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Evaluation of enhanced particle swarm optimization techniques for design of RC structural elements

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ABSTRACT

In this paper, the use of extended versions of basic particle swarm optimization (PSO) namely constriction factor PSO, democratic PSO and probabilistic PSO have been presented for optimal design of reinforced concrete (RC) structural elements. The design and optimization procedure follows specifications of Indian codes. Driving idea for carrying out this work was to explore extended versions of PSO for their capabilities to maximize 'exploration area' and minimize 'exploration time'. These algorithms are thereby employed to study their effect on minimizing the cost of RC structural members. Optimal cross-sectional size and reinforcement for the members have been obtained by the use of computer aided environment, whereby whole process of design and optimization has been coded in C++. The design variables have been considered as continuous functions and rounded off appropriately to imbibe practical relevance to the present study. The effectiveness of these algorithms was also tested using certain benchmark functions. Various test cases of beams and columns were considered to confirm the results, and they all indicated good capabilities of these extended algorithms in terms of exploration, convergence behaviour and time. The results were also compared amongst themselves to understand adaptability of an algorithm under specific conditions.

1 Introduction

An excellent response of reinforced concrete in terms of compressive strength, durability and low maintenance cost has enhanced its popularity in construction industry; but still the material cost is an important issue in the design and construction of reinforced concrete structures. The material cost can be reduced considerably by an intelligent exploration in the initial stages of construction. Good engineers are those capable of designing low cost structures without compromising its function or violating code requirements for strength and serviceability. The structural design codes do not primarily dwell on the optimization front and this factor is mostly based on the experience of a particular designer - which

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in any case cannot be considered a substitute for the tested and validated principles of optimization techniques. But, for the vast varieties of structural options for a given requirement involving a large number of variables, any particular technique cannot cater for all structural optimization problems. A given optimization technique that gives good result in a particular situation may not hold good for other situations, or for that matter on other fronts in the same situation. This leads to a point where it is important to be able to identify the usefulness of a particular technique in a given situation and also to explore the factors that could increase the efficiency of the technique. Many evolutionary optimization methods have been developed during the last few decades for solving linear and nonlinear optimization problems such as genetic algorithms, harmony search, simulated annealing, particle swarm optimization and ant colonies, to explore solutions for constrained problems and researchers have tried to take advantage of all these optimization techniques to fulfill the requirement of safe and low cost structural designs.

2 Review of related works and motivation

A number of optimization techniques have been applied for optimum design of reinforced concrete structural elements with varying degree of success. Some notable research works on optimization of RC structural elements in the last decade, included the optimization of RC beams using Genetic Algorithm (GA) [1] and Augmented Simulated Annealing (SA) methods [2]. The application of GA for the optimum detailed design of reinforced concrete continuous beams based on Indian Standard (IS) specifications has been presented in [3,4]. Optimum detailed design of reinforced concrete continuous beams using the Harmony Search (HS) algorithm was proposed in [5]. The values of all the variables are required to be selected from a design pool which contains discrete values for these variables. The cost optimization of structural RC beams and PC (prestressed concrete) beams using the Genetic Algorithm has been presented in [6]. The optimum design of biaxial columns was visualized in [7]. Also, a large number of papers are available on optimization of RC frame structures in which beam and column members are optimized separately. Optimum detailed design of RC frame in accordance with IS code requirements has been performed in [8]. The flexural design of reinforced concrete frames in accordance with ACI code provisions using a Genetic Algorithm has been suggested in [9, 10]. The Harmony Search algorithm was employed to optimize RC frames in [11, 12]. An integrated Genetic Algorithm complemented with Direct Search has been applied for optimum design of RC frames based on predetermined section database in which a database of all possible cross sections has been formulated and sorted according to their strengths [13, 14]. The CO₂ optimization of reinforced concrete frames by simulated annealing has been studied in which the optimum design of a reinforced concrete frame was related to the amount of CO₂ gas emitted to minimize pollution [15]. Many researchers have used hybrid optimization techniques to get the optimum design of RC frames. The optimum design of reinforced concrete frames using a hybrid of different methods: Heuristic Big Bang-Big Crunch (HBB-BC) and a HS scheme to deal with the variable constraint and Heuristic Particle Swarm Ant Colony Optimization (HPSACO) algorithm, which is a combination of Particle Swarm with Passive Congregation (PSOPC), Ant Colony Optimization (ACO), and HS algorithms has been researched in [16-17]. Optimum design of reinforced concrete frames using a combination of particle swarm optimization and multi-criterion decision making has been presented in [18].

