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Fish School Search Algorithm for Solving Optimal Reactive Power Dispatch Problem

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Abstract

This paper presents an algorithm for solving the multi-objective reactive power dispatch problem in a power system. Modal analysis of the system is used for static voltage stability assessment. Loss minimization and maximization of voltage stability margin are taken as the objectives. Generator terminal voltages, reactive power generation of the capacitor banks and tap changing transformer setting are taken as the optimization variables. This paper presents fish school search a novel method of swarm intelligence for solving above problem. Fish school search Algorithm, which was inspired by the natural schooling behaviours of fish, a powerful stochastic optimization technique has been utilised to solve the reactive power optimization problem.

Keywords: Modal analysis, optimal reactive power, Transmission loss, fish school search, Optimization.

I. Introduction

Optimal reactive power dispatch problem is one of the difficult optimization problems in power systems. The sources of the reactive power are the generators, synchronous condensers, capacitors, static compensators and tap changing transformers. The problem that has to be solved in a reactive power optimization is to determine the required reactive generation at various locations so as to optimize the objective function. Here the reactive

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power dispatch problem involves best utilization of the existing generator bus voltage magnitudes, transformer tap setting and the output of reactive power sources so as to minimize the loss and to enhance the voltage stability of the system. It involves a nonlinear optimization problem. Various mathematical techniques have been adopted to solve this optimal reactive power dispatch problem. These include the gradient method [1-2], Newton method [3] and linear programming [4-7].

The gradient and Newton methods suffer from the difficulty in handling inequality constraints. To apply linear programming, the input- output function is to be expressed as a set of linear functions which may lead to loss of accuracy. Recently global Optimization techniques such as genetic algorithms have been proposed to solve the reactive power flow problem [8, 9]. Fish School search (FSS) [10] is a novel method of swarm intelligence for searching the global optimum, which was inspired by the natural schooling behaviours of fish. The FSS has been proved effective in function optimization, parameter estimation, combinatorial optimization, and least squares support vector machine and geo-technical engineering problems.

The remarkable property of this algorithm is that it is capable of global search in a rather large space, insensitive to initial values and not easy to stick in the local optimal solution. In this paper, we propose this powerful algorithm for solving reactive power dispatch problem .The effectiveness of the proposed approach is demonstrated through IEEE-30 bus system. The test results show the proposed algorithm gives better results with less computational burden and is fairly consistent in reaching the near optimal solution. In recent years, the problem of voltage stability and voltage collapse has become a major concern in power system planning and operation. To enhance the voltage stability, voltage magnitudes alone will not be a reliable indicator of how far an operating point is from the collapse point [11]. The reactive power support and voltage problems are intrinsically related. Hence, this paper formulates the reactive power dispatch as a multi-objective optimization problem with loss

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minimization and maximization of static voltage stability margin (SVSM) as the objectives. Voltage stability evaluation using modal analysis [12] is used as the indicator of voltage stability.

II. Voltage Stability Evaluation

A. Modal analysis for voltage stability evaluation

Modal analysis is one of the methods for voltage stability enhancement in power systems. In this method, voltage stability analysis is done by computing eigen values and right and left eigen vectors of a jacobian matrix. It identifies the critical areas of voltage stability and provides information about the best actions to be taken for the improvement of system stability enhancements. The linearized steady state system power flow equations are given by.

$$\begin{bmatrix} \Delta P \\ \Delta Q \end{bmatrix} = \begin{bmatrix} J_{p\theta} & J_{pv} \\ J_{q\theta} & J_{QV} \end{bmatrix} \tag{1}$$

where

ΔP = Incremental change in bus real power.

ΔQ = Incremental change in bus reactive, Power injection

$\Delta\theta$ = incremental change in bus voltage angle.

ΔV = Incremental change in bus voltage, Magnitude

$J_{p\theta}$, J_{PV} , $J_{Q\theta}$, J_{QV} jacobian matrix are the sub-matrixes of the System voltage stability is affected by both P and Q. However at each operating point we keep P constant and evaluate voltage stability by considering incremental relationship between Q and V.

To reduce (1), let $\Delta P = 0$, then.

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$$\Delta Q=[J_{QV} - J_{Q\theta} J_{P\theta}^{-1} J_{PV}]\Delta V = J_R \Delta V \quad (2)$$

$$\Delta V = J^{-1} \Delta Q \quad (3)$$

Where

$$J_R= (J_{QV} - J_{Q\theta} J_{P\theta}^{-1} J_{PV}) \quad (4)$$

J_R is called the reduced Jacobian matrix of the system.

