world football championship for amateurs*, and took responsibility for administer the event (Reyes 1999; History of the World Cup Final Draw 2006). The principal international competition in football is the *World Cup* which is formed by FIFA (FIFA.com). This competition holds over every 4 years. Almost 190–200 national teams challenge in qualifying tournaments within the scope of continental confederations for a place in the finals. The finals tournament,

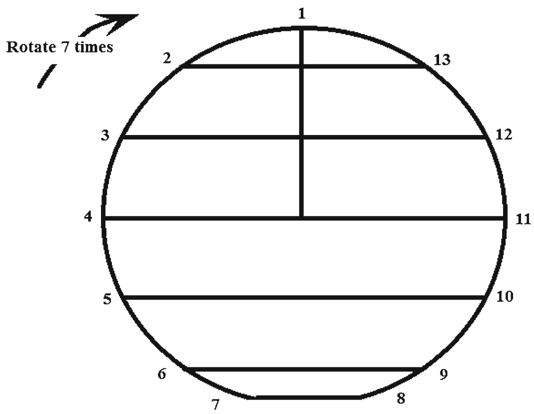

Fig. 1 Round-robin schedule span diagram

which is taken place every 4 years, involves 32 national teams competing over a 4-week period (Chowdhury 2006).

It has a twofold stage: the group stage followed by the knockout stage (FIFA.com). In the group stage, teams challenge within eight groups of four teams. Eight teams are seeded, consisting of the hosts, with the other seeded teams separated by developing a formula based on the *FIFA World Ranking* and (or) performances in the recent World Cups, and drawn to separate groups (FIFA.com; FIFA World Cup Origin 2007). The other teams are allocated to variant *pots*, usually based on geographical criteria, and teams in each pot are drawn at random to the eight groups. Since 1998, restrictions have been implemented to the draw to certify that no group includes more than two European teams or more than one team from any other confederation. Previously, due to there being fewer finals places and a bigger ratio of European finalists, there had been several occasions where three European teams were in a single group, for example 1986 (West Germany, Scotland and Denmark), 1990 (Italy, Czechoslovakia and Austria) and 1994 (Italy, Republic of Ireland and Norway) (Formats of the FIFA World Cup Final Competitions 2010).

The competition type among these groups is round-robin tournament (or all-play-all tournament). In this type of tournament each team is scheduled to compete against all other contestants in turn (G. & C. Merriam Co. 1980). The scheduling algorithm of round-robin tournament is given below.

For n number of competitors, a pure round-robin needs $\frac{n}{2}(n-1)$ challenges. If n becomes even, for each of $(n-1)$ turn, $\frac{n}{2}$ challenges can be run in parallel, provided there exist adequate origins. If n becomes odd, there will be (n) turns, each with $\frac{(n-1)}{2}$ challenges, and one opponent has no challenge in that round. The above schedule is represented by a graph in below (Fig. 1).

The last round of challenge of each group is scheduled at the same time to withhold fairness among all four teams (FIFA.com; G. & C. Merriam Co. 1980). Two teams with higher prominence from each group promote to the knockout stage. Grant points are employed to rank the teams within a group. The knockout stage is a single-elimination tournament in which teams play each other in one-off challenges, with extra time and penalty shootouts utilized to select the winner if necessary. It starts with the second round in which the winner of each group plays versus the runner-up of another group. This is pursued by the quarter finals, the semi-finals, the third-place match (contested by the losing semi-finalists) and the final.

3 Proposed World Cup Optimization (WCO) Algorithm

In recent years, meta-heuristic algorithms are inspired from different phenomena. These phenomena can be natural, social, etc. Physical annealing in simulated annealing, evolution in evolutionary algorithms, swarm intelligence in particle swarm optimization and imperialistic development in imperialist competitive algorithm are some examples of this phenomena. There are a lot of meta-heuristic algorithms which are introduced for minimizing or maximizing the optimization problems. Here, because of the stochastic nature of these algorithms, in some definite problems one algorithm performs better than others, whereas this algorithm may be lose toward the other algorithms in crossing with other tasks; e.g., GA toward PSO has good performance in graph theory, whereas PSO performs better than GA in the control systems. In this paper, we introduce a new competitive-based algorithm for employing it to control the AVR control systems.

Here, a new global socio-politically search algorithm is introduced by motivating the FIFA tournaments and competitions among the countries (teams) to win the World Cup. FIFA World Cup™ is the biggest single-event sporting competition in the world. It is also played by 250 million players in over 150 countries, making it the world's most popular sport (Sugden and Tomlinson 1998). The proposed meta-heuristic algorithm (WCO) is inspired by the teams challenging around the world to win the World Cup championship. The entire team groups usually are classified into some seeds (*seeding step*) based on their *Ranks*. Rank is a definite method of FIFA handicapping based on their past activities, lost and wins. Since the ranking of these teams has a direct effect to their success, seeds are divided based on the team's strength. This makes the first seed comprising n strong teams and the second seed comprising teams with less power rather than seed one, etc. Accordingly the strong teams never compete with each other in the initial step and make them to have higher odds to improve them into the superior step. After seeding the teams, the challenge starts. In this challenge, teams compete with each other to win the game and collect more points for the next games and cups (collect the points for improving their rank to the next cup competi-

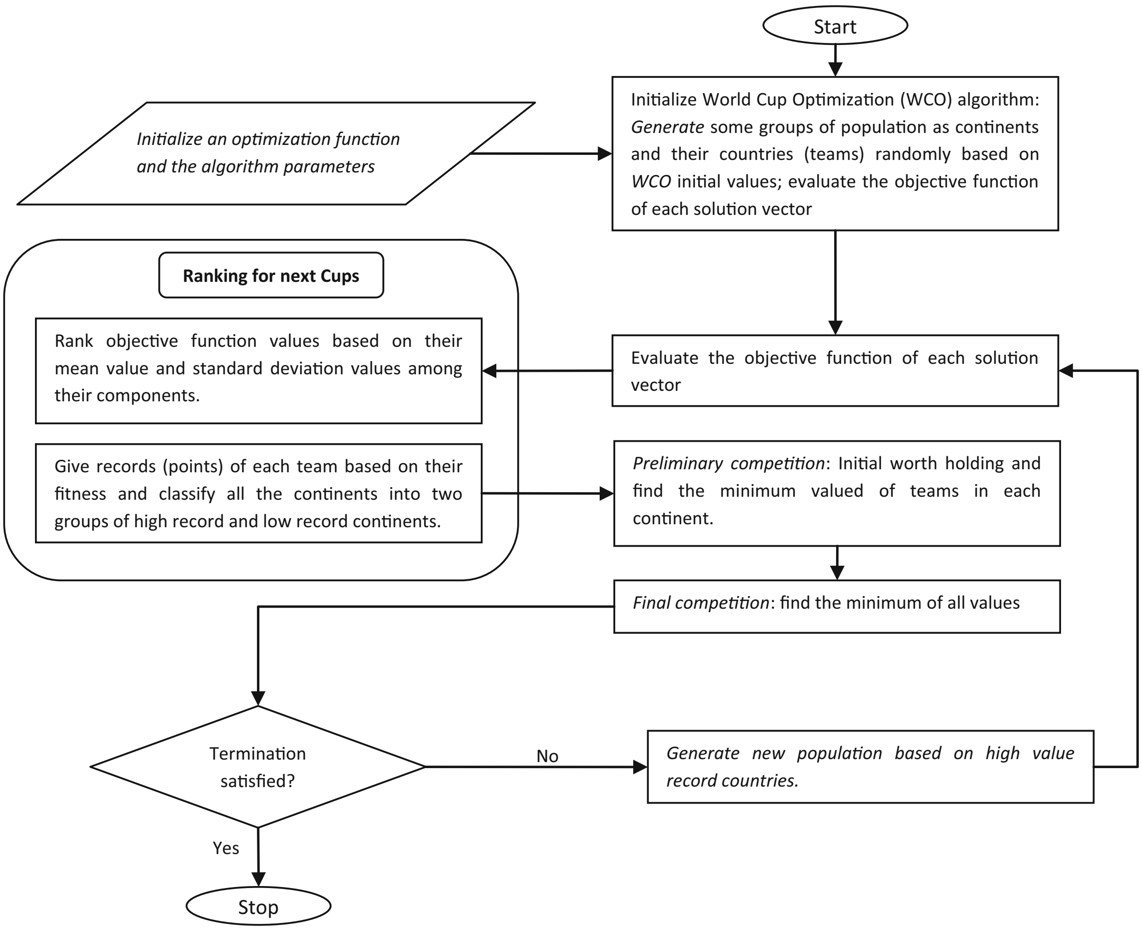

Fig. 2 Flowchart of World Cup Optimization algorithm

tions). This challenge starts with a preliminary competition among the teams in small groups through the world. After the preliminary competitions, two top teams of each group (which can be consisting of the teams of one continent) rise into the upper level (competition) and the other teams will be eliminated. This stage of competition is performed by different methods and designs each cup. The third place of each competition group is also competing with each other to get a chance to improve them into the next stage (*play off*). This competition resumes in multistages. The final stage holds between two powerful teams, and the winner wins the cup.

A flowchart of the proposed algorithm is shown in Fig. 2. Cooperation of the group members is called continents directs to compete by other continents to detect the most powerful continent and especially the strongest team, like other competitive techniques which results in finding a global solution as determined by a fitness function. The fitness function is utilized to provide a measure of how individuals have acted in the problem domain. In the case of a minimization problem, the maximum fit individuals will have the lowest numerical value of the cooperated fitness function (Grefenstette 1987). The fitness function can be written as below:

$$F(x) = g(f(x)) \tag{2}$$

where f is the fitness function, g commutes the value of the fitness function into a nonnegative number, and F is the relative consequence fitness. This mapping is always necessary when the fitness function is to be minimized as the lower fitness function values correspond to the fitter individuals.

In continuous optimization problems, the conjecture of a solution is performed by putting the values of decision variables into the fitness function. This measures the function value, which includes efficiency, cost and/or error. The formal model of continuous optimization can be defined as:

$$O = (S, \omega, f) \tag{3}$$

where S is a search space characterized over a finite set of continuous decision variables, ω is as a set of constraints among the variables, and f is the fitness function to be minimized. The search space (S) is defined as a set of N continuous variables $(x_i, i = 1, \ldots, N)$, where N is the number of design variables. Solving a continuous optimization problem requires at least one global minimum.

3.1 Generating Continents and Their Teams

Forming the initial values for the problem variables in the search space is a key topic to solve optimization problems. In GA and PSO terminologies this array is called *Chromosome* and *Particle Position*, respectively. But here in World Cup Optimization (WCO) algorithm it is called *Team*; teams stand in groups of clusters; these clusters are assigned as*Continents*. Every continent has been set in different positions in the search space. Since the position in which it has more teams in it shows that WCO is going to be optimized. In this algorithm, the voting operation gives to the best and powerful teams based on their ranks. This process continues until the best team with optimized value is achieved and most of the teams are gathered around the same continent based on their rank.

