DEVELOPMENT OF A NOVEL OPTIMIZATION ALGORITHM: FISH SHOAL OPTIMIZATION

The non-linear optimization problem, as formulated, needs to identify the most suitable type of riprap stone for the optimal design of an earthen canal whose side slopes are riveted with loose riprap and bottom is unlined. The PSO technique, developed by Eberhart and Kennedy (1995) and Kennedy and Eberhart (1995), has already been applied by several researchers (Angeline 1998; Bonabeau 1999; Coelho and Sierakowski 2008; Eberhart et al. 1996; Gupta and Singh 2012; Kennedy et al. 2001; Parsopoulos and Vrahatis 2002) for solving global optimization problems. It is said to be efficient to handle tough cost functions (McCaffrey 2011) with many local minima, and is relatively easy to apply with a few parameters to adjust (Haupt and Haupt 2004). It was found to handle only one type of riprap stones, thus it worked with a pre-assigned type of riprap stone (Gupta et al. 2013) and could not compare the performance of different types of stones in its single computation program. Thus, the application of Particle Swarm Optimization needed three separate programs for three types of the riprap stones (with different sets of penalty functions for each type of riprap stone) to evaluate their performance for cost optimality. Therefore, it seems better to evaluate them on a single benchmark by involving one program with the same set of penalty functions. This would be similar to giving the same question paper with the same negative marking scheme to all the students for the award of some scholarships. Thus, it leaves a scope of further investigation into the problem of the minimum cost earthen channel design by applying a different/new optimization algorithm that can handle all types of riprap stones in its computational run. In order to resolve this problem, a novel feature has been introduced to add a new capability to the PSO technique. The novel PSO variant has been referred to as Fish Shoal Optimization algorithm because of its resemblance with the Fish Shoal found in oceans/seas.

6. 1 Fish Shoal Optimization

An optimization algorithm that can identify not only the most suitable type of riprap stone but also determine the optimal features of the minimum cost earthen canal whose side slopes are riveted with loose riprap and bottom is unlined, is developed. The features, operational philosophy and operating algorithms are given in following subsections.

6.1.1 The solution array

FSO involves a randomly generated population of solution members. Each solution member is an array having dimension equal to one more than the original dimension of the problem. Each element (a random number from 0-1 range) of an array represents a physical variable except the additional element that reflects the subgroup of the solution (type of riveted stone for the present study) with which it associates. Every solution member finds equal opportunity to update the values of its constituent elements according to the relative strengths of global and local best members, thus the population mimics a well-organized aggregated behaviour of a fish shoal in nature.

6.1.2 Delineated subgroups

The additional dimension added to the original dimension (5-D for the present study) extends the Euclidean search space (6-D) of the problem. This dimension segregates the population into numbers of subgroups/communities/classes, hence a heterogeneous population mix is created that accommodates various types of solution candidates in population. Initial application of uniform distribution function assigns random number at every constituent place of a solution array. The range of random number, i.e., [0, 1] for additional dimensional place is divided into numbers of equal sized class-intervals to delineate different subgroups. Each class-interval characterizes a specific subgroup. This way, the population of a fish school transforms into a shoal that comprises mixed species of fish/solution candidates.

6.1.2.1 Discriminated subgroups

A discriminative approach can be adopted to generate a specific community dominated population by involving a Gaussian distribution function or any other, if a particular class/subgroup needs to be given a priority. An extended range of random numbers for this additional place (for example, [0-2] instead of [0-1]) can be applied to discriminately classify the subgroups' population size. It is, however, essential to maintain the population size large enough to create an adequate number of solution candidates in each subgroup. Different subgroups may have different properties, therefore, the range of physical variables need to be defined separately for each subgroup; for example, the range of decision variables, z_1 and z_2 (see columns 5 and 6 in Table 1) are described differently for three types of riprap stones. The ranges of other variables may remain valid for all subgroups, however, they can be varied as per the need of the problem or per the whims of the FSO user.

6.1.3 Fish shoal

The different types (subgroups) of the solution candidates constitute the initial population. This population is hereafter referred to as Fish Shoal in conformity with the term used in the biological sciences. The Fish Shoaling is a special case of fish aggregation that includes fishes of disparate sizes and/or mixed-species. The mixed species of fish aggregation moving together in an interactive and social way is called as fish shoaling (http://en.wikipedia.org/wiki/Shoaling_and_schooling). Fish schooling is a special case of shoaling where the same species of fishes are involved. For example, Tuna fish schools often accompany dolphins to protect themselves against predator sharks (http://en.wikipedia.org/wiki/Tuna), thus they constitute a fish shoal.

6.1.4 Sustaining shoal character

The heterogeneous character of a fish shoal is essential at each generation to ensure a healthy competition among the dissimilar members of the shoal. This permits the best fish to capture the role of a leader that steers the movement of a shoal. The best fish (type of the riprap stone for the present study) may emerge out from any subgroup that maneuvers the shoal movement during successive generation. Thus, FSO provides an ambience for solutions from different subgroups to compete-one of the features of Genetic Algorithms and allows the best member that emerges out as a leader from a specific subgroup after a stiff competition among the dissimilar members of various subgroups to drive the movement of the shoal- a typical feature of PSO.