A considerable research in the field of design optimization of RC structural members has shown that the researchers adopted different methodologies, optimization techniques and code specifications in their studies. Among all, 'genetic algorithm' (GA) - an artificial intelligent method, inspired by biological phenomenon has been widely used for many RC structural design problems. It has also been viewed that only a few studies have been carried out for optimum design of RC structural members using Indian specifications. In the present study, an endeavor has been made to use enhanced versions of PSO to optimize the RC frame elements using Indian design standards. An advantage of PSO is that, while GA has many parameters, to be tuned in comparison to PSO, PSO has only few parameters to adjust, thus making it particularly attractive from a practitioner's point of view. Secondly, PSO showed fast convergence than GA in many benchmark and real life problems. Although the enhanced versions of basic PSO had been applied for several truss and other structural design problems [19-22], they have not been applied to RC structural elements. Hence, the objectives of the present work is to study the efficiency of enhanced PSO algorithms for optimum design of RC elements with the help of examples with a view to providing designers with a methodology for the optimum cost design of RC members and improve the overall design of the structure. The methodology consists of formulating the optimization problem on the basis of design variables. The present paper is organized as follows: In section 3, the background of basic PSO and extended versions of PSO have been discussed. Section 4 presents formulation of the problem. The application of all these techniques has been presented in section 5 and conclusions drawn are discussed in section 6.

3 PSO and extended versions: Theoretical background

3.1 Standard particle swarm optimization (SPSO)

Standard particle swarm optimization technique (SPSO) - a heuristic optimization technique developed by Kennedy and Eberhart, 1995 - is based on bird and fish flock movement behaviour [23-24]. The technique uses swarm intelligence of birds for searching food to search an optimal solution for a set of moving particle vectors, based on a fitness function. Each i^{th} particle vector represents a potential solution and has a position x_i^k and a velocity v_i^k at k^{th} iteration in the problem space. Each i^{th} vector keeps a record of its individual best position P_i^k , which is associated with its own best fitness achieved so far, at any time in the iteration process. This value has been denoted as ‘pbest’. Moreover, the optimum position among all the particles obtained so far in the swarm is stored as the global best position P_g^k . This location has been called ‘gbest’. The new velocity of particle is updated as follows:

$$v_{i,j}^{k+1} = wv_{i,j}^k + c_1r_1(P_{i,j}^k - x_{i,j}^k) + c_2r_2(P_{g,j}^k - x_{i,j}^k) \quad (1)$$

$$x_{i,j}^{k+1} = x_{i,j}^k + v_{i,j}^{k+1} \quad (2)$$

Thus, $v_{i,j}^k$ and $x_{i,j}^k$ are the velocity and position of particle ‘ i ’ at k^{th} iteration. w is the inertia weight at k^{th} iteration which represents the memory of a particle during search. The inertia weighting function, at each iteration, is given as:

$$w = w_{max} - (w_{max} - w_{min}) \times itr/itr_{max} \quad (3)$$

w_{max} and w_{min} are the maximum and minimum values of inertia weight respectively. The lower values of inertia weights speed up the convergence and higher values of inertia weights increase exploration of the search space. itr_{max} is the maximum number of iterations and itr is the current iteration number. The first right hand term in (1) is the ‘inertia component’ which enables each particle to perform a global search by exploring a new search space and is responsible for keeping the movement of particles in the same direction in which they are originally heading, whereas the last two terms represent ‘cognitive component’ and ‘social component’ respectively in which c_1 and c_2 are positive numbers illustrating the weights of the acceleration terms that guide each particle toward the individual best and the swarm best positions respectively. r_1 and r_2 are uniformly distributed random numbers in the range 0 to 1, and N is the number of particles in the swarm. Each particle changes its position based on the updated velocity according to equation (2) which is known as flight formula. In this way, ‘velocity updating’ (1) and ‘flight formula’ (2) help the particles to locate an optimal solution in the search space. In order to keep the particles from moving too far beyond the search space, their velocities have been clamped by limiting the maximum velocity ‘ v_{max} ’ of each particle. Most of the time, value of maximum velocity is selected empirically, according to the characteristics of the problem. If the value of this parameter is too high, the particles move erratically thereby going beyond a good solution, and if it is too small, the particle’s movement is limited and the optimal solution may not be obtained.

3.2 Constriction factor particle swarm optimization (CFPSO)

An improvement over standard PSO (introduced by Clerc, 1999) has been considered in the present work to improve the rate of convergence. An additional convergent agent known as constriction factor ‘ χ ’ to speed up the convergence (shown below) has been introduced:

$$\chi = \frac{2}{2 - \phi - |\phi^2 - 4\phi|} \quad (4)$$

The characteristic of convergence for any system can be controlled by the convergence factor ϕ ($\phi = c_1 + c_2 > 4$). As ϕ increases, the constriction factor ‘ χ ’ decreases and diversification is reduced, yielding slower response. Unlike other evolutionary computation methods, this approach ensures stability and convergence of the search procedure based on the mathematical theory. Therefore, the constriction factor approach generates higher quality solutions, thereby preventing the particles to converge at local optima. Moreover, it is difficult to set an appropriate value for v_{max} due to its main effect on the convergence rate. Hence, to omit this obstacle, the constriction factor approach has been considered. The velocity

equation (1) takes the form of equation (5) in this case, and new position of the particles is determined as in equation (6) by same flight formula as given in equation (2).