In N variable dimensional (N_{var}) optimization problem with M number of continents, a continent is an array of $1 \times N_{\text{var}}$ which represents the current participating teams of the continents in the competitions. This array is defined as follows:

$$\text{Continent} = \left[\text{country}_1, \text{country}_2, \ldots, \text{country}_{N_{\text{var}}}\right] \tag{4}$$

$$\text{country}_i = \left[x_1, x_2, \ldots, x_{N_{\text{var}}}\right] \tag{5}$$

where x_i shows the ith team of the country. All of the variables $(x_1, x_2, \ldots, x_{N_{\text{var}}})$ are floating points. The rank for each continent can be achieved by valuation of rank function f_r at a continent of $(x_1, x_2, \ldots, x_{N_{\text{var}}})$. Therefore:

$$\text{Rank} = f_r(\text{continent}) = f_r(x_1, x_2, \ldots, x_{O_{\text{var}}}), \tag{6}$$

$$O = N \times M \tag{7}$$

where N describes the variable dimension and M is the number of continents. Initializing step is one of the best advantages of this algorithm; in this technique, each continent consists of different values of random teams by different standard deviations. The defined interval is divided into some continents, and each continent produces some different random teams in the considered range. Therefore, the convergence time in this algorithm gets much faster than the other algorithms.

The algorithm starts by generating some candidate continents matrix of size $N_{\text{pop}} \times N_{\text{var}}$ where N_{pop} defines the number of teams and N_{var} is the number of variables in the problem. Some of the randomly made teams are supposed for each of these initial continents. In the original FIFA, there are five continents and each of them includes four teams. These values are utilized as the initial limitations of team's dedication to each continent at different iterations.

3.2 Competition Among Teams

After initializing and seeding the teams, the next step is to evaluate each continent's score. This score is not so clear, because there is maybe a continent with teams that one of them has the most score (minimum fitness), while the others have weak scores toward the other teams of the other continents. To solve this problem, in this algorithm a specific technique is applied.

1. Acquire all continents
2. Compute mean value and standard deviation of each continent as below:

$$\overline{X} = \frac{1}{n}\sum_{i=1}^{n} X_i \tag{8}$$

$$\sigma = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(X_i - \overline{X})^2} \tag{9}$$

   where $\overline{X}$ is the mean value of the continent X, n is the number of members in X, and σ is the standard deviation of the continent X.
3. Scoring the continents with the following formula:

$$Rank = \frac{(\beta \times \sigma + \overline{X})}{2} \tag{10}$$

   where *Rank* is a sorting operator and β is a coefficient term for the increase or decrease in the standard deviation effect and is in the interval [0, 1].
4. Sorting all continents in a vector based on their rank (with assuming five continents and n teams as default):

$$\begin{aligned} X_1 &= [X_{11}, \ldots X_{1n}]^T, \\ X_2 &= [X_{21}, \ldots X_{2n}]^T, \\ &\ldots, \\ X_5 &= [X_{51}, \ldots X_{5n}]^T \end{aligned} \tag{11}$$

$$X_{\text{Total}} = \left[X_{11}, \ldots X_{1n}, X_{21}, \ldots X_{2n}, \ldots, X_{51}, \ldots X_{5n}\right]^T \tag{12}$$

   Here n describes the number of teams for each continent, and T shows the vector transpose. After applying this algorithm, two minimum values of each continent are separated and are placed into a vector variable (X_{Rank}) for the next championship and the minimum value of X_{Total} is selected as the current cup's champion (Figs. 3, 4):

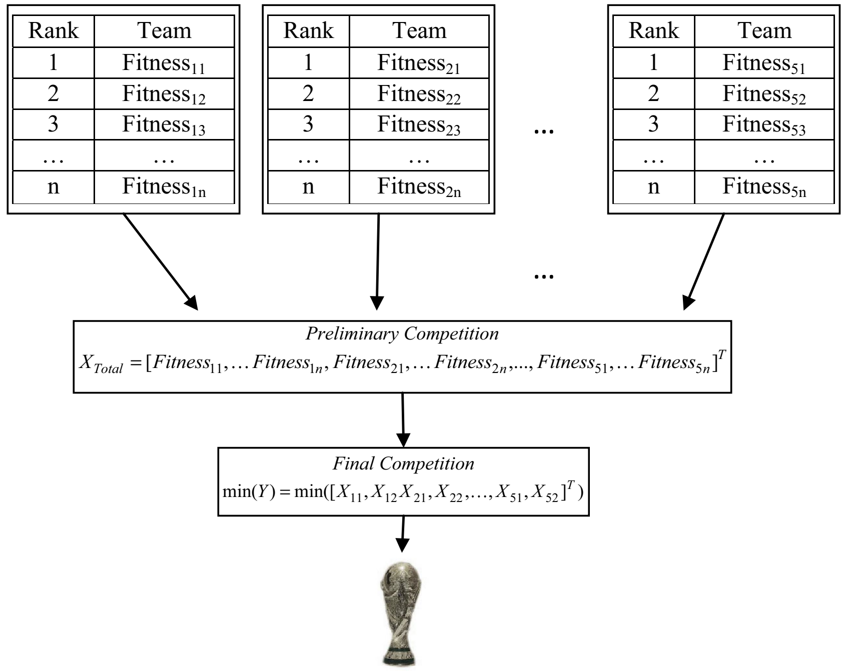

Fig. 3 Compute the champion of the current cup competition

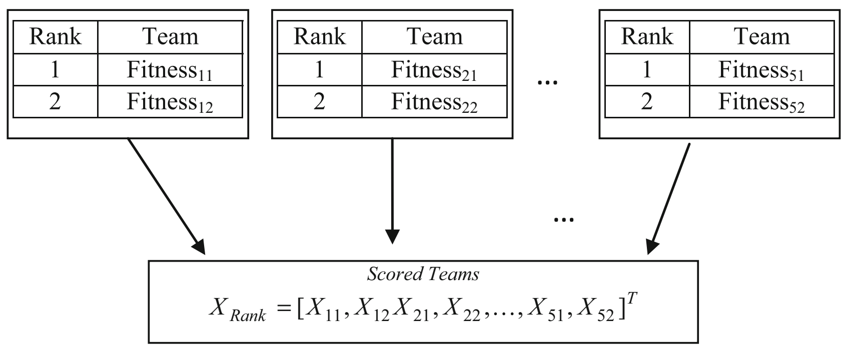

Fig. 4 Scoring the continents

$$X_{\text{Rank}} = [X_{11}, X_{12}, X_{21}, X_{22}, \dots, X_{51}, X_{52}]^T \tag{13}$$

$$\begin{aligned} X_{\text{champion}} &= \min(X_{\text{Total}}) \\ &= \min\left([X_{11}, \dots X_{1n}, X_{21}, \dots X_{2n}, \dots, X_{51}, \dots X_{5n}]^T\right) \end{aligned} \tag{14}$$

3.3 Update: Preparing Teams for the Next Competition

After the champion team of the current cup is determined, new population (continents and their teams) is defined based on the prior cup and the ranking of the teams. This part is different from the real FIFA and will have a heuristic mode. To do this, a two part vector is utilized as below:

$$\text{Pop} = X_{\text{total}} = [X_{\text{Best}}, X_{\text{Rand}}] \tag{15}$$

where $\text{Pop}(X_{\text{total}})$ is the total new population with the size of $(N \times M)$, X_{Rand} is a random value between the problem limitation intervals, and X_{Best} is a vector by the following characteristics:

$$L < X_{\text{Best}} < U \tag{16}$$

$$U = \frac{1}{2} \times \text{ac} \times (\text{Ub} + \text{Lb}) \tag{17}$$

$$L = \frac{1}{2} \times \text{ac} \times (\text{Ub} - \text{Lb}) \tag{18}$$

where ac is accuracy coefficient between Ub and Lb as high and low bounds (limitation) for the considered problem.

The next step is to improve the algorithm by two important characteristics: exploration and exploitation. Exploration and exploitation are two cornerstones of the problem solving by searching (Macready and Wolpert 1998). X_{Rand} is applied as the exploration term, while X_{Best} includes the exploitation term of the population. X_{Rand} is the process of full inspection of the new regions of a search space, and X_{Best} is the process of inspecting those regions of a search space within the neighborhood of the formerly visited points.

Selecting a good ratio between exploration and exploitation parts can make the system to be successful in the search algorithm (De Jong 2002; Chen et al. 2009; Črepinšek et al.

2013). The size of X_{Rand} and X_{Best} can be separated and changed due to the problem statements with a value of *Cross Point* (CP) as below:

$$\begin{aligned} X_{\text{Rand}} &= \text{Pop}(1{:}\text{CP}, M) \\ X_{\text{Best}} &= \text{Pop}(\text{CP}+1{:}N, M) \end{aligned} \tag{19}$$

After generating the new population, it will be divided into m teams of n continents:

$$\text{Pop} = [X_{\text{Best}}, X_{\text{Rand}}] \rightarrow \begin{matrix} X_{1\text{new}} = [\text{Pop}(1{:}k)] \\ X_{2\text{new}} = [\text{Pop}(k+1{:}l)] \\ X_{1\text{new}} = [\text{Pop}(l+1{:}r)] \\ X_{1\text{new}} = [\text{Pop}(r+1{:}s)] \end{matrix} \tag{20}$$

4 Comparative Study

In this section, to see how WCO is more suitable with comparing by the other meta-heuristic algorithms, we compare WCO with two popular and high-performance stochastic heuristic algorithms, GA and PSO theoretically. In addition, an experimental comparison is given in the next section by these algorithms and also a new popular algorithm, ICA, for representing the ability of the proposed algorithm. To do a good comparison, we start by a review on GA and PSO algorithms in detail.

4.1 GA Algorithm

GA is a technique for solving optimization problems which is based on a natural selection process. It imitates biological evolution. The algorithm modifies the solutions by a repetitive process. The pseudocode of GA is defined in below:

(1) Choose initial population
(2) Evaluate each individual's fitness
(3) Determine population's average fitness
(4) Repeat

    select best-ranking individuals to reproduce
    mate pairs at random
    apply crossover operator
    apply mutation operator
    evaluate each individual's fitness
    determine population's average fitness

(5) Until terminating condition (e.g., until at least one individual has the desired fitness or enough generations have passed)

4.2 WCO Versus GA

1. WCO and GA can solve problems with multiple solutions.
2. Both of algorithms are easy to understand, and they practically have no need a deep knowledge of mathematics.
3. Both of GA and WCO are easily transferred to existing simulations and models.
4. Some special case of problems (they are called variant problems) cannot be solved by means of genetic algorithms. This problem occurs because of the generation of bad chromosome blocks instead of good ones in the crossover process but WCO because of its competitive nature, selects just good teams and the teams which are lost in the present competition and have good results in the past competitions can have less effect by reducing the ranking score value.
5. Genetic algorithm has not a good performance in the real-time applications and is limited because of random solutions and convergence; therefore, it is unreasonable to use genetic algorithms for online controls in real systems without testing them first on a simulation model. But anyway, WCO algorithm has a good performance into the GA according to its time convergence.