B. Modes of Voltage instability:

Voltage Stability characteristics of the system can be identified by computing the eigen values and eigen vectors

Let

$$J_R = \xi \wedge \eta \quad (5)$$

Where,

ξ = right eigenvector matrix of J_R

η = left eigenvector matrix of J_R

$\wedge$ = diagonal eigenvalue matrix of J_R and

$$J_R^{-1}=\xi\wedge-1\eta \quad (6)$$

From (3) and (6), we have

$$\Delta V=\xi\wedge^{-1}\eta\Delta Q \quad (7)$$

Or

$$\Delta V = \sum_i \frac{\xi_i \eta_i}{} \Delta Q \quad (8)$$

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λi

where ξi is the ith column right eigenvector and η the i^{th} row left eigenvector of JR.

λ_i is the ith eigen value of JR.

The i^{th} modal reactive power variation is,

$$\Delta Q_{mi}=K_i\xi_i \qquad (9)$$

where,

$$K_i = \sum_j \xi_{ij}^{2} - 1 \qquad (10)$$

Where

ξji is the jth element of ξi

The corresponding i^{th} modal voltage variation is

$$\Delta V_{mi}= [1/\ \lambda i]\ \Delta Q_{mi} \qquad (11)$$

It is seen that, when the reactive power variation is along the direction of ξi the corresponding voltage variation is also along the same direction and magnitude is amplified by a factor which is equal to the magnitude of the inverse of the i^{th} eigenvalue. In this sense, the magnitude of each eigenvalue λi determines the weakness of the corresponding modal voltage. The smaller the magnitude of λi, the weaker will be the corresponding modal voltage. If $|\lambda_i| = 0$ the i^{th} modal voltage will collapse because any change in that modal reactive power will cause infinite modal voltage variation.

In (8), let $\Delta Q = e_k$ where e_k has all its elements zero except the k^{th} one being 1. Then,

$$\Delta V = \sum_i \frac{\eta_{1k}\ \xi_1}{\lambda_1} \qquad (12)$$

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η_{1k} k th element of η_1

V –Q sensitivity at bus k

$$\frac{\partial V_K}{\partial Q_K} = \sum_i \frac{\eta_{1k}\ \xi_1}{\lambda_1} = \sum_i \frac{P_{ki}}{\lambda_1} \tag{13}$$

A system is voltage stable if the eigenvalues of the Jacobian are all positive. Thus the results for voltage stability enhancement using modal analysis for the reduced jacobian matrix is when eigen values λ i > 0, the system is under stable condition eigen values λ i < 0 , the system is unstable eigen values λi = 0 , the system is critical and collapse state occurs.

III. Problem Formulation

The optimal reactive power dispatch problem is formulated as an optimization problem in which a specific objective function is minimized while satisfying a number of equality and inequality constraints. The objectives of the reactive power dispatch problem considered here is to minimize the system real power loss and maximize the static voltage stability margins (SVSM). This objective is achieved by proper adjustment of reactive power variables like generator voltage magnitude (*gi*) *V* , reactive power generation of capacitor bank (Qci), and transformer tap setting (tk).Power flow equations are the equality constraints of the problems, while the inequality constraints include the limits on real and reactive power generation, bus voltage magnitudes, transformer tap positions and line flows. This objective function is subjected to the following constraints:

A. Minimization of Real Power Loss

It is aimed in this objective that minimizing of the real power loss (*Ploss*) in transmission lines of a power system. This is mathematically stated as follows.

$$P_{loss} = \sum^{n}_{\substack{k=1 \\ k=(i,j)}} g_{k(V_i^2+V_j^2-2V_i V_j \cos\theta_{ij})} \tag{14}$$

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Where *n* is the number of transmission lines, *gk* is the conductance of branch *k*, *Vi* and *Vj* are voltage magnitude at bus *i* and bus *j*, and *θij* is the voltage angle difference between bus *i* and bus *j*.

B. Minimization of Voltage Deviation

It is aimed in this objective that minimizing of the

Deviations in voltage magnitudes (*VD*) at load buses. This is mathematically stated as follows.

$$\text{Minimize VD} = \sum_{k=1}^{nl} |V_k - 1.0| \qquad (15)$$

Where *nl* is the number of load busses and *Vk* is the voltage magnitude at bus *k*.