$$v_{i,j}^{k+1} = \chi \{ v_{i,j}^k + c_1 r_1 (P_{i,j}^k - x_{i,j}^k) + c_2 r_2 (P_{g,j}^k - x_{i,j}^k) \} \quad (5)$$

$$x_{i,j}^{k+1} = x_{i,j}^k + v_{i,j}^{k+1} \quad (6)$$

3.3 Democratic particle swarm optimization (DPSO)

Particle swarm optimization (PSO) technique has proven itself a powerful search technique through its application in a wide variety of optimization problems in several fields. The interaction between particles to determine the best positions of particles is the base of PSO. All the particles communicate with each other in search of best position and adjust their velocities according to their positions and the global best position for all the particles. Though simplicity and fair search potential are positive traits of the algorithm, but less exploration capability and chances to get trapped in local optima encouraged many researchers to improve its performance through their continuous efforts. Kaveh and Zolghadr [19] introduced democratic PSO (DPSO) as an extended version of the standard PSO to improve its limitations. DPSO is an effort to provide a better tactic for searching the solution domain by taking the experiences of all kinds of particles (either good or bad) and this strategy can avoid premature convergence. The improvement is obtained by adding a new term to the velocity vector. The velocity vector of DPSO is expressed in equation (7).

$$v_{i,j}^{k+1} = \chi [w v_{i,j}^k + c_1 r_1 (P_{i,j}^k - x_{i,j}^k) + c_2 r_2 (P_{g,j}^k - x_{i,j}^k) + c_3 r_3 d_{i,j}^k] \quad (7)$$

c_3 is a parameter which controls the weight of the democratic vector. $d_{i,j}^k$ stands for j^{th} variable of the vector D for the i^{th} particle. The vector D denotes the democratic influence of the other particles of the swarm on the movement of the i^{th} particle and is considered as:

$$D_i = \sum_{k=1}^n Q_{ik} (X_k - X_i) \quad (8)$$

Q_{ik} is the weight of the k^{th} particle in the democratic movement of the i^{th} particle and is calculated as:

$$Q_{ik} = \frac{E_{ik} \frac{f_{best}^{(k)}}{f^{(k)}}}{\sum_{j=1}^n E_{ij} \frac{f_{best}^{(j)}}{f^{(j)}}} \quad (9)$$

in which f is cost function value. In addition, f_{best} is the value of cost function for the best particle in current iteration, X is the particle's position vector, and E is the eligibility parameter. For minimization problems, E is defined as:

$$E_{ik} = \begin{cases} 1 & \frac{f^{(k)} - f^{(i)}}{f_{worst} - f_{best}} > rand \cup f^{(k)} < f^{(i)} \\ 0 & else \end{cases} \quad (10)$$

f_{worst} is the value of cost function for worst particle, and f_{best} is the value of cost function for best particle in the current iteration. After calculating velocity by Eq. (7), the new positions of the particles in DPSO algorithm are defined similar to the standard PSO.

$$x_{i,j}^{k+1} = x_{i,j}^k + v_{i,j}^{k+1} \quad (11)$$

in which the velocity vector can be added to the position vector. It is clear that the information provided by all the members of the swarm is utilized by DPSO with the purpose of determining the new position of each particle.

3.4 Probabilistic particle swarm optimization (PPSO)

The enhanced version of PSO has been introduced in which probabilistic functions are added to operate global and local search more efficiently. The velocities of particles are governed by equation (12) and the positions updated as stated in equation (2).

$$v_{i,j}^{k+1} = \alpha w v_{i,j}^k + \beta c_1 r_1 (P_{i,j}^k - x_{i,j}^k) + \gamma c_2 r_2 (P_{g,j}^k - x_{i,j}^k) \quad (12)$$

Where α , β , and γ are probabilistic functions and are defined as

Case1: $\alpha \neq 0, \beta = 1, \gamma = 1$.

if $p < p_1$ local search towards the combination of global and local best.

Case2: $\alpha = 0, \beta = 1, \gamma = 1$.

← local search towards the combination of global and local best.

Case 3: $\alpha = 0, \beta = 0, \gamma = 1$. *if $p > p_2$*

← local search towards the global best

p is a random number in the interval $[0, 1]$ and p_1 and p_2 are predefined levels of probabilities set by the user. β and γ are parameters for selection of the type of search. $\beta = 1$ provides local search towards local best and $\gamma = 1$ provides local search towards global best. Thus the values of β and γ were selected to be 0 or 1. On the other hand, α controls the amount of global search and it should be chosen from a range of real numbers rather of 0 or 1. Inertia weight is a factor used to better control the scope of search. Thus, in this study the following alternatives have been considered in order to find the best α

- i. The constant value of 1 was considered for α .
- ii. A linear varying value in the format of Eq. (13) was assigned to α :

$$\alpha = 1 - \frac{iter}{iter_{max}} \tag{13}$$

- iii. A random number in the interval $[0, 1]$ was considered to define α .

As stated in [20], the third strategy to define α improves the exploration and exploitation capabilities of the algorithm simultaneously.