4.3 PSO Algorithm

PSO is a simulation of the social behavior (flock of birds). This meta-heuristic algorithm tries to achieve the best solution based on the population of particles by employing an operator according to the fitness information obtained from the environment. In other word, in this algorithm the cooperation among the individuals is the reason of the success. The pseudocode of PSO is defined in below:
For each particle:
Initialize particle

(1) Do:

  (a) For each particle:
    (1) Calculate fitness value
    (2) If the fitness value is better than the best fitness value (pBest) in history
    (3) Set current value as the new pBest
    End

(b) For each particle:

  (1) Find in the particle neighborhood, the particle with the best fitness
  (2) Calculate particle velocity according to the velocity Eq. (1)
  (3) Apply the velocity constriction

(4) Update particle position according to the position Eq. (2)
(5) Apply the position constriction

End

While maximum iterations or minimum error criteria are not attained

4.4 WCO Versus PSO

1. Both of WCO and PSO are based on the intelligence.
2. WCO and PSO have no overlapping and mutation calculation.
3. During the development of iterations, in PSO only the most optimist particle can transmit information onto the other particles and in WCO only the most optimist teams can go to the upper level,
4. The speed of researching in both PSO and WCO is very fast.
5. WCO, because of the *Cross Point* operator, has good exploration, and hence, it does not trap into the local minima easily, whereas PSO easily sticks in the local minima.

5 Simulation Results

In this section the proposed World Cup Optimization (WCO) algorithm is applied on some commonly used and popular benchmark functions and other applications. For selecting the proper parameters in GA and PSO algorithms in the problem, we used the methods from (Melanie 1999; Kennedy and Eberhart 1995).

5.1 Benchmark Fitness Functions to Achieve Zero Values

In order to analyze the proposed algorithm performance, we utilized some benchmark problems as below:

(a) Rastrigin
It is a generic sample of nonlinear multimodal function. It was first proposed by Rastrigin (Törn and Zilinskas 1989). Rastrigin is a hard problem due to its large search space and its large number of local minima. It can be defined as:

$$F(x_j) = \sum_{j=0}^{n-1} x_j^2 - 10 \times \cos 2\pi \times x_j + 20$$
$$-5.12 \le x_j \le 5.12 \quad n = 10 \tag{21}$$

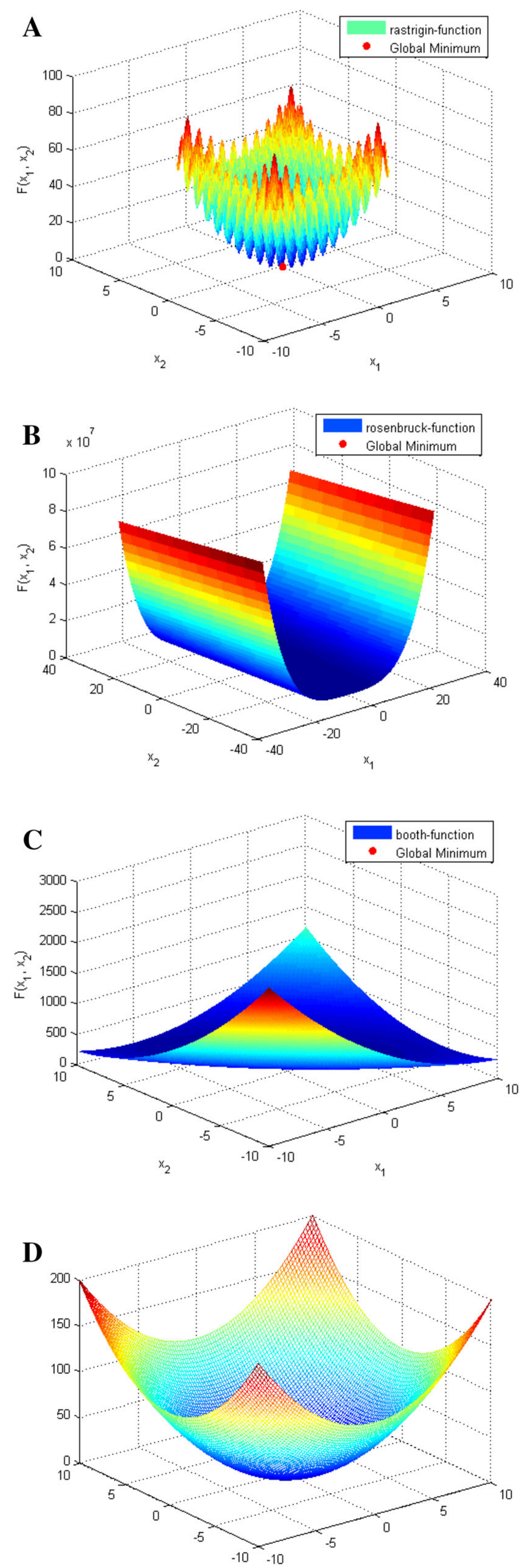

Fig. 5 3D schematic of test functions: **a** Rastrigin, **b** Rosenbrock, **c** Booth and **d** Cubic

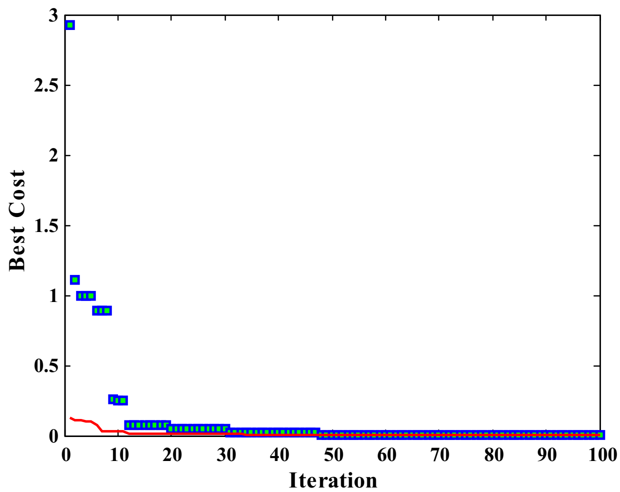

Fig. 6 Cost minimization plot of function Rastrigin with GA (*red line*) and WCO (*blue dots*) (Color figure online)

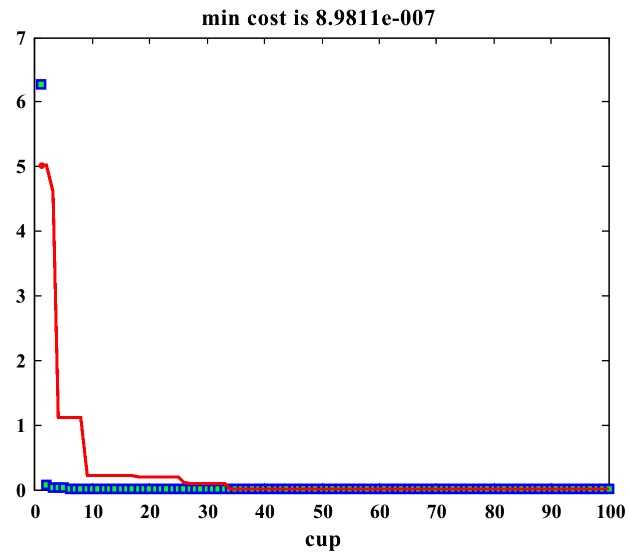

Fig. 7 Cost minimization plot of function Rastrigin with PSO (*red line*) and WCO (*blue dots*) (Color figure online)

where x_j defines the function interval and n is the number of variables.

(b) Rosenbrock
The Rosenbrock function (also known as Rosenbrock's valley or Rosenbrock's banana) is a nonconvex function utilized as a performance index problem for optimization algorithms introduced by Rosenbrock (1960). In this function, the global minimum is inside a long, limited, parabolic-shaped flat valley.

$$F(x_j) = \sum_{j=0}^{n-1} \left(100 \times (x_{j+1} - x_j)^2 + (x_j - 1)^2\right); \quad -30 \leq x_j \leq 30; \quad n = 30 \tag{22}$$

(c) Booth
This function consists of two separate variables:

$$F(x, y) = (x + 2 \times y - 7)^2 + (2 \times x + y - 5)^2 \quad -10 \leq x, y \leq 10; \quad n = 2 \tag{23}$$

(d) Cubic
Cubic is a function with a number of variables. This function can be presented as below:

$$f(x) = \sum_{i=1}^{n} x_i^2 \quad -2 \leq x \leq 2; \quad n = 1 \tag{24}$$

Three-dimensional plots of the presented functions are shown below (Fig. 5).

Rastrigin function is first analyzed by the algorithms. The initial numbers of continents are 5, and the number of teams in each continent is considered 20. The ratio of teams which will arise within the play-off rule is assigned 4 % of new generation. Convergence is achieved at iteration 7. WCO algorithm has achieved the global minimum in just 7 iterations. As it can be seen in Fig. 6, one group of countries in the iteration 5 which arise to the next step by the play-off rule develop the global minimum in the search space. In iteration 45 the countries reached into the global minimum value. And finally at iteration 47 there is almost one country which remained as the champion and best solution. This country defines the global minimum of the problem. The comparison of WCO, PSO and continuous WCO, GA is shown below.

The initial population for the GA is also set to 20, and mutation and selection rates are set to 0.2 and 0.5, respectively. For PSO cognitive and social parameters are both set to 2. Due to the fact that different initial populations of each method affect directly to the final result and the speed of algorithm and to have a mean expectance of performance for each method, test runs are repeated 30 times.