C. System Constraints

In the minimization process of objective functions, some problem constraints which one is equality and others are inequality had to be met. Objective functions are subjected to these constraints shown below. Load flow equality constraints:

$$P_{Gi} - P_{Di} - V_{i\sum_{j=1}^{nb} V_j} \begin{bmatrix} G_{ij} & \cos\theta_{ij} \\ +B_{ij} & \sin\theta_{ij} \end{bmatrix} = 0, i = 1,2 \dots, nb \qquad (16)$$

$$Q_{Gi} - Q_{Di}\, V_{i\sum_{j=1}^{nb} V_j} \begin{bmatrix} G_{ij} & \cos\theta_{ij} \\ +B_{ij} & \sin\theta_{ij} \end{bmatrix} = 0, i = 1,2 \dots, nb \qquad (17)$$

where, *nb* is the number of buses, *PG* and *QG* are the real and reactive power of the generator, *PD* and *QD* are the real and reactive load of the generator, and *Gij* and *Bij* are the mutual conductance and susceptance between bus *i* and bus *j*. Generator bus voltage (*VGi*) inequality constraint:

$$V_{Gi}^{min} \le V_{Gi} \le V_{Gi}^{max}, i \in ng \qquad (18)$$

Load bus voltage (*VLi*) inequality constraint:

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$$V_{Li}^{min} \le V_{Li} \le V_{Li}^{max}, i \in nl \qquad (19)$$

Switchable reactive power compensations (*QCi*) inequality constraint:

$$Q_{Ci}^{min} \le Q_{Ci} \le Q_{Ci}^{max}, i \in nc \qquad (20)$$

Reactive power generation (*QGi*) inequality constraint:

$$Q_{Gi}^{min} \le Q_{Gi} \le Q_{Gi}^{max}, i \in ng \qquad (21)$$

Transformers tap setting (*Ti*) inequality constraint:

$$T_{i}^{min} \le T_{i} \le T_{i}^{max}, i \in nt \qquad (22)$$

Transmission line flow (SLi) inequality constraint:

$$S_{Li}^{min} \le S_{Li}^{max}, i \in nl \qquad (23)$$

Where, *nc*, *ng* and *nt* are numbers of the switchable reactive power sources, generators and transformers. During the simulation process, all constraints satisfied as explained below [15].

The load flow equality constraints are satisfied by Power flow algorithm. The generator bus voltage (*VGi*), the transformer tap setting (*Ti*) and the Switchable reactive power Compensations (*QCi*) are optimization variables and they are self-restricted between the minimum and maximum value by the GSA algorithm *The limits on active power generation at the slack bus(*PGs*), load bus voltages *(VLi)* and reactive power generation (*QGi*), transmission line flow *(SLi)* are state variables. They are restricted by adding a penalty function to the objective functions.

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Where

N_B number of buses in the system

N_g number of generating units in the system

t_k tap setting of transformer branch k

P_{sl} real power generation at slack bus

V_i voltage magnitude at bus i

P_i, Q_i real and reactive powers injected at bus i

P_{gi}, Q_{gi} real and reactive power generations at bus i

G_{ij}, B_{ij} mutual conductance and susceptance between bus i and j

G_{ii}, B_{ii} self-conductance and susceptance of bus i

θ_{ij} voltage angle difference between bus i and j

IV. Fish School Search (FSS)

Fish school search a novel approach for searching in high-dimensional spaces based on the behaviors of fish schools. As any other intelligent technique based on population, Fish School Search (FSS) greatly benefits from the collective emerging behavior that increases mutual survivability. Broadly speaking, FSS is composed of operators that can be grouped in the following categories: feeding, swimming and breeding. Together, these operators provide computing behavior such as: (i) high-dimensional search ability, (ii) automatic selection between exploration and exploitation, and (iii) self-adaptable guidance towards sought solutions.

This chapter seeks to explain the main ideas behind FSS to researchers and practitioners.

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In addition, we include examples and simulations aimed at clarifying the simplicity and potentials of FSS. Several oceanic fish species, as with other animals, present social behavior. This phenomenon's main purpose is to increase mutual survivability and may be viewed in two ways: (i) for mutual protection and (ii) for synergistic achievement of other collective tasks. By protection we mean reducing the chances of being caught by predators; and by synergy, we refer to an active means of achieving collective goals such as finding food. Apart from debating whether the emergent behavior of a fish school is due to learning or genetic reasons, it is important to note that some fish species live their entire lives in schools.