Table 1- Enhanced versions of basic particle swarm optimization (PSO)

S. No.	Versions of PSO	Features	Velocity Equation
1.	SPSO (Standard Particle Swarm Optimization)	Search optimal solution but sometimes struck in local optima	$v_{i,j}^{k+1} = [w v_{i,j}^k + c_1 r_1 (P_{i,j}^k - x_{i,j}^k) + c_2 r_2 (P_{g,j}^k - x_{i,j}^k)]$
2.	CFPSO (Constriction Factor Particle Swarm Optimization)	Fast convergence than SPSO using constriction factor (χ)	$v_{i,j}^{k+1} = \chi [w v_{i,j}^k + c_1 r_1 (P_{i,j}^k - x_{i,j}^k) + c_2 r_2 (P_{g,j}^k - x_{i,j}^k)]$
3.	DPSO (Democratic Particle Swarm Optimization)	Each particle plays a significant role in search of global optima	$v_{i,j}^{k+1} = \chi [w v_{i,j}^k + c_1 r_1 (P_{i,j}^k - x_{i,j}^k) + c_2 r_2 (P_{g,j}^k - x_{i,j}^k) + c_3 r_3 d_{i,j}^k]$
4.	PPSO (Probabilistic Particle Swarm Optimization)	Increases exploration using probabilistic functions α, β, γ .	$v_{i,j}^{k+1} = [\alpha w v_{i,j}^k + \beta c_1 r_1 (P_{i,j}^k - x_{i,j}^k) + \gamma c_2 r_2 (P_{g,j}^k - x_{i,j}^k)]$

4 Formulation of optimization problem

Elastic behaviour of the structure was considered and limit state method was adopted for design of different elements. Formulation of design problem included the definition of objective function, design variables and all code constraints of

IS456: 2000 (Plain and Reinforced Concrete – Code of Practice) [25]. Some of the important design considerations for all frame elements are:

- The lower and upper bound of cross sectional dimensions were 300 mm and 1000 mm respectively.
- At least four bars were used in four cross sides of column.
- The minimum cover of concrete was taken as 40 mm.
- Minimum diameter of transverse steel was 10 mm.

4.1 Objective function

The cost of reinforced concrete structural element primarily includes the costs of concrete and steel. Therefore, the objective function took the following form

$$C = C_{st}V_{st} + C_C V_C \quad (14)$$

C is the total cost of structural element; C_{st} cost per unit volume of steel; V_{st} total volume of steel ; C_C cost per unit volume of concrete; V_C total volume of concrete. Dividing equation (14) by C_C as follows,

$$\frac{C}{C_C} = \frac{C_{st}}{C_C} V_{st} + V_C$$

Substituting $\frac{C}{C_C} = Z$ (Objective function), $\frac{C_{st}}{C_C} = \alpha$ (Cost ratio), and $V_C = V_G - V_{st}$ in the above equation, it becomes

$$Z = (\alpha - 1)V_{st} + V_G \quad (15)$$

Since C_C is a constant parameter for a given place, the objective function Z represents total cost of the RC structural member that shall be minimized. Volume of steel (V_{st}) depends upon area of steel and the length provided. Area of steel included both longitudinal as well as transverse steel. Similarly, gross volume of the element (V_G) depends upon its cross sectional area and length.

4.2 Design variables and constraints for beam optimization

In the present study, all input design parameters have been considered fixed. These included span of beam, grade of reinforcement and concrete, intensity of dead and live loads, effective cover of concrete and cost ratio. The independent design variables of the beam considered in this model are width (b_B) and effective depth (d_B) of the beam. The areas of longitudinal reinforcement and shear reinforcement were calculated as dependent design parameters. Designs constraints were considered in accordance with Indian codal provisions for RC beam design (IS 456: 2000) and other publications, [25-27].

4.2.1 Moment capacity consideration

For a given beam, the cross-sectional dimensions (depth and width) and area of steel to be provided at the ends and at bottom shall be such that its design moment of resistance is greater than actual moments to be borne by it at the respective sections.

$$0.87 f_y A_{stend} \left(d_B - \frac{f_y A_{stend}}{f_{ck} b_B} \right) > M_h$$

$$0.87 f_y A_{stmid} \left(d_B - \frac{f_y A_{stmid}}{f_{ck} b_B} \right) > M_s$$

A_{stend} = Area of steel at the beam end; A_{stmid} = Area of steel in the middle of the beam;

M_h = Hogging moment applied at the beam end; M_s = Maximum sagging moment;

f_{ck} = Characteristic compressive strength of concrete; f_y = Characteristic strength of steel

4.2.2 Deflection consideration

For spans up to 10 m, the vertical deflection (d_B) of a continuous beam shall be considered within limits if the ratio of its span (l) to its effective depth is less than 26. For spans above 10 m, factor 26 is multiplied by $\frac{10}{l}$. Mathematically, it can be expressed as:

$$\frac{l}{d_B} \leq 26, \text{ when span} \leq 10 \text{ m}$$

$$\frac{l}{d_B} \leq 26 \left(\frac{10}{l} \right), \text{ when span} > 10 \text{ m (} l \text{ and } d_B \text{ are in meter)}$$

4.2.3 Minimum width of beam

From practical consideration, the beam shall be wide enough to accommodate at least two bars of tensile steel of given diameter. Minimum width has been kept as input parameter.

