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## Research Paper

## 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) to Reinforced Concrete (RC) structural elements has been presented. The aim of extended versions of basic particle swarm optimization techniques to seek the global optima by maximizing the explorations area and minimizing the exploration time. Optimal sizing and reinforcement of RC structural members have been found by employing these techniques. The algorithms are coded in C++ and their effectiveness was tested in some benchmark mathematical functions. The different variables of each structural element have been considered as continuous functions and rounded off appropriately to imbibe the practical relevance of the present study.

## 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 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 of strength and serviceability. The structural design codes normally do not deal on the optimization front and this factor is mostly based on the experience of a particular designer - which 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 to a given requirement and big number of variables involved, any particular technique cannot cater to all

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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 increases the efficiency of the technique. Many evolutionary optimization methods have been developed during 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, have shown the study of optimization of RC beams using Genetic Algorithm (GA) [1] and Augmented Simulated Annealing (SA) method [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 is 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 [6]. The optimum design of biaxial columns was visualized in [7]. However, a large number of papers have been available on optimization of RC frame structures in which beam and column members are optimized separately. Optimum detailed design of RC frame as per IS code requirements has been performed in [8]. The flexural design of reinforced concrete frames as per ACI code provisions using a genetic algorithm has been suggested in [9, 10]. The authors employed Harmony search algorithm 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, then sorted them according to their strengths [13, 14]. The CO<sub>2</sub> optimization of reinforced concrete frames by simulated annealing has been studied in which authors related the optimum design of a reinforced concrete frame to the amount of CO<sub>2</sub> gas emitted in order 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 two different methods: Heuristic big bang-big crunch (HBB-BC), which is based on big bang-big crunch (BB-BC) and a harmony search (HS) scheme to deal with the variable constraint, and (HPSACO) algorithm, which is a combination of particle swarm with passive congregation (PSOPC), ant colony optimization (ACO), and harmony search scheme (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 as per Indian specifications. In present study, an endeavor has been made to use enhanced versions of PSO to optimize the RC frame elements as per Indian design standards. An advantage of PSO is that, GAs has many parameters, to be tuned in comparison to PSO. PSO has only few parameters to adjust that make 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], yet not been tested for RC structural elements. The one of 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. Secondly, guide designers to a methodology for the optimum cost design of RC members which improves 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, and is implemented to search an optimal solution, which is explored from 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 ' $\chi$ ' 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  $\phi$  ( $\phi = c_1 + c_2 > 4$ ). As  $\phi$  increases, the constriction factor ' $\chi$ ' 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, whereby it prevents the particles to converge on 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 position of particles is the base of PSO. All the particles communicate with each other in search of best position and adjust its velocity according to particle's own position and the global best position of all the particles. Though the 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 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 particles or bad particles and this strategy can avoid the premature convergence. The improvement is obtained by adding a new term to the velocity vector. The velocity vector of DPSO is expressed as below:

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

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

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

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 particles 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 produced by all of members of the swarm is utilized by DPSO with the purpose of determine 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 velocity of particles is governed as following equation (12) and position is updated as (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  $\alpha$ ,  $\beta$ , and  $\gamma$  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.  $\beta$  and  $\gamma$  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  $\beta$  and  $\gamma$  were selected to be 0 or 1. On the other hand,  $\alpha$  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 another way is considered for  $\alpha$  to find the best one as given below.

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

$$\alpha = 1 - \frac{iter}{iter\ max} \quad (13)$$

- iii. A random number in the interval [0, 1] is considered to define  $\alpha$ .