Figure 6 shows a sample cost minimization plot of Rastrigin function for GA in 100 iterations. As it can be seen from Fig. 6, GA has been reached into the global minimum at 32nd iteration. In this example we show the best condition of GA against the average condition value of WCO; from the results, the exploration of the WCO operates so well and it has a high exploration into the better solution. So we can say that if the initial condition has an improper value, WCO algorithm will compensate this condition in less iteration. Figure 7 displays cost minimization of Rastrigin function using PSO algorithm. From Fig. 7, it is so clear that the PSO algorithm has been reached into the global minimum at 33th iteration, while WCO has been reached to the global mini-

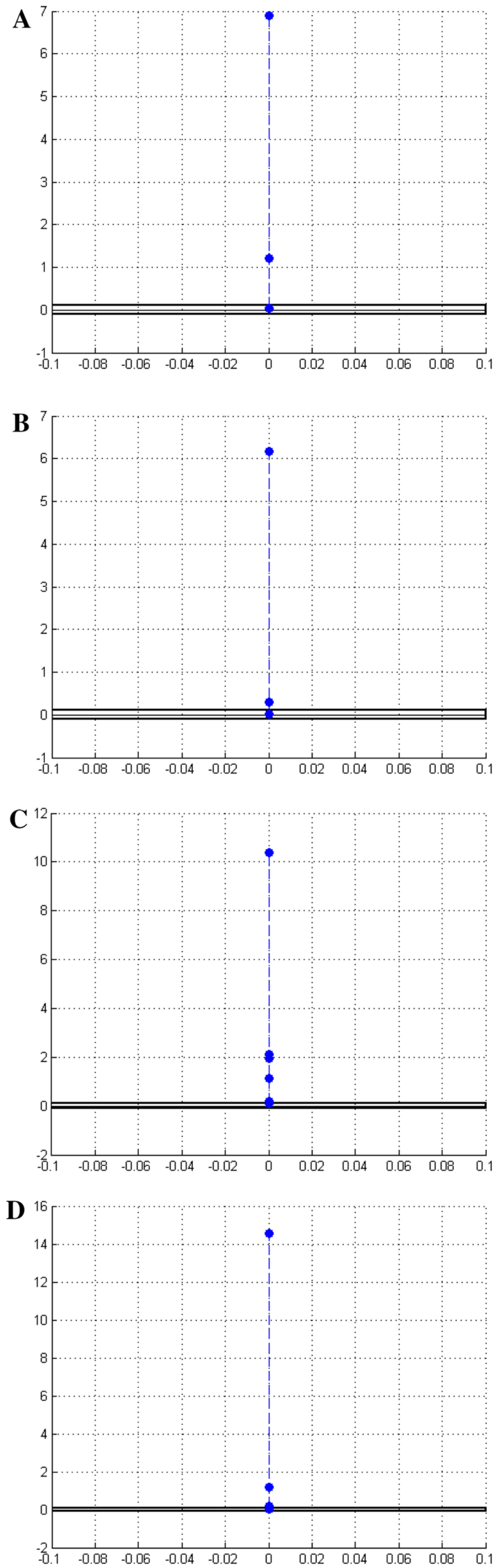

Fig. 8 Zero approaching of the competitors into the zero point (championship) for Rastrigin function in WCO in the **a** first run, **b** second run, **c** third run and **d** fourth run

Table 1 Time and fitness value for the Rastrigin function

	Play off =2 %	Play off =4 %	Play off =5 %	Play off =6 %
Time (s)	2.93	3.26	2.953	2.88
Value	0.0332	0.0099	0.01	0.119

Table 2 α Changes in WCO algorithm and its effects on cost function and elapsed time for Rastrigin minimization problem (num. of population: 50, num. of iteration: 100, play off = 3)

Image	Alpha (α)	Cost function value	Time
(A)	0.1	0.0102	4.037
(B)	0.3	0.0111	4.372
(C)	0.5	0.0997	4.51
(D)	0.7	0.0103	4.36
(E)	0.9	0.0141	4.36

mum at the second iteration; these runs are the best runs for both PSO and WCO algorithms.

Figure 8 shows the minimization process of the algorithm for some steps.

Table 1 shows the time variations of the algorithm with different ratios of play-off coefficient; in other words, the play-off changes do not have sensible effect on the algorithm. Table 2 shows the cost function and elapsed time changes with different values of α (Fig. 9).

Table 3 illustrates the cost function and the elapsed time variation for three different values of play-off coefficients and Fig. 10 shows their mean value results for 100 iterations.

The general conclusion so far suggests that WCO algorithm has high-performance against GA and PSO. For more studies, we apply these three optimization algorithms on some other test functions like Rosenbrock, Booth and Cubic. Figures 11, 12, 13, 14, 15 and 16 show the cost function minimization results for all three algorithms for the presented functions in a random run.

From the above results, we can result that the WCO algorithm has a better initializing step in most cases. It can also conclude that the potential of reaching to the minimum point in WCO algorithm is better than those for GA and PSO.

5.2 Benchmark Fitness Functions to Achieve Nonzero Values

To show the generality of the proposed algorithm for different problems, we also analyze the WCO algorithm by a single fitness function with a target of nonzero value. To do this, we utilize one so-called *Beale* function; Beale is a function with 2 numbers of variables. This function can be presented as below:

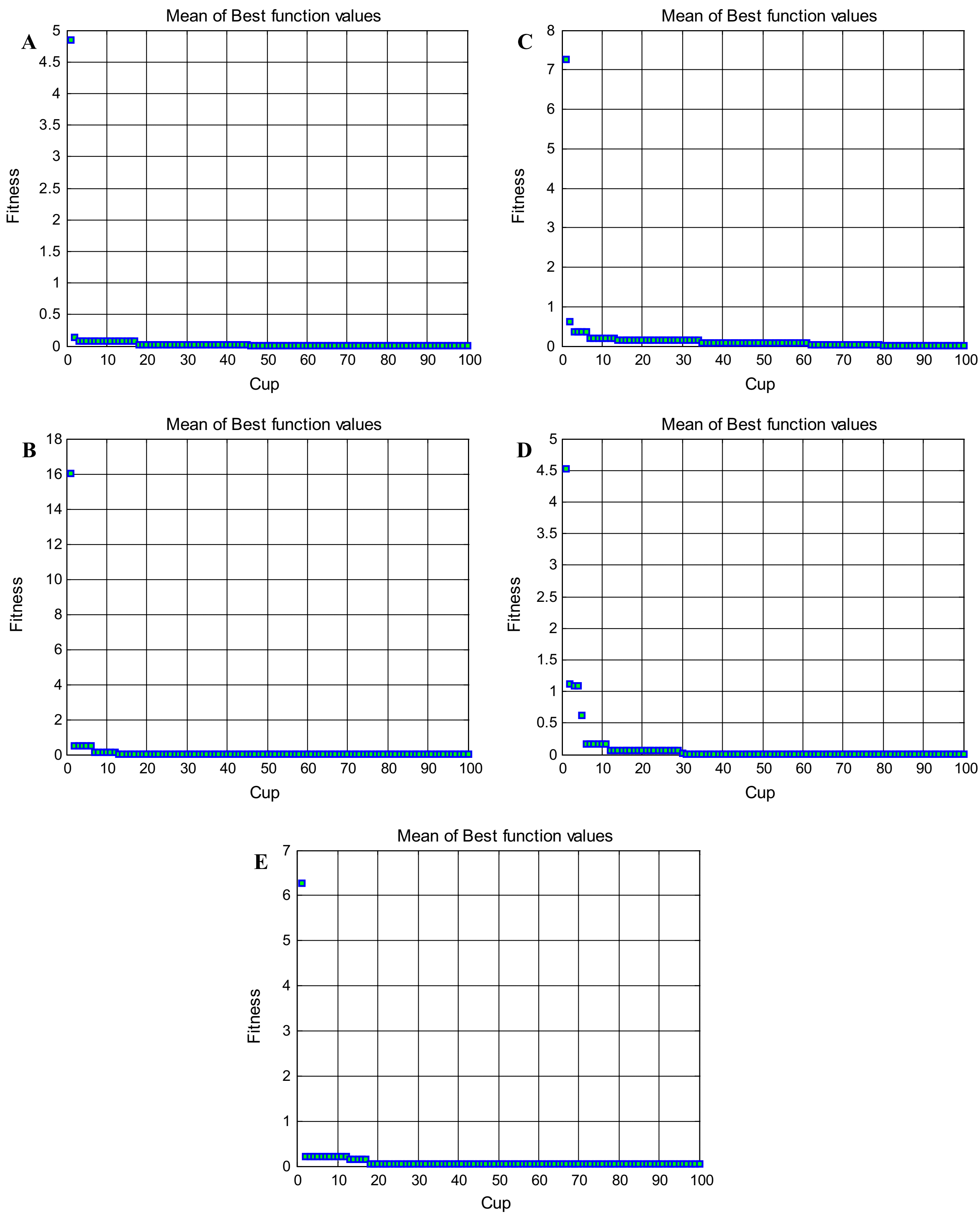

Fig. 9 Minimum value convergence history for the Rastrigin function for presented values from the table above

$$F(x, y) = (1.5 - x + xy)^2 \left(2.25 - x + xy^2\right)^2 + \left(2.625 - x + xy^3\right)^2 \quad -4.5 \le x, y \le 4.5; \quad n = 2 \tag{25}$$

Three-dimensional plot of the presented Beale function is shown below (Fig. 17).

Table 3 Play-off changes in WCO algorithm and its effects on cost function and elapsed time for Rastrigin minimization problem (num. of population: 50, num. of iteration: 100, $\alpha = 0.3$)

Image	Play off	Cost function value	Time
(A)	2	0.0157	4.01
(B)	4	0.0029	4.2
(C)	5	0.001	4.00

The ability of WCO algorithm in solving the Beale function is analyzed, and it is compared with GA and PSO algorithms. The initial numbers of continents are 4, and the number of teams is considered as 30. The play-off percentage of the teams includes 5 % of new generation. The convergence is achieved in iteration 5. WCO has achieved the global minimum in just 9 iterations. As it can be seen from Figs. 15 and 16, a group of countries in iteration 5 which are arisen to the next step, by the help of play-off rule, are developed to reach the global minima. The comparison of WCO, PSO and continuous WCO, GA is shown as follows.