$$b_B \geq b_{B_{min}}$$

$b_{B_{min}}$ = Minimum width of beam

4.2.4 Depth of neutral axis

To ensure that tensile steel does not reach its yield stress before concrete fails in compression so as to avoid brittle failure, the maximum depth of neutral axis has been restrained.

$$\frac{0.87 f_y A_{stend}}{0.36 f_{ck} b_B d_B} < \frac{x_m}{d_B} \text{ and } \frac{0.87 f_y A_{stmid}}{0.36 f_{ck} b_B d_B} < \frac{x_m}{d_B}$$

x_m = Limiting depth of neutral axis

$\frac{x_m}{d_B}$ value varies with the grade of steel and is given as:

$$\frac{x_m}{d_B} = 0.53, \text{ when } f_y = 250 \text{ N/mm}^2$$

$$\frac{x_m}{d_B} = 0.48, \text{ when } f_y = 415 \text{ N/mm}^2$$

$$\frac{x_m}{d_B} = 0.46, \text{ when } f_y = 500 \text{ N/mm}^2$$

4.2.5 Minimum and maximum reinforcement steel

The minimum and maximum area of tensile steel to be provided shall be taken as

$$A_{stend(min)} \geq \frac{0.85 b_B d_B}{f_y} ; A_{stend(max)} \leq 0.04 b_B D_B$$

$$A_{stmid(min)} \geq \frac{0.85 b_B d_B}{f_y}, \quad A_{stmid(max)} \leq 0.04 b_B D_B$$

$A_{stmid(min)}$ = Minimum area of steel at the beam mid; $A_{stmid(max)}$ = Maximum area of steel at the beam mid

4.3 Design variables and constraints for column optimization

Column optimization involves the determination of depth and width of the columns, with ‘percentage area of longitudinal reinforcement’ and ‘ratio of depth of neutral axis to depth of column’ as design variables. The following constraints have been considered:

4.3.1 Axial load capacity of column

The axial load carrying capacity of the column shall be greater than the load to be borne by it.

$$0.36 f_{ck} b_c k D_c + \sum_{i=1}^n (f_{si} - f_{ci}) \frac{p_i b_c D_c}{100} \geq P$$

b_c and D_c - Width and depth of column; $k D_c$ - Depth of NA from extreme compression fibre; f_{si} and f_{ci} - Stresses in the reinforcement and concrete at the i^{th} row of reinforcement; n - Number of rows of reinforcement; P - Actual value of axial load as applied on the column. p_i = Percentage area of steel in the i^{th} row of reinforcement.

4.3.2 Moment capacity of column

The moment carrying capacity of the column shall be greater than the moment to be borne by it.

$$0.36 f_{ck} b_c k D_c^2 (0.5 - 0.416k) + \sum_{i=1}^n (f_{si} - f_{ci}) \left(\frac{p_i}{100 f_{ck}} \right) \left(\frac{y_i}{D_c} \right) \geq M$$

y_i = Distance of the i^{th} row of reinforcement steel, measured from the centroid of the section. It is positive towards the highly compressed edge and negative towards the least compressed edge.

M = actual value of bending moment as applied on the column.

4.3.3 Longitudinal reinforcement in column

The cross-sectional area of longitudinal reinforcement shall vary between 0.8 to 4 per cent of the gross cross-sectional area of the column (although the Indian code permits a higher limit of 6 per cent, but due to practical difficulties in placing and compacting concrete at places where bars are to be lapped, a lower percentage has been adopted).

$$p \geq 0.8 \quad \text{and} \quad p \leq 4.0$$

p = Percentage area of longitudinal reinforcement

4.3.4 Minimum number of longitudinal rebars

The number of longitudinal bars provided in a column shall not be less than 4.

$$\frac{\text{total area of longitudinal reinforcement}}{\text{area of one bar}} \geq 4$$

4.3.5 Maximum peripheral distance between longitudinal rebars

The spacing of longitudinal bars measured along the periphery of column shall not be more than 300 mm.

$$d_p \leq 300$$

d_p = Maximum peripheral distance among longitudinal bars of the column

5 Evaluation of performance

5.1 Performance evaluation of some benchmark functions

To evaluate the performance of Standard PSO (SPSO) and other versions of PSO, some benchmark functions were tested before their application to real life problem. A set of solution was obtained by applying SPSO, CFPSO, PPSO and DPSO algorithms separately. The constant parameters to get best and consistent results from the algorithms are presented in Table 2.

Table 2- Values of algorithm’s constant parameters

Constant parameter	Algorithm			
	SPSO	CFPSO	PPSO	DPSO
Swarm size	20	20	20	20
C_1	1.0	2.05	1.0	2
C_2	1.0	2.05	1.0	2
C_3	-	-	-	4
w	0.9 to 0.4		0.9 to 0.4	0.9 to 0.4
χ	-	0.729	-	0.5
p_1	-	-	0.6	-
p_2	-	-	0.8	-

The population size and maximum number of iterations are fixed parameters taken as 20 and 1000 respectively for the algorithms. The stopping criterion, in each case, is the maximum number of iterations. It is necessary to define the upper and lower bounds of design variables of each element for the random selection of the population.