6.1.5 Operating mechanism

After constitution of the initial shoal, costs (fitness) of solution members from different subgroups are determined. The number of cost functions equals the number of created subgroups in population as the price of items involved in cost calculation may differ from one subgroup to another. Prior to the cost calculation, each shoal member qualifies a test to decide as to which subgroup it needs to join. Random number at the additional dimension place is compared with the class-intervals assigned for different subgroups. A solution member joins the subgroup whose class-interval entraps the value of random number at its additional dimension place. For example, if the random number (say 0.2) at the additional dimension place lies within the class interval (say [0-0.33]) of a specific subgroup (say No.1), the shoal member joins that subgroup (No. 1), and cost of the member is determined using its associated fitness function. All members are clubbed together to constitute the shoal population. A competition among the shoal members allows the minimum cost member to become the global leader who may emerge out from any subgroup. The leader steers the movement of the shoal according to the weights assigned to previous experience of an individual shoal member and the leader.

6.1.6 Potential of the fish shoal optimizer

FSO compares the performances of solutions from not only a specific subgroup/sector but also from different subgroups. It allows shoal members from different subgroups to compete for global leader position. Thus, FSO becomes a relatively more powerful tool to handle the optimization problems in areas of science, engineering, business management, and social sciences where varieties of solution alternatives are available for a given problem. For example, in stock market, a combination of equity/shares of different companies (conceived as a subgroup) from energy sector can be compared simultaneously with alternative combinations from other sectors (say hospitality, metals, and real estate etc.). This way, FSO identifies not only the most beneficial sector but also offers the optimal solution(s) from one or more sectors, if they exist.

6.1.7 Fish shoal optimization algorithm

Application of Fish Shoal Optimization involves the following steps:

1. Adopt the dimension of Euclidean search space to be one more than the actual dimension of the problem. The additional dimension of the

search space is used to categorize the population into a number of subgroups.

2. Initialize a population of solution vectors applying a uniform probability distribution function for random positions and velocities in the γ-dimensional Euclidean space at iteration number *i* as:

$$X_i = \{x_{i1}, x_{i2}, \ldots, x_{i\gamma}\}^T \quad (6.1)$$

$$V_i = \{x_{i1}, x_{i2}, \ldots, x_{i\gamma}\}^T \quad (6.2)$$

Actual dimension of the problem is (γ-1), and γ^{th} dimension is introduced to categorize the population into a desired number of subgroups.

3. Create delineating boundaries to categorize the whole population into a number of subgroups to characterize the population as a fish shoal. The range of random number at γ^{th} dimensional space is divided into class-intervals, i.e., range [0, 1] is divided into a desired number of class-intervals, say [0, 0.2],]0.2, 0.4], …,]0.8, 1.0], for creating 5 subgroups.
4. Pick up every member to verify as to which subgroup it associates. The random number at γ^{th} dimensional space is compared with the class intervals defined for various subgroups.
5. Calculate fitness of each shoal member using cost function of the subgroup it associates. The minimization type fitness function needs to be applied.

6. Combine all subgroup members to constitute a fish shoal for comparison of fitness of all shoal members.
7. Compare the present fitness of each member with its own best fitness achieved so far during earlier iterations (referred to as SM_{best}). If the present fitness of a given member is better than SM_{best}, reset SM_{best} to the present position with replaced corresponding fitness value. *SM* denotes the shoal member.
8. The present SM_{best} values of all shoal members are compared with the fitness of previous generation shoal leader (referred to as G_{best}). If any SM_{best} is better than G_{best}, reset G_{best} to the corresponding index array and value of the dominating member.
9. Update the position and velocity of the shoal members applying expressions of relatively newer version of PSO (Eberhart and Shi 1998; Shi and Eberhart 1998a; Shi and Eberhart 1998b) as:

$$V_{i+1} = \chi\left[wV_i + c_1\, r_1 \otimes \left(p_i\, \Theta\, x_i\right) + c_2\, r_2 \otimes \left(g_i\, \Theta\, x_i\right)\right] \tag{6.3}$$

$$x_{i+1} = x_i \oplus V_{i+1} \tag{6.4}$$

where c_1 and c_2 are the cognitive (adjustment towards the personal best) and social (adjustment towards the global best) parameters, respectively, which are responsible for the aggregated behavior of the swarm; and $\oplus, \Theta, \otimes$ are the point wise arithmetic operators for vector variables. The constriction coefficient (χ), introduced by Clerc and Kennedy (2002), keeps the particles' velocities under control, and relates with c_1 and c_2 for eliminating the need for determining value of an extra parameter as:

$$\chi = \frac{2}{\psi - 2 + \sqrt{\psi^2 - 4\psi}} \qquad (6.5)$$

where $\psi = c_1 + c_2 > 4$

10. Loop to step number 4 until a termination criterion, defined in terms of maximum number of iterations or acceptable limit of fitness convergence, is met.