The initial population of the GA is also set to 40, and mutation and selection rates are set to 0.3 and 0.5, respectively. For PSO cognitive and social parameters are both set to 2. Due to the fact that different initial populations of each method affect directly to the final result and the speed of

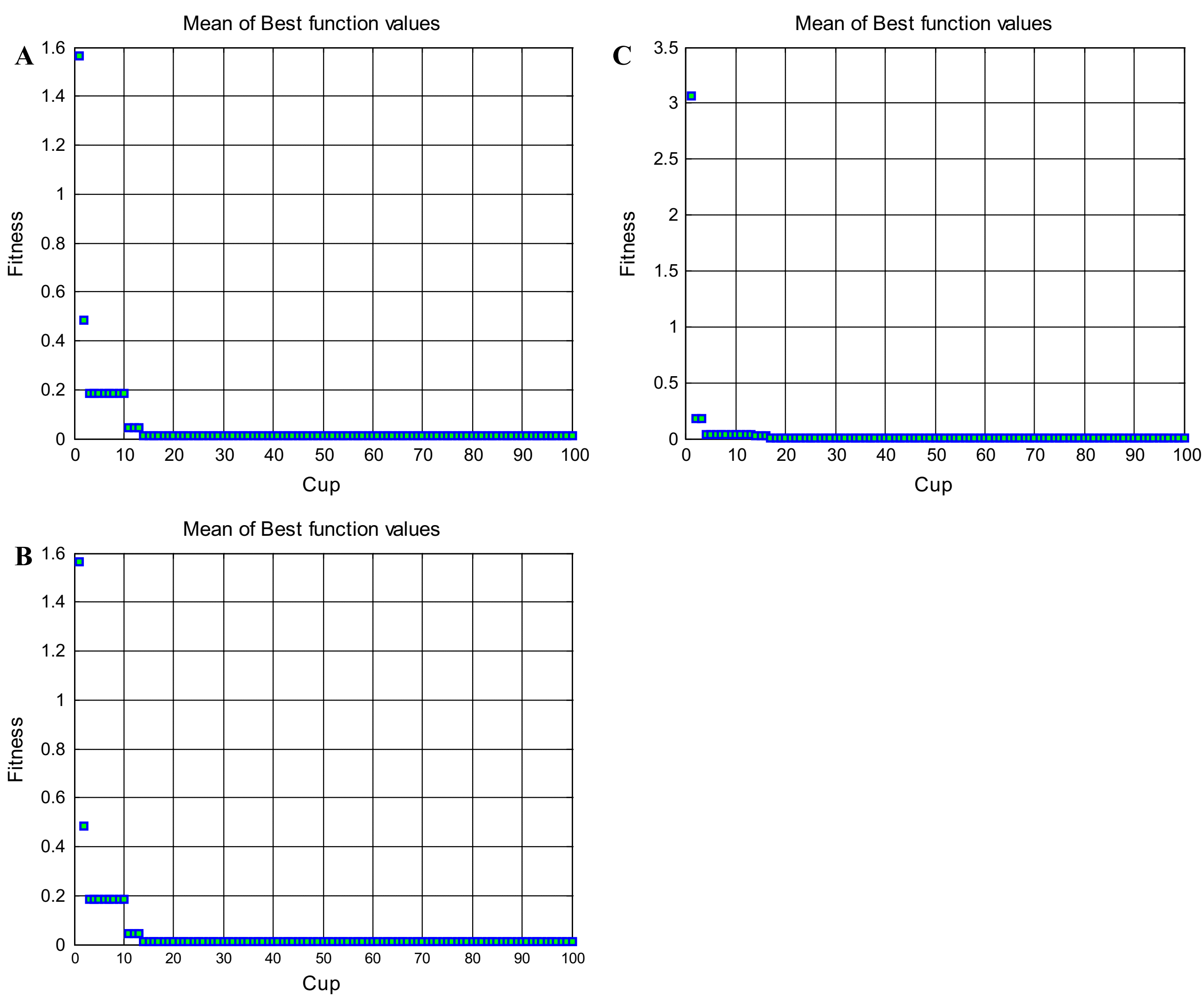

Fig. 10 Minimum value convergence history for the Rastrigin function for presented values from the table above

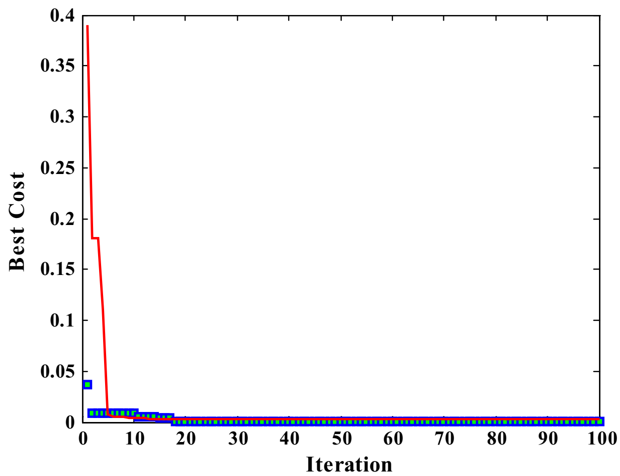

Fig. 11 Cost minimization plot of function Rosenbrock with GA (*red line*) and WCO (*blue dots*) (Color figure online)

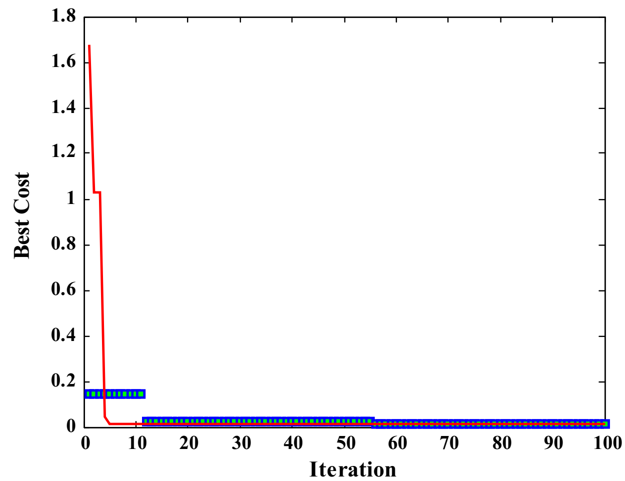

Fig. 13 Cost minimization plot of function Booth with GA (*red line*) and WCO (*blue dots*) (Color figure online)

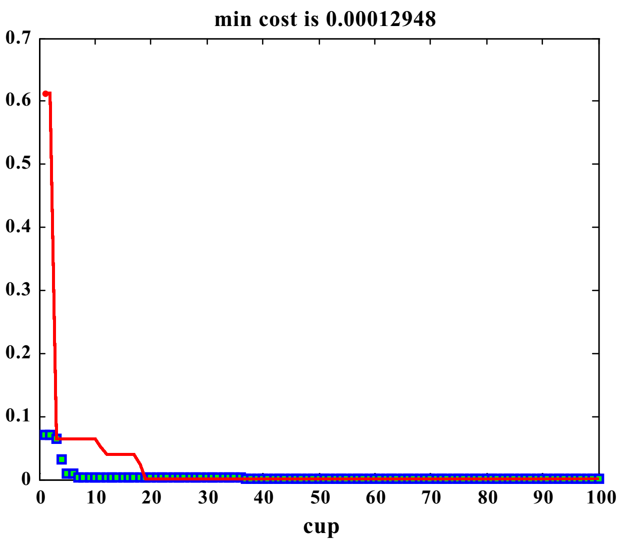

Fig. 12 Cost minimization plot of function Rosenbrock with PSO (*red line*) and WCO (*blue dots*) (Color figure online)

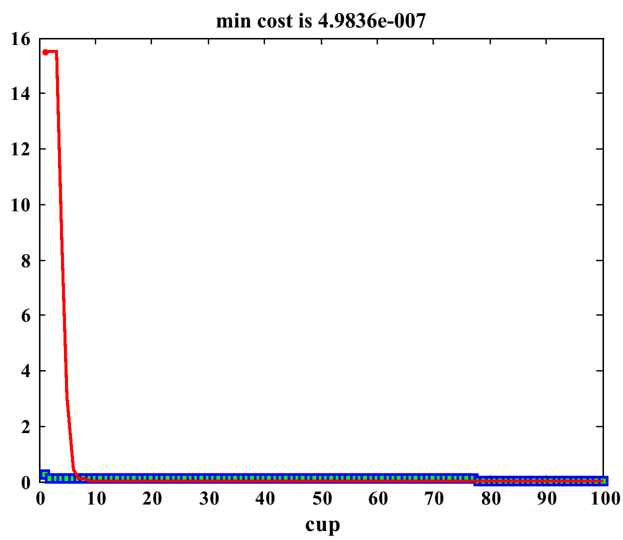

Fig. 14 Cost minimization plot of function Booth with PSO (*red line*) and WCO (*blue dots*) (Color figure online)

algorithm and to have a mean expectance of performance for each approaches, test runs are repeated 20 times.

The general conclusion so far suggests that WCO algorithm has high-performance against the GA and the PSO. For more studies we apply these three optimization algorithms on the Beale test function. Figs. 18 and 19 show the cost minimization plot of WCO algorithm, genetic algorithm and PSO algorithm for the presented function.

5.3 Optimized PID Design for System Control

Voltage control in the power systems has a major rule in the network stability. Since the power system equipment has a definitive nominal voltage, grid voltage must have a standard value. If the grid voltage level has a high value rather than the nominal voltage, it will effect on the system performance, and therefore, the failure rate in the equipment will be increased. Hence, voltage control has an important role in decreasing the power network losses. Network losses depend on reactive power, and on the other hand, reactive power depends on the network nominal voltage; therefore, we need a voltage control to decrease the system losses. A traditional approach is to utilize automatic voltage regulator (AVR); AVR system is generally applied on the power generation units to solve the considered control problem (Mukherjee and Ghoshal 2007).

A study on the recent works on AVR systems presents some different methods to optimize the dynamic response. The previous literature presented that optimal determination of the control system parameters in comparison with other modern control approaches has better performance. AVR

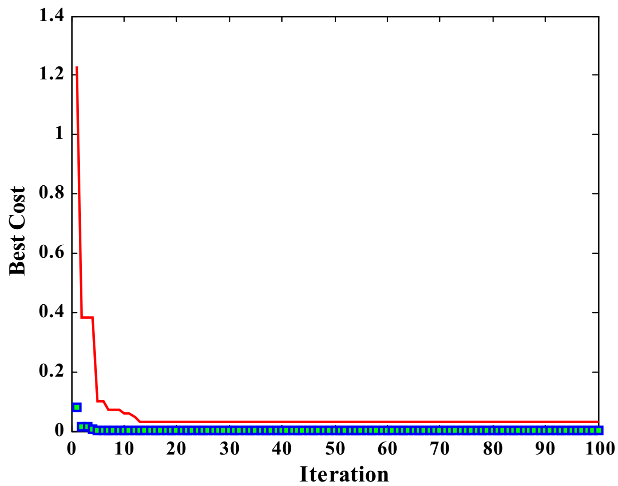

Fig. 15 Cost minimization plot of function Cubic with GA (*red line*) and WCO (*blue dots*) (Color figure online)

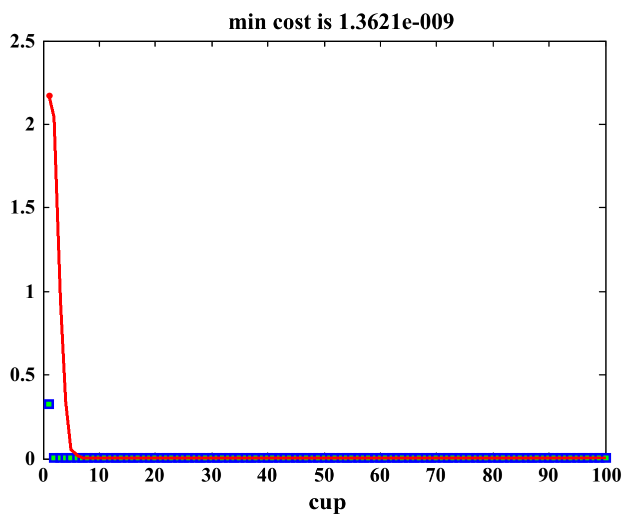

Fig. 16 Cost minimization plot of function Cubic with PSO (*red line*) and WCO (*blue dots*) (Color figure online)