The design procedures for each structural element were developed in a generalized form which accepts different parametric values related to geometry of the structure, loads acting on it and properties of material. All optimization runs are carried out on a standard PC with a Intel® Core™ i3 CPU M350 @2.27 GHz frequency and 3 GB RAM memory. The algorithm has been coded in Turbo C++ installed in Window 7. (32 bit operating system).

C_1 and C_2 are the cognitive and social coefficients, C_3 is the coefficient to control democratic vector in DPSO, w is the inertia weight, χ is the constriction factor to avoid divergence and p_1 & p_2 are the predefined levels of probabilities in PPSO. Twenty runs of each minimization optimization cycle were performed and their results are presented in Table 3.

Table 3- Minimization results of some benchmark functions

Mathematical function	Dim	Range of functions	Standard PSO	Democratic PSO	Probabilistic PSO
$F_i(x) = \sum_{i=1}^n x_i^2$	20	[-5,12.5,12]	8.387e-14	6.46e-24	6.46e-24
$F_i(x) = \sum_{i=1}^2 (x_i^2 - \cos(18x_i))$	2	[-1,1]	-1.999	-2.0	-2.0
$F_i(x) = 4x_1^2 - 2.1x_1^4 + \frac{1}{3}x_1^6 + x_1x_2 - 4x_2^2 + 4x_2^4$	2	[-5,5]	-1.036	-1.036	-1.036

The enhanced versions of basic PSO has proven to be very efficient for balancing between the global and local exploration abilities. For this reason, these techniques are used in research problems.

5.2 Performance evaluation of RC structural elements

5.2.1 Optimal beam design

In order to evaluate the performance of the above techniques, a beam (5m) span which is a part of any frame has been selected. The given set of loads for the beam, namely gravity load 'w' (30 kN/m) and end moments 'M₁' (50 kN-m) and 'M₂' (100 kN-m) are shown in Fig.1. The configuration and steel reinforcement are the design variables to be optimized to satisfy the objective criteria. Grades of concrete and steel ($f_{ck} = 30 \text{ N/mm}^2$ and $f_y = 415 \text{ N/mm}^2$ respectively) as well as cost ratio (100) have been considered as input variables. Effective cover to the reinforcement has been considered as 40mm. The maximum depth to width ratio has been kept between 1.5 and 3, to avoid thin sections.

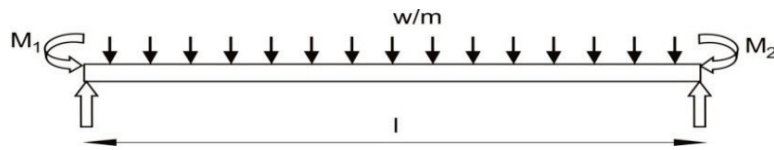


Fig. 1- Loading conditions of beam

For the above mentioned parameters, optimum algorithms suggested the optimum depth and optimum width of the beam as 500 mm and 300 mm respectively and the optimum percentage of steel as 1.53% of cross sectional area. The design improvements by PSO's extended versions are shown in Figures 2-4.

The design example of a simply supported beam with one row of reinforcing steel (Camp & Pezeshk, 2003) [8] was also tested and optimized by PSO's versions. Although, the results of present optimum design when compared with those obtained by RC-GA program - used in the previous study - were found to be in good agreement with each other, the required computational time was much less than RC-GA program. The present optimum design procedure required about 'four seconds' of computing time for twenty thousand evaluations as compared with a twenty five seconds of computing time for hundred generations quoted in the previous study.