This reduces individual freedom in terms of swimming movements and increases competition in regions with scarce food. However, fish aggregation is a fact and the benefits largely outweigh the drawbacks. This chapter aims at presenting a novel computational intelligent search technique inspired by the above- mentioned behavior. Along with the development of this technique we have taken great care not to depart from the original inspiration source, but FSS contains a few abstractions and simplifications that have been introduced to afford efficiency and usability to the algorithm. The main characteristics derived from real fish schools and incorporated into the core of our approach are sound. They are grouped into two observable cat- egories of behaviors as follows:

- Feeding: inspired by the natural instinct of individuals (fish) to find food in order to grow strong and to be able to breed. Notice that food here is a metaphor for the evaluation of candidate solutions in the search process. We have considered that an individual fish can lose as well as obtain weight, depending on the regions it swims in.

- Swimming: the most elaborate observable behavior utilized in our approach. It aims at mimicking the coordinated and the only apparent collective movement produced by all the fish in the school. Swimming is primarily driven by feeding needs and, in the algorithm; it is a metaphor for the search process itself.

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A.FSS Computational Principles

The search process in FSS is carried out by a population of limited-memory individuals the fish. Each fish represents a possible solution to the problem. Similar to PSO or GA, search guidance in FSS is driven by the success of some individual members of the population. The main feature of the FSS paradigm is that all fish contain an innate memory of their successes – their weights. In comparison to PSO, this information is highly relevant because it can obviate the need to keep a log of the best positions visited by all individuals, their velocities and other competitive global variables. Another major feature of FSS is the idea of evolution through a combination of some collective swimming, i.e. "operators" that select among different modes of operation during the search process, on the basis of instantaneous results. As for dealing with the high dimensionality and lack of structure of the search space, the authors believe that FSS should at least incorporate principles such as the following:

i. Simple computation in all individuals;

ii.Various means of storing distributed memory of past computation;

iii.Local computation (preferably within small radiuses);

iv.Low communication between neighboring individuals;

v.Minimum centralized control (preferably none); and

vi.Some diversity among individuals.

A brief rationale for the above-mentioned principles is given, respectively: (i) this reduces the overall computation cost of the search; (ii) this allows for adaptive learning; (iii), (iv) and (v) these keep computation costs low as well as allowing some local knowledge to be shared, thereby speeding up convergence; and finally, (vi) this might also speed up the search due to the differentiation/specialization of individuals. These principles incorporated in FSS lead the authors to believe that FSS can deal with multimodal problems better than the PSO

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approaches. To understand the operators, a number of concepts need to be defined. The concept of food is related to the function to be optimized in the process. For example, in a minimization problem the amount of food in a region is inversely proportional to the function evaluation in this region. The “aquarium” is defined by the delimited region in the search space where the fish can be positioned. The operators are grouped in the same manner in which they were observed when drawn from the fish school. They are as follows:

- Feeding: food is a metaphor for indicating to the fish the regions of the aquarium that are likely to be good spots for the search process.
- Swimming: a collection of operators that are responsible for guiding the search effort globally towards subspaces of the aquarium that are collectively sensed by all individual fish as more promising with regard to the search process.

B. FSS Operators

C. The Feeding Operator

As in real situations, the fish of FSS are attracted to food scattered in the aquarium in various concentrations. In order to find greater amounts of food, the fish in the school can move independently .As a result, each fish can grow or diminish in weight, depending on its success or failure in obtaining food. We propose that fish’s weight variation be proportional to the normalized difference between the evaluation of fitness function of previous and current fish position with regard to food concentration of these spots. The assessment of ‘food’ concentration considers all problem dimensions, as shown in (24),

$$W_i(t+1)= W_i(t)+\frac{f[x_i(t+1)]-f[x_i(t)]}{max\{|f[x_i(t+1)]-f[x_i(t)]|\}} \tag{24}$$

where Wi (t) is the weight of the fish i, xi (t) is the position of the fish i and f [xi (t)] evaluates the fitness function (i.e. amount of food) in xi (t).

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A few additional measures were included to ensure rapid convergence toward rich areas of the aquarium, namely:

- Fish weight variation is evaluated once at every FSS cycle;
- An additional parameter, named weight scale (Wscale) was created to limit the weight of a fish. The fish weight can vary between"1" and Wscale.
- All the fish are born with weight equal to Wscale/2.