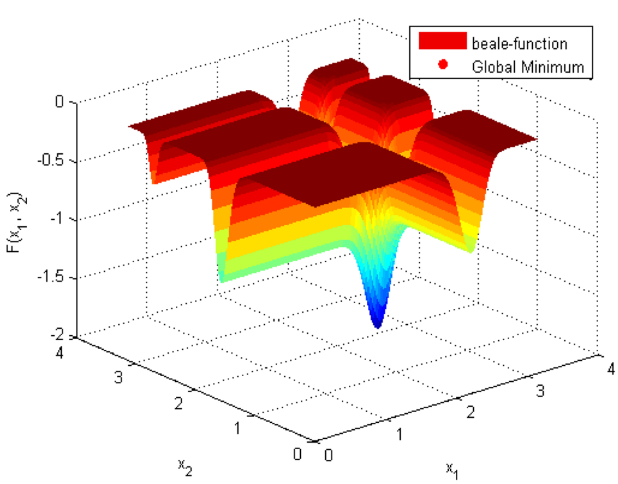

Fig. 17 3D schematic of Beale function

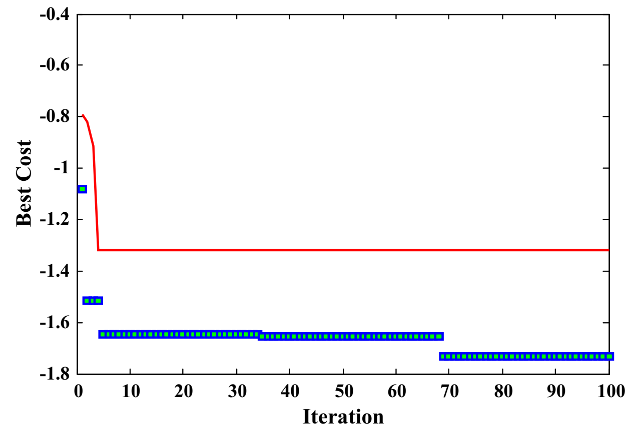

Fig. 18 Mean cost minimization plot of function Beale with GA (*red line*) and WCO (*blue dots*) for 20 iterations (Color figure online)

system with self-tuning control was initiated in the years of 1990s. Afterward, Finch used a global predictive control method like a self-tuning control algorithm at the same time (Mukherjee and Ghoshal 2007). Optimization algorithm based on adaptive controllers was presented by control engineers since the early of twentieth century. Therefore using artificial intelligent algorithms to determine the parameters of PID controller in AVR system is a good choice (Mukherjee and Ghoshal 2007). The parameters of a PID controller in AVR system by using artificial intelligent algorithms consisting of PSO and GA are determined, and the results were compared by Rahimian and Raahemifar (2011). Kim and Cho (2006) proposed a hybrid method of genetic algorithm and bacterial foraging optimization (BFO) algorithm to expand the performance parameters of PID controller in AVR system. Mukherjee and Ghoshal (2007) introduced a fuzzy-based method for self-tuning the algorithm based on CRPSO for PID controller; a novel fitness function is also proposed in this approach. After all, CRPSO results are compared with GA based on controller solutions. In the following, we use WCO algorithm to determine the optimal parameter values of the PID controller. The transient response of the AVR system by WCO algorithm is compared by the PSO and ICA algorithms.

5.3.1 Imperialist Competitive Algorithm (ICA)

Imperialism is the policy of developing the potency and rule of a government beyond its own boundaries. A country may attempt to dominate others by direct rule or by less obvious means such as a control of markets for goods or raw materials which is often called *neocolonialism* (The Hutchinson Dictionary of World History 1999). Imperialist competitive algorithm (ICA) is a new evolutionary algorithm which uses imperialism and imperialistic comparative process as a source of inspiration (Atashpaz-Gargari and Lucas 2007).

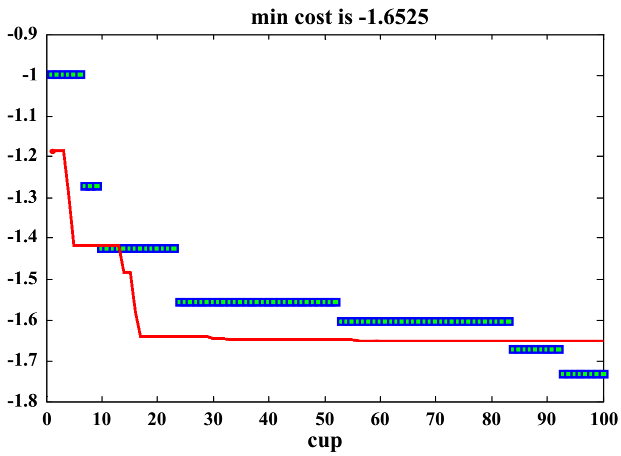

Fig. 19 Cost minimization plot of function Beale with PSO (*red line*) and WCO (*blue dots*) for 20 iterations (Color figure online)

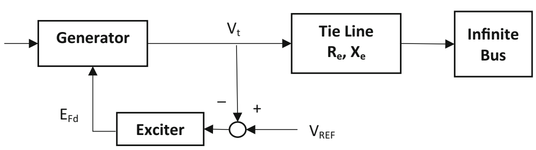

Fig. 20 The block diagram of AVR system

The pseudocode of imperialist competitive algorithm is presented below:

1. Initialize the empires by selecting random points on the function.
2. Colonies movement into their relevant imperialist (assimilation).
3. Random changing of the position of some colonies (revolution).
4. If there is a colony in an empire which has lower cost than the imperialist, replace the positions of that colony and the imperialist.
5. Unify similar empires.
6. Calculate the total cost of whole empires.
7. Set the weakest colony (colonies) from the weakest empires and give it (them) to one of the empires (imperialistic competition).
8. Discard weak empires.
9. If stop conditions are reached, stop, if not go to 2.

ICA, like other evolutionary algorithms, commences with an initial population. In this algorithm each member of the population is known as *country*. Some of the foremost countries in the population are selected as *imperialist states*, and all the remained countries are selected as the *colonies* of these imperialists; after that initial colonies of population will be partitioned among the assigned imperialists based on their power which is inversely proportional to their cost. Afterward, these colonies start moving into their relevant imperialist country. This movement is an easy model of *assimilation* policy that was surveyed by some imperialist states (Jasour et al. 2008).

5.3.2 Simulation and Modeling the AVR System

AVR keeps of the synchronous generator in the nominal voltage. A voltage-level sensor continuously senses the output voltage, and then it is rectified and is smoothed to compare with a direct current reference signal in the comparator. After that, error voltage signal is transferred to the amplifier. The amplified signal is finally used to control the generator field winding by the exciter (Mukherjee and Ghoshal 2007; Rahimian and Raahemifar 2011). The block diagram and simulated of the AVR system are shown in below (Fig. 20).

Figure 21 shows a simple model of the AVR system. The AVR system contains five transfer functions including exciter, amplifier, generator, terminal voltage sensor and comparator. An uncontrolled unit step response of this sys-

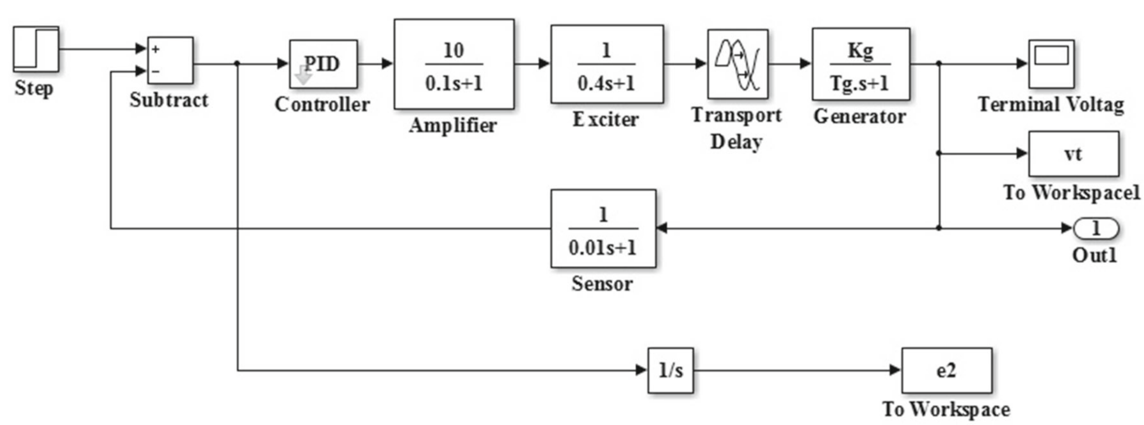

Fig. 21 Simulink model for AVR system

Table 4 Transfer function and parameter limits of AVR system with PID controller

PID controller	$K_p + \frac{K_i}{s} + K_d s$	$0.2 \leq K_p, K_i, K_d \leq 2$	$K_p, K_i, K_d =$ Optimum value
Amplifier	$\frac{K_a}{(1+sT_a)}$	$0.02 \leq T_a \leq 0.1$	$T_a = 0.1$
		$10 \leq K_a \leq 40$	$K_a = 10$
Exciter	$\frac{K_e}{(1+sT_e)}$	$0.4 \leq T_e \leq 1$	$T_e = 0.4$
		$1 \leq K_e \leq 10$	$K_e = 1$
Generator	$\frac{K_g}{(1+sT_g)}$	K_g: depends on	$T_g = 1$
		load $(0.7 - 1.0)$	$K_g = 1$
Sensor	$\frac{K_s}{(1+sTs)}$	$1.0 \leq T_g \leq 2.0$	$T_s = 0.01$
		$0.001 \leq T_s \leq 0.06$	$K_s = 1$

tem has some oscillations which reduces the performance of the regulation. Hence, a control technique must be applied to the AVR system. A small signal model of this system which is constituted through the transfer functions of these components is presented in Fig. 21, and the limits of the parameters used in these transfer functions are depicted in Table 4 (Rahimian and Raahemifar 2011). The PID control is still a simple controller method used by industries owing to their easy implementation of hardware and software; especially, when the PID control is utilized to adjust the gains robust against time operating changes. For this reason, an optimized PID controller is preferred in this work. To control the operating points of the AVR system, gain and time constant of the generator transfer function are considered. The operating points for the analyzing AVR system are presented in Table 5.

In addition to these advantages of PID controller, a steady-state error reduction is also provided as well as a development of the dynamic response by applying the proposed control technique. Since a steady-state error reduction is achieved by adding a pole at the origin with the help of the integral controller, the system order is increased once; transient response development may be achieved by the action of derivative controller that adds a finite zero to the open-loop transfer function (Mukherjee and Ghoshal 2007).

$$\text{ITAE} = \int_0^{t_{\text{sim}}=10} t\,|\Delta v|\,\mathrm{d}t \tag{26}$$

5.3.3 Problem Formulation

Here, the parameters minimization could be chosen as the objective. To demonstrate a robust performance of the proposed methods, two performance metrics are selected: the integral of the simulation time-multiplied absolute value of the error (ITAE) based on the system performance characteristics. In this paper, error is the terminal voltage of generator.