As per [20], the third strategy to define  $\alpha$  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 ( $\chi$ )	$v_{i,j}^{k+1} = \chi [v_{i,j}^k + c_1 r_1 (P_{i,j}^k - x_{i,j}^k) + c_2 r_2 (P_{g,j}^k - x_{i,j}^k)]$
3.	DPSO (Democratic Particle Swarm Optimization)	Each particle plays a significant role in search of global optima	$v_{i,j}^{k+1} = \chi [w v_{i,j}^k + c_1 r_1 (P_{i,j}^k - x_{i,j}^k) + c_2 r_2 (P_{g,j}^k - x_{i,j}^k)]$
4.	PPSO (Probabilistic Particle Swarm Optimization)	Increases exploration using probabilistic functions $\alpha$ , $\beta$ , $\gamma$ .	$v_{i,j}^{k+1} = [\alpha w v_{i,j}^k + \beta c_1 r_1 (P_{i,j}^k - x_{i,j}^k) + \gamma c_2 r_2 (P_{g,j}^k - x_{i,j}^k)]$

## 4 Formulation of optimization problem

Elastic behavior of the structure has been considered and limit state method has been adopted for design of different elements. Formulation of design problem includes 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 are 300mm and 1000mm respectively.
- At least four bars are used in four cross sides of column.
- The minimum cover of concrete is taken as 40mm.
- Minimum diameter of transverse steel is 10mm.

### 4.1. Objective function

The cost of reinforced concrete structural element primarily includes cost of concrete and steel. Therefore objective function takes 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 of steel per unit volume of steel;  $V_{st}$  total volume of steel ;  $C_C$  cost of concrete 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 its provided length. Area of steel includes 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 include 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 present model are width ( $b_B$ ) and effective depth ( $d_B$ ) of the beam. The areas of longitudinal reinforcement and shear reinforcement are calculated as dependent design parameters. Designs constraints considered in the present study not only considers Indian codal provisions for RC beam design (IS 456: 2000), but also few practical aspects [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 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:

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

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

#### 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.

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

$x_m$  = 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

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

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

$A_{stmid(\min)}$  = 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 consists in 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. 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.

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

$b_c$  and  $D_c$  - Width and depth of column;  $kD_c$  - Depth of NA from extreme compression fibre;  $f_{si}$  and  $f_{ci}$  - Stresses in the reinforcement and concrete at the  $i^{\text{th}}$  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  $i^{\text{th}}$  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.

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

$y_i$  = Distance of the  $i^{\text{th}}$  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 percent of the gross cross-sectional area of the column (although the Indian code denotes higher limit to be 6 percent, but due to practical difficulties in placing and compacting of concrete at places where bars are to be lapped, a lower percentage has been recommended).

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

$p$  = 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 are tested before its application to real life problem. A set of solution is obtained by applying SPSO, CFPSO, PPSO and DPSO algorithms separately. The constant parameters of the algorithms those will be found fine tuned with them are as follows:

**Table 1- Values of algorithm’s constant parameters**

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
$X$	-	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 applied algorithms. The stopping criterion is maximum number of iterations in each case. 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 are 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,  $\chi$  is the constriction factor to avoid divergence and  $p_1$  &  $p_2$  are the predefined levels of probabilities in PPSO. The 20 runs of each minimization optimization cycle are performed and their results are tabulated as follows:

**Table 2- 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 'M<sub>1</sub>' (50 kN-m) and 'M<sub>2</sub>' (100 kN-m) are shown in Fig.1. The configuration and steel reinforcement are the design variables those are considered to be optimized so as to reach 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 to 3, to avoid thin sections.

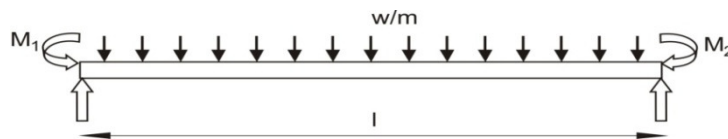
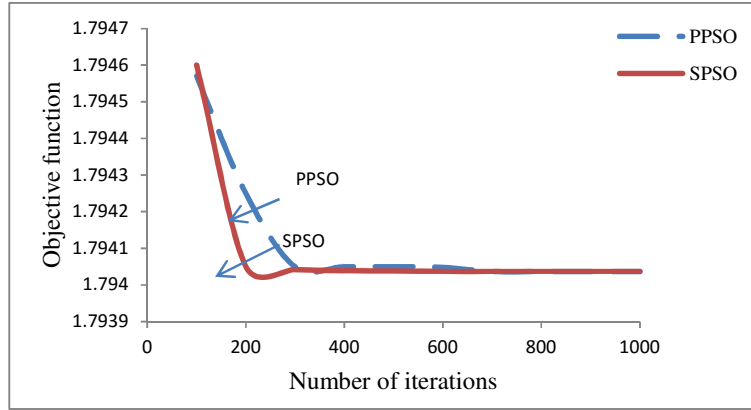