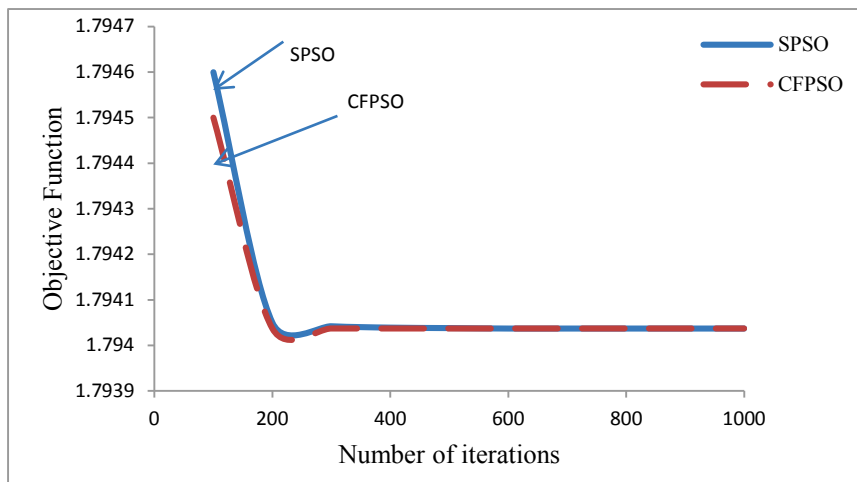


Fig.2- Convergence trend for optimum beam design using SPSO and CFPSO

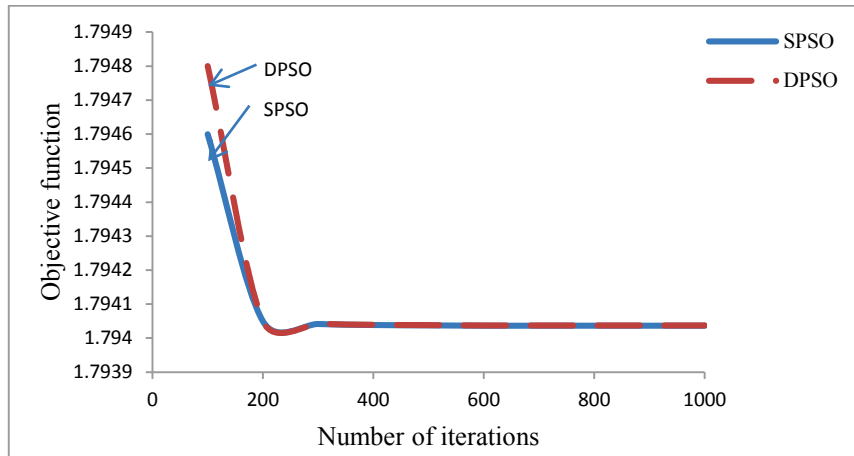


Fig.3- Convergence trend for optimum beam design using SPSO and DPSO

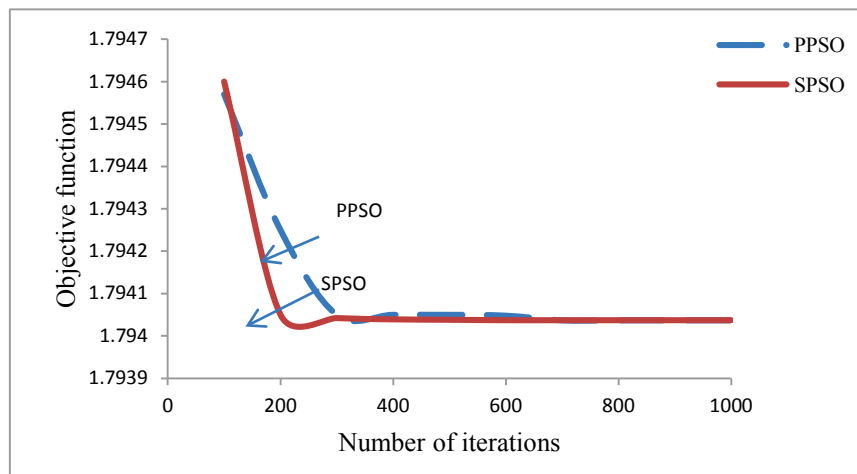


Fig.4- Convergence trend for optimum beam design using SPSO and PPSO

5.2.2 Optimal column design

The reinforced concrete columns are considered as uniaxial ones, and their designs are dependent on stresses in the reinforcing steel [27].

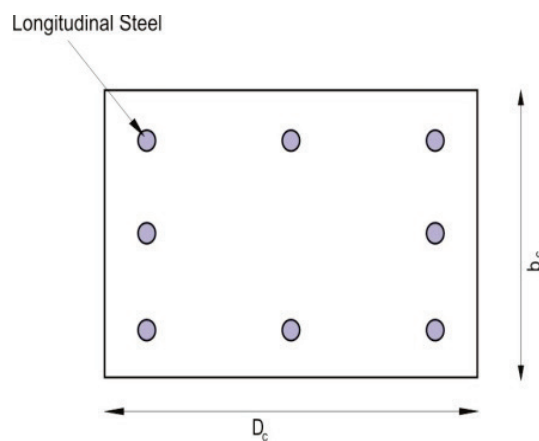


Fig. 5- Generalized sectional view of column

Feasible solutions were generated based on the restrictions and specifications outlined in section 4.3. A computer aided design program has been developed that considers all possible load and moment combinations for a given cross section, for calculating the strength of a column. A column that is part of a given frame has been designed using PSO's extended versions, for a given axial load of 960 kN and uniaxial moment of 250 kN-m. The minimum dimension of the column was considered not to be less than 300 mm. Similarly, the 'cover ratio' and minimum 'column depth to width ratio' were set as 0.1 and 1.0 respectively. The grades of concrete and steel were taken as $f_{ck} = 30 \text{ N/mm}^2$ and $f_y = 415 \text{ N/mm}^2$ respectively. The unsupported length of column was considered to be 3 m. Also, effective length ratio for the columns was kept as 1.2 and cost ratio as 100. For these given set of input values, optimum design parameters obtained were cross-sectional dimensions of the column, namely 730 mm depth and 300 mm width, and optimum percentage of longitudinal reinforcement as 0.8% of cross-sectional area. The CFPSO algorithm showed convergence at 344 iterations and the convergence curves are shown in Figures 6-8. The time taken for optimum design of column was 'four seconds'. The generalized cross sectional view of the column in which number of longitudinal bars may vary as per the design is illustrated in Fig.5.