D. The Swimming Operators

A basic animal instinct is to react to environmental stimulation (or sometimes, the lack of it). In our approach swimming is considered to be an elaborate form of reaction regarding survivability. In FSS, the swimming patterns of the fish school are the result of a combination of three different causes (i.e. movements). For fish, swimming is directly related to all the important individual and collective behaviors such as feeding, breeding, escaping from predators, moving to more livable regions of the aquarium or, simply being gregarious. This panoply of motivations to swim away inspired us to group causes of swimming into three classes: (i) individual, (ii) collective-instinct and (iii) collective-volition. Below we provide further explanations on how computations are performed on each of them.

E. Individual Movement

Individual movement occurs for each fish in the aquarium at every cycle of the FSS algorithm. The swim direction is randomly chosen. Provided the candidate destination point lies within the aquarium boundaries, the fish assesses whether the food density there seems to be better than at its current location. If this is not the case or if the step-size is not possible (i.e. it lies outside the aquarium or is blocked by, say, reefs), the individual movement of the fish does not occur. Soon after each individual movement, feeding occurs, as detailed above.

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For this movement, we define a parameter to determine the fish displacement in the aquarium called individual step (stepind). Each fish moves stepind if the new position has more food than the previous position. Actually, to include more randomness in the search process we multiply the individual step by a random number generated by a uniform distribution in the interval [0,1]. In our simulation we decrease the individual step linearly in order to provide exploitation abilities in later iterations. Fig. 1 shows an illustrative example of this swimming operator. One can note that just the fish that found spots with more food had moved.

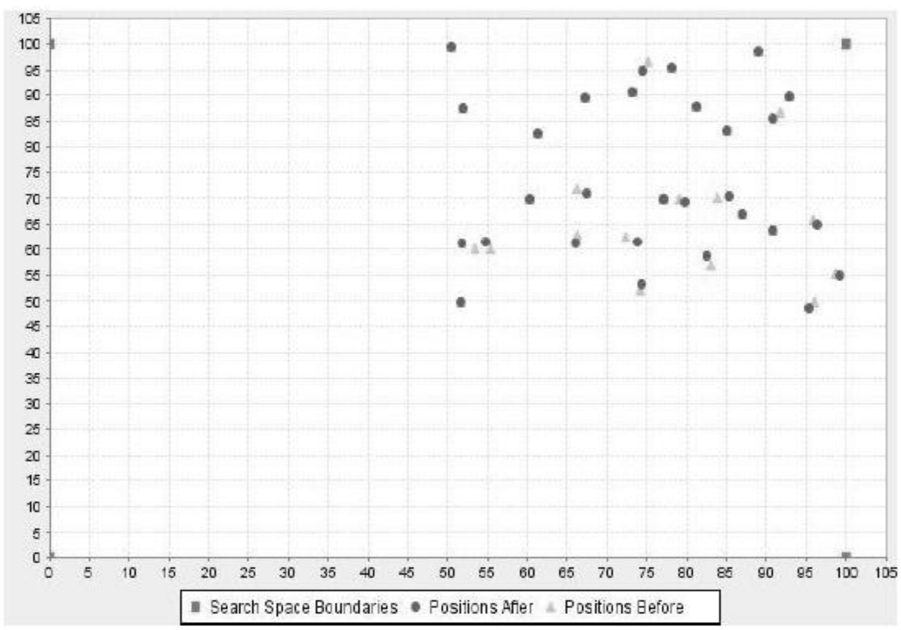

Fig. 1 Individual movement is illustrated here before and after its occurrence; circular dots are fish positions after and triangular dots are the same fish before individual movement.

F. Collective-Instinctive Movement

After all fish have moved individually, a weighted average of individual movements based

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on the instantaneous success of all fish of the school is computed. This means that fish that had successful individual movements influence the resulting direction of movement more than the unsuccessful ones. When the overall direction is computed, each fish is repositioned. This movement is based on the fitness evaluation enhancement achieved, as shown in (25).

$$X_i\,(t+1) = X_i(t) + \frac{\sum_{i=1}^{N} \Delta X_{indi\{f\,[x_i\,(t+1)]-f[x_i(t)]\}}}{\sum_{i=1}^{N}\{f\,[x_i\,(t+1)]-f[x_i(t)]\}} \qquad (25)$$

where ΔX_{indi} is the displacement of the fish i due to the individual movement in the FSS cycle. Fig. 2 shows the influence of the collective-instinctive movement in the example presented in Fig. 1. One can note that in this case all the fish had their positions adjusted.