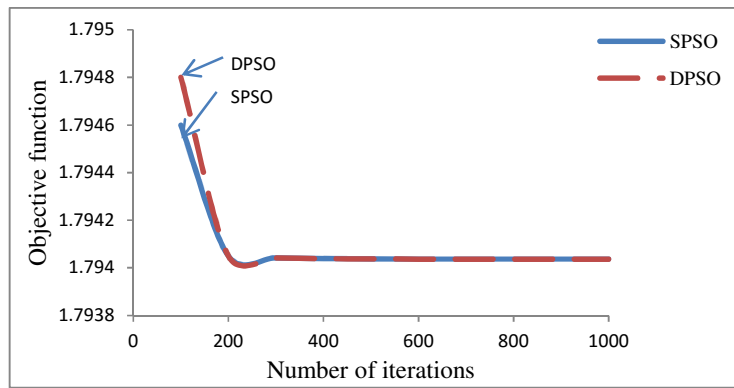
Fig. 1- Loading conditions of beam

For the above mentioned parameters, optimum algorithms suggests the optimum depth and optimum width of the beam as 500 mm and 300 mm respectively and the optimum percentage of steel has been obtained as 1.53% of cross sectional area. The design improvements by PSO's extended versions are shown in Fig.2, Fig.3 & Fig.4.

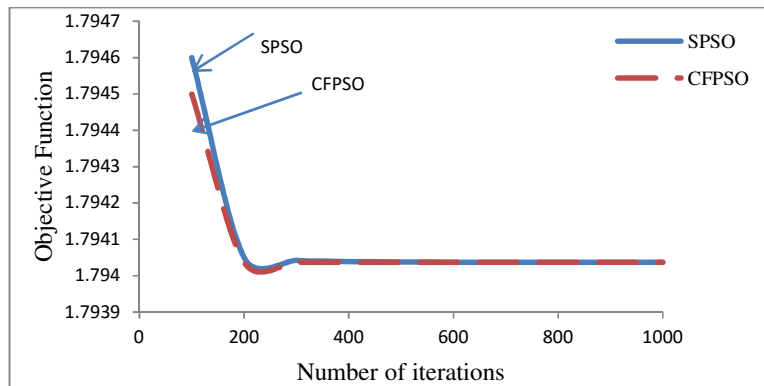
The beam design example of simply supported beam with one row of reinforcing steel (Camp & Pezeshk, 2003) [8] was also tested and optimized by PSO's versions. Although, the results of present optimum design when compared with those obtained by RC-GA program - used in the previous study - were found in 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 to long time quoted in the previous study.



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



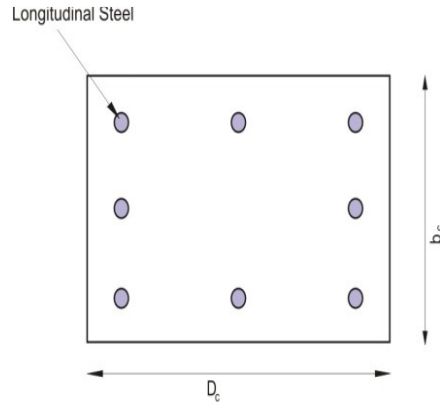
**Fig.3- Convergence trend for optimum beam design using SPSO and DPSO**