The settling times, gains of PID controller and the maximum overshoots of the voltage variation curves are measured

Table 5 Operation points for transfer function of generator

Case no	K_g	T_g
1	0.77	1.33
2	0.87	1.89
3	0.95	1.67
4	1.01	1.96
5	0.72	1.42
6	0.8	0.95

Table 6 Parameters of the PID controller by changing the operating points for algorithms

Fitness function	Algorithm	K_p	K_i	K_d
ITAE	WCO	0.8130	0.1787	0.2205
	PSO	1.0472	0.3772	0.5778
	ICA	0.7716	0.3494	0.2516

with transient response analysis as represented in below to characterize the performance of the proposed AVR system. Tables 6 and 7 represent the results of the transient response analysis and operating points.

In Tables 4 and 5, gains which has been taken from the generator transfer function are presented, where K_g depends on load (0.7–1.0) and T_g (1.0–2.0 s) is time constant. The same model has been taken in the present work.

5.4 The Simulation Results

This section presents the results of the proposed World Cup Optimization (WCO) approach by a comparison with the results of genetics algorithm (GA), particle swarm optimization (PSO) and imperialist competitive algorithm (ICA) method.

Three parameters of the PID controller are determined by WCO and PSO algorithms. It is apparently from the results that [0, 2] is a good choice for PID controller gains. In the PSO algorithm, parameters are selected as below (Kennedy and Eberhart 2001):

Table 7 Transient response analysis for the operating point

Case no	WCO		PSO		ICA	
	MO	Setting time (s)	MO	Setting time (s)	MO	Setting time (s)
ITAE						
1	0.0058	2.94	0.0801	1.0765	0.075	1.0362
2	0.00038	1.2096	0.1082	1.2102	0.1028	1.1435
3	0.0018	1.0832	0.0975	1.0723	0.0975	1.0951
4	0.0101	1.1142	0.1096	1.1421	0.1096	1.9248
5	0.0065	3.3213	0.0870	1.7520	0.0870	2.3957
6	0.0068	3.85	0.9405	1.8654	0.9405	1.2843

Table 8 The obtained results for the AVR system analyzing by WCO algorithm for 24 operating points

K_g	T_g	Type of controller	K_p	K_i	K_d	O_{sh}	t_{st} (s)	ITAE
0.7	1.0	WCO-PID	0.8400	0.3195	0.2103	1.7124e−4	0.9179	0.0024
0.7	1.2	WCO-PID	0.8325	0.2989	0.2224	2.0262e−4	1.5194	0.0028
0.7	1.4	WCO-PID	0.8329	0.3225	0.2304	4.3677e−4	3.5480	0.0055
0.7	1.6	WCO-PID	0.8376	0.3214	0.2208	5.9033e−4	3.7828	0.0067
0.7	1.8	WCO-PID	0.8321	0.3101	0.2332	6.0284e−4	4.4181	0.0086
0.7	2.0	WCO-PID	0.8168	0.3149	0.2105	8.0718e−4	4.6127	0.0087
0.8	1.0	WCO-PID	0.8114	0.3710	0.2378	2.4641e−4	2.8628	0.0024
0.8	1.2	WCO-PID	0.8158	0.3231	0.2277	3.6892e−4	3.4896	0.0053
0.8	1.4	WCO-PID	0.8273	0.3144	0.2093	5.5438e−4	3.2128	0.0054
0.8	1.6	WCO-PID	0.8896	0.3226	0.2052	7.8925e−4	2.9907	0.0067
0.8	1.8	WCO-PID	0.8668	0.3324	0.2182	8.4830e−4	4.6504	0.0069
0.8	2.0	WCO-PID	0.8525	0.3158	0.2288	7.9080e−4	4.7153	0.0074
0.9	1.0	WCO-PID	0.8558	0.3081	0.2132	1.8532e−4	0.7805	0.0043
0.9	1.2	WCO-PID	0.7825	0.2983	0.2173	3.5091e−4	3.4519	0.0059
0.9	1.4	WCO-PID	0.8976	0.3012	0.2260	4.4911e−4	2.7189	0.0063
0.9	1.6	WCO-PID	0.8777	0.3091	0.2269	5.9818e−4	3.7185	0.0063
0.9	1.8	WCO-PID	0.8713	0.3123	0.2217	7.6012e−4	4.1151	0.0068
0.9	2.0	WCO-PID	0.9129	0.3120	0.2246	8.4999e−4	4.1835	0.0085
1.0	1.0	WCO-PID	0.8887	0.3014	0.2124	2.0856e−4	0.9538	0.0039
1.0	1.2	WCO-PID	0.7916	0.2915	0.2119	3.3709e−4	3.3544	0.0061
1.0	1.4	WCO-PID	0.8192	0.2866	0.2143	4.4163e−4	3.4512	0.0063
1.0	1.6	WCO-PID	0.8114	0.3294	0.2202	7.4844e−4	4.4212	0.0065
1.0	1.8	WCO-PID	0.8447	0.3219	0.2388	7.2980e−4	4.7502	0.0091
1.0	2.0	WCO-PID	0.8216	0.3210	0.2220	9.2678e−4	4.8242	0.009

Population size = 70
$W = 0.9$
$C_1, C_2 = 2$
Number of iterations = 40
Number of runs = 2

In the ICA method, the parameters are selected as below (Jasour et al. 2008):

Countries = 100
Imperialists = 10
Decades = 40
Revolution Rate = 0.3
Beta = 2
Gamma = 0.5
Alpha = 0.1
Damp ratio = 0.99
Number of iterations = 40

In the WCO algorithm, the parameters are as below:
Number of population = 50
The play-off coefficient = 0.3
Alpha = 0.6
Number of runs = 2

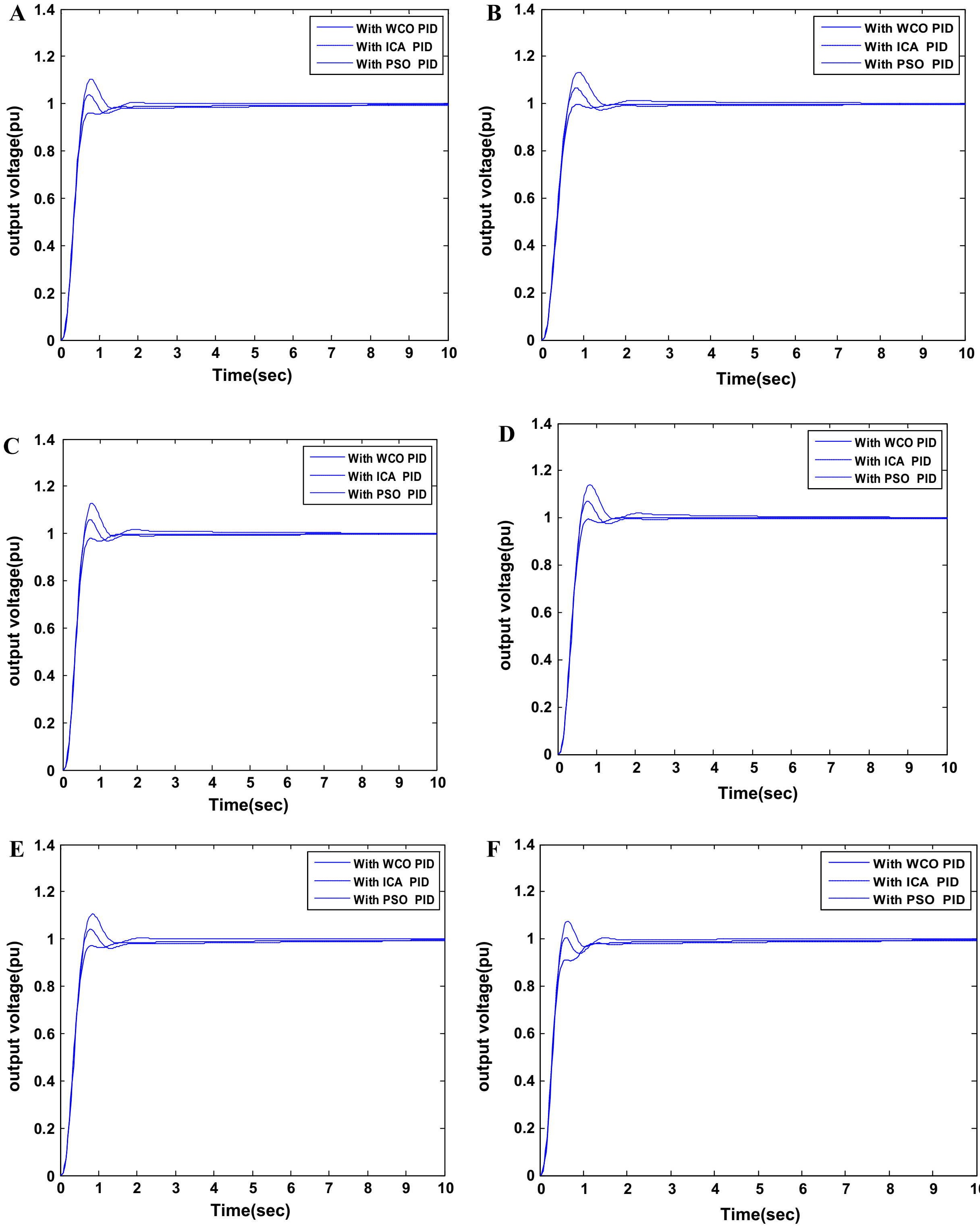

Fig. 22 The voltage variation curves for ITAE [WCO (*solid*), ICA (*dashed*) and PSO (*dotted*)] **a** $K_g = 0.77$, $T_g = 1.33$, **b** $K_g = 0.87$, $T_g = 1.89$, **c** $K_g = 0.95$, $T_g = 1.67$, **d** $K_g = 1.01$, $T_g = 1.96$, **e** $K_g = 0.72$, $T_g = 1.42$, **f** $K_g = 0.8$, $T_g = 0.9$

Table 9 The obtained results of the AVR system analyzing by ICA algorithm for 24 operating points