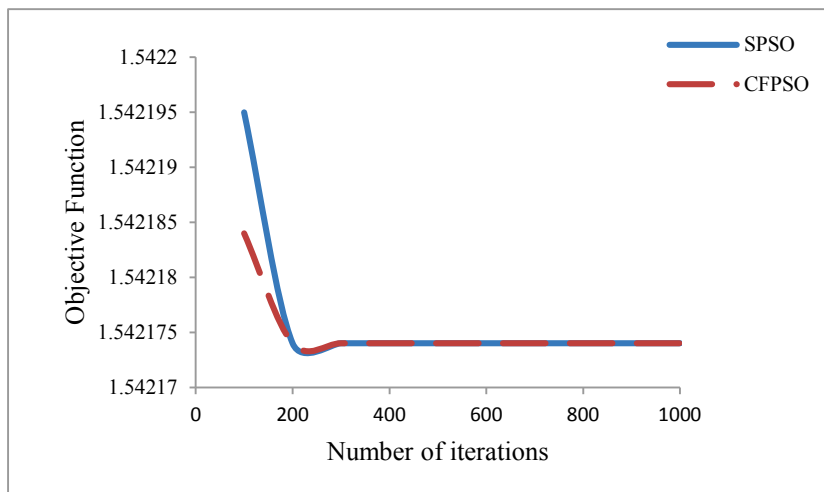


Fig.6- Convergence trend for optimum column design using SPSO and CFPSO

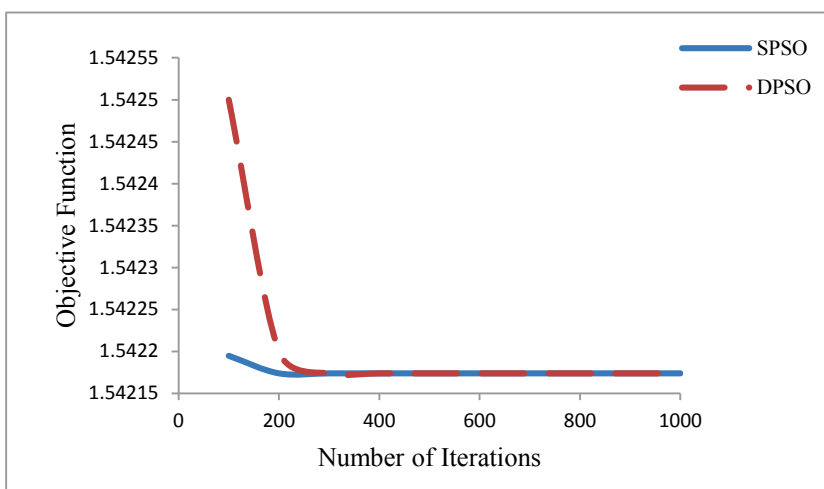


Fig.7- Convergence trend for optimum column design using SPSO and DPSO

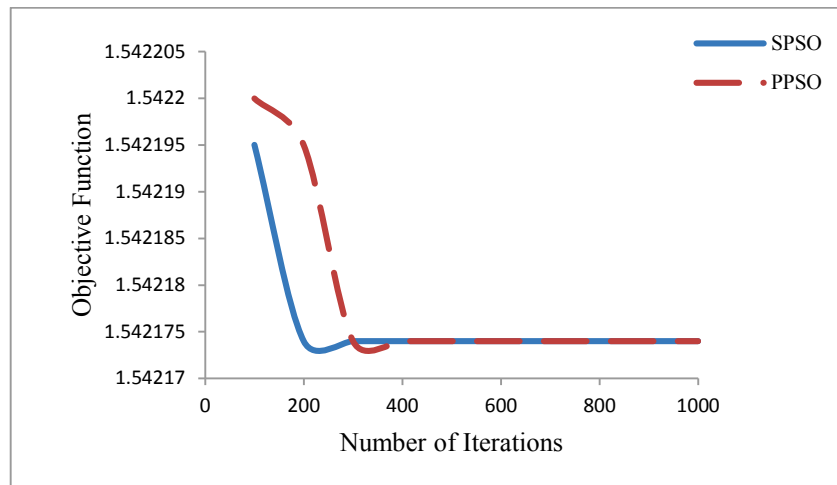


Fig.8- Convergence trend for optimum column design using SPSO and PPSO

6 Conclusions

This paper presents the use of additional new variants as enhanced versions of PSO to achieve better performance of existing standard PSO. Performance was evaluated on the basis of convergence rate, better solution and exploration capability in the problem of optimum design of RC structural members. The limitation of classical velocity updating scheme in SPSO is that its steady form does not allow dynamically alternate exploration and exploitation to the optimization process in the current iteration which has been overcome in PPSO by introducing the probabilistic functions in it. Also three different searches can be performed i.e. global search, local search towards global best and local search towards the combination of global and local best. The DPSO showed the concept of democratizing the search space while choosing the global optimum solution. The advantages of DPSO over SPSO are to achieve enhanced exploration capability, participation of all particles and to reduce premature convergence. The CFPSO showed the better convergence behaviour. Also, the idea of using DPSO and PPSO are more appropriate in problems with variable global optimum and their successful implementation in the design of RC structural members have improved the reliability and quality of solution in terms of time and convergence rate.

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