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

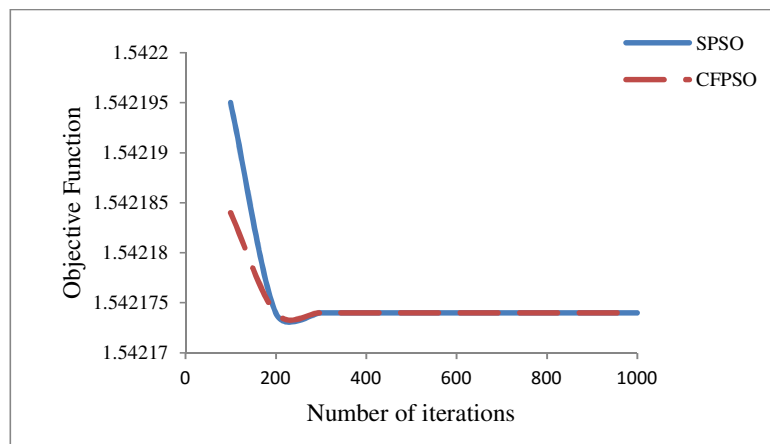
**5.2.2. Optimal column design**

The reinforced concrete columns are considered as uniaxial ones, and their design is dependent on stresses in the reinforcing steel [27]. The generalized sectional view of the column is shown in Fig.5.

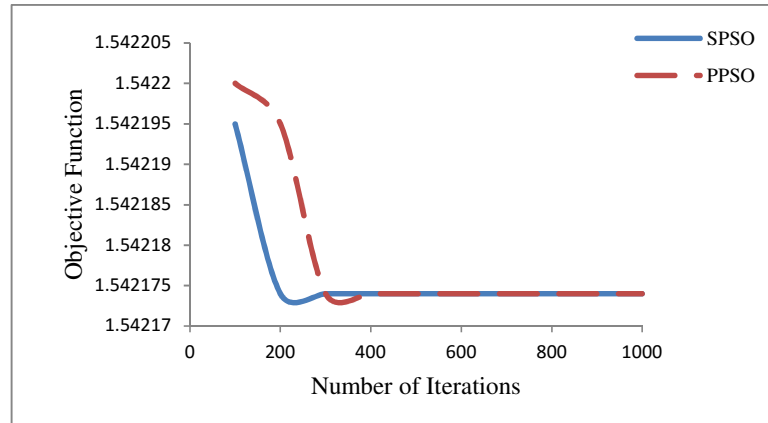


**Fig. 5- Generalized sectional view of column**

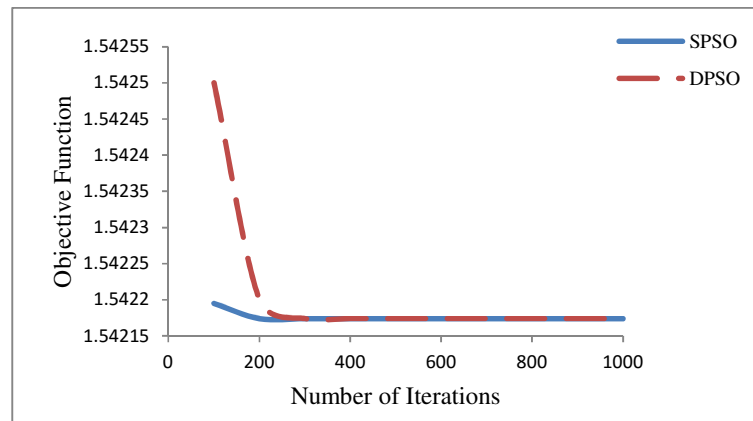
Feasible solutions were generated based on the restrictions and specifications outlined in section 4.3. A computer aided design program has been developed that considers all possible load and moment combinations for a given cross section, for calculating the strength of a column. A column that is part 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 is considered not to be less than 300 mm. Similarly, the 'cover ratio' and minimum 'column depth to width ratio' are set as 0.1 and 1.0 respectively. The grades of concrete and steel are taken as  $f_{ck} = 30 \text{ N/mm}^2$  and  $f_y = 415 \text{ N/mm}^2$  respectively. The unsupported length of column is considered to be 3 m. Also, effective length ratio for the columns is kept 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 convergence curves are shown in Fig. 6, Fig. 7, & Fig. 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.



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



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



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

## 6. Conclusions

This paper presents the use of additional new variants as enhanced versions of PSO to achieve better performance of existing standard PSO. The performance is 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 democratize 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. Although, the idea of using DPSO and PPSO are more appropriate in the problems those have a variable global optimum but its 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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