K_g	T_g	Type of controller	K_p	K_i	K_d	O_{sh}	$t_{st}(s)$	ITAE
0.7	1.0	ICA-PID	0.8518	0.3025	0.2142	7.9075e−4	0.9195	0.08455
0.7	1.2	ICA-PID	0.8486	0.3023	0.2377	1.8409e−4	1.0523	0.01074
0.7	1.4	ICA-PID	0.8502	0.3239	0.2120	5.2319e−4	2.7456	0.05384
0.7	1.6	ICA-PID	0.8288	0.3163	0.2306	5.3489e−4	4.0139	0.01112
0.7	1.8	ICA-PID	0.8379	0.3106	0.2137	6.6970e−4	3.9231	0.03908
0.7	2.0	ICA-PID	0.8604	0.2954	0.2227	6.3275e−4	4.0258	0.04252
0.8	1.0	ICA-PID	0.8503	0.3142	0.2303	2.0099e−4	1.9275	0.07133
0.8	1.2	ICA-PID	0.8585	0.2939	0.2320	1.9475e−4	0.9562	0.09443
0.8	1.4	ICA-PID	0.8568	0.2884	0.2282	3.2529e−4	2.4529	0.0167
0.8	1.6	ICA-PID	0.8168	0.2925	0.2147	5.3784e−4	3.5139	0.3475
0.8	1.8	ICA-PID	0.8873	0.3174	0.2297	6.9377e−4	4.0539	0.04341
0.8	2.0	ICA-PID	0.8491	0.3353	0.2274	9.0104e−4	4.8225	0.02570
0.9	1.0	ICA-PID	0.8325	0.2989	0.2224	2.1131e−4	2.1508	0.06260
0.9	1.2	ICA-PID	0.7329	0.3225	0.2304	3.8943e−4	3.6548	0.03577
0.9	1.4	ICA-PID	0.8379	0.3214	0.2208	5.4674e−4	3.7851	0.03271
0.9	1.6	ICA-PID	0.8321	0.3101	0.2332	5.7433e−4	4.3204	0.06656
0.9	1.8	ICA-PID	0.8186	0.3149	0.2105	8.3675e−4	4.3572	0.09851
0.9	2.0	ICA-PID	0.8114	0.3071	0.2378	7.7770e−4	5.1176	0.01903
1.0	1.0	ICA-PID	0.8273	0.3144	0.2093	2.8248e−4	2.7339	0.04194
1.0	1.2	ICA-PID	0.8896	0.3226	0.2052	5.9706e−4	2.5602	0.05546
1.0	1.4	ICA-PID	0.8068	0.3324	0.2182	6.2621e−4	4.1817	0.04856
1.0	1.6	ICA-PID	0.8525	0.3158	0.2288	6.2570e−4	4.2228	0.08324
1.0	1.8	ICA-PID	0.8558	0.3081	0.2132	8.2894e−4	4.1156	0.09386
1.0	2.0	ICA-PID	0.7825	0.2983	0.2173	8.4846e−4	4.9139	0.01460

Number of iterations = 40
Simulation time for AVR system = 10 s

Simulation results are shown in Table 8 for different values of operating points and step response of incremental change in terminal voltage of PID controller-based AVR system and the convergence profile of WCO, PSO and ICA algorithms are shown in Fig. 22.

In order to analyze the single operating points, the results of the optimized parameters for 24 operating points by optimization algorithms are presented in Tables 8, 9 and 10.

At the end of the analysis, the maximum overshoots of the control system which is optimized by WCO algorithm are as small as about 40 % of PSO algorithm and as small as about 25 % of ICA method. Simulation result showed that the WCO algorithm gets better performance than the ICA and PSO algorithms according to the transient response analysis. In the WCO algorithm with the increasing of the play-off coefficient and decreasing of the alpha parameter the output response of AVR system is improved. Therefore the superiority of the WCO can be proved by the results toward the other human base optimization algorithms.

The main reasons which make us to use PID are: simple structure, easy to implement, easiness of the operation in understanding rather than most other advanced controllers and premier of all, robust performance in a wide range of operating conditions. Now for more illustrating the system performance toward the other algorithms, a disturbance is applied on the nominal operating point of the generator ($K_g = 1$, $T_g = 1$). The system response (with considering the voltage disturbance equal to 2 PU) for the algorithms is shown in below (Fig. 23).

By considering the voltage disturbance in the AVR system, it can be shown that the existence disturbance voltage stability in system is decreased. The main purpose in this part is to use WCO algorithm as an optimization approach to design a robust control on the voltage disturbances for the AVR system. After that, a comparison between WCO-based PID controller is compared by GA-, PSO- and ICA-based controllers. The results show the priority of the WCO-based PID controller versus other approaches. The results of simulations in Fig. 4 also show the excellence of the WCO approach for stability terminal voltage control problem in voltage disturbance condition of AVR system. It is obvious that the advantages of the proposed algorithm in the control systems can be depicted as follows.

Table 10 The obtained results of the AVR system analyzing by PSO algorithm for 24 operating points

K_g	T_g	Type of controller	K_p	K_i	K_d	O_{sh}	$t_{st}(s)$	ITAE
0.7	1.0	PSO-PID	0.8013	0.3204	0.2272	2.1870e−4	2.3828	0.0040
0.7	1.2	PSO-PID	0.8518	0.3025	0.2142	7.9075e−5	0.9195	0.0019
0.7	1.4	PSO-PID	0.8486	0.3023	0.2367	1.0453e−4	1.0821	0.0028
0.7	1.6	PSO-PID	0.8502	0.3239	0.2120	1.8350e−4	0.8816	0.0027
0.7	1.8	PSO-PID	0.8288	0.3163	0.2306	1.6940e−4	1.0456	0.0035
0.7	2.0	PSO-PID	0.8568	0.3201	0.1989	2.8135e−4	1.3153	9.3861e−4
0.8	1.0	PSO-PID	0.8749	0.3238	0.1976	3.3549e−4	1.3152	9.0231e−4
0.8	1.2	PSO-PID	0.8410	0.3353	0.2086	2.5018e−4	1.4831	8.4513e−4
0.8	1.4	PSO-PID	0.8472	0.3393	0.2028	3.1580e−4	1.5192	9.0174e−4
0.8	1.6	PSO-PID	0.8731	0.3262	0.2100	2.2376e−4	1.2330	9.3719e−4
0.8	1.8	PSO-PID	0.8269	0.3075	0.2092	1.2110e−4	0.9181	0.0023
0.8	2.0	PSO-PID	0.8675	0.3014	0.2249	4.9111e−5	0.9562	0.0020
0.9	1.0	PSO-PID	0.8592	0.3170	0.2318	1.3235e−4	0.9875	0.0030
0.9	1.2	PSO-PID	0.8655	0.3001	0.2332	6.7320e−5	1.0152	0.0023
0.9	1.4	PSO-PID	0.8578	0.2897	0.2284	2.8169e−5	1.0454	0.0018
0.9	1.6	PSO-PID	0.8013	0.3204	0.2272	2.1870e−4	2.3828	0.0040
0.9	1.8	PSO-PID	0.8518	0.3025	0.2142	7.9075e−5	0.9195	0.0019
0.9	2.0	PSO-PID	0.8486	0.3023	0.2367	1.0453e−4	1.0821	0.0028
1.0	1.0	PSO-PID	0.8502	0.3239	0.2120	1.8350e−4	0.8816	0.0027
1.0	1.2	PSO-PID	0.8288	0.3163	0.2306	1.6940e−4	1.0456	0.0035
1.0	1.4	PSO-PID	0.8558	03526	0.22467	3.4592e−4	3.2596	0.0053
1.0	1.6	PSO-PID	0.8539	0.3189	0.2269	5.98128e−4	3.7185	0.00863
1.0	1.8	PSO-PID	0.8274	0.33369	0.2275	8.2894e−4	4.1156	0.005372
1.0	2.0	PSO-PID	0.8349	0.2792	0.2437	8.5364e−4	4.2692	0.005749

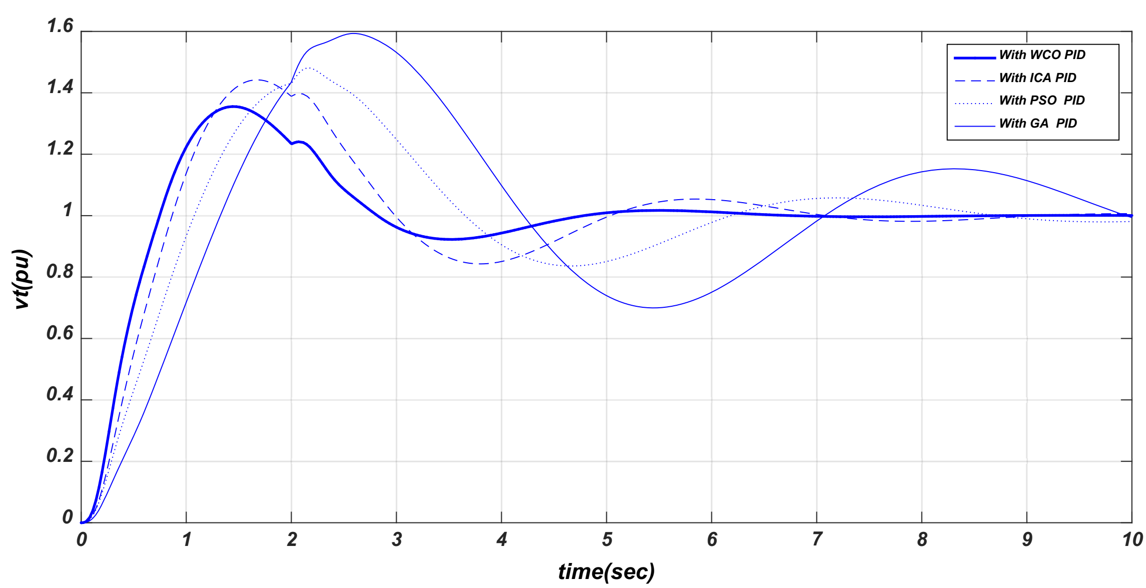

Fig. 23 Terminal voltage of AVR system with voltage disturbance by WCO, ICA and PSO-PID controller

(1) It selects good parameters for using in the system control purposes toward the other popular algorithms
(2) It decreases the settling time in the system control because of its good convergence
(3) The system overshoot is decreased
(4) The system is quickly reached into the stable state

6 Conclusions

In this paper, a new meta-heuristic algorithm inspired from FIFA World Cup competitions is presented. A significant property of FIFA contests is the intelligent competition of the humankind and their greed in postponing the rivals to reach the champion status. This characteristic has been the motivation to develop the proposed optimization algorithm. Different parameters from rank of countries to play-off coefficients help the system to solve different types of optimization, and the simplicity of the algorithm makes it faster than the other algorithms. Like other competition algorithms, World Cup competition (WCO) is also based on population and uses a population of solutions to proceed to the global solution. The population is considered as the rival countries where each one likes to win and postpone the others. The proposed algorithm is tested on some popular benchmark optimization problems and a real case study which includes the optimized design of PID controller to the AVR control system with uncertainties (robust control). The proposed algorithm is also applied on a system with considering the disturbance to show the system resistant toward uncertainties, and the results are compared again by the GA, PSO and ICA. The comparison of the WCO with standard versions of PSO, GA and ICA shows its superiority in a more quick convergence to the global optima. This optimizing algorithm can be utilized for the different optimization design applications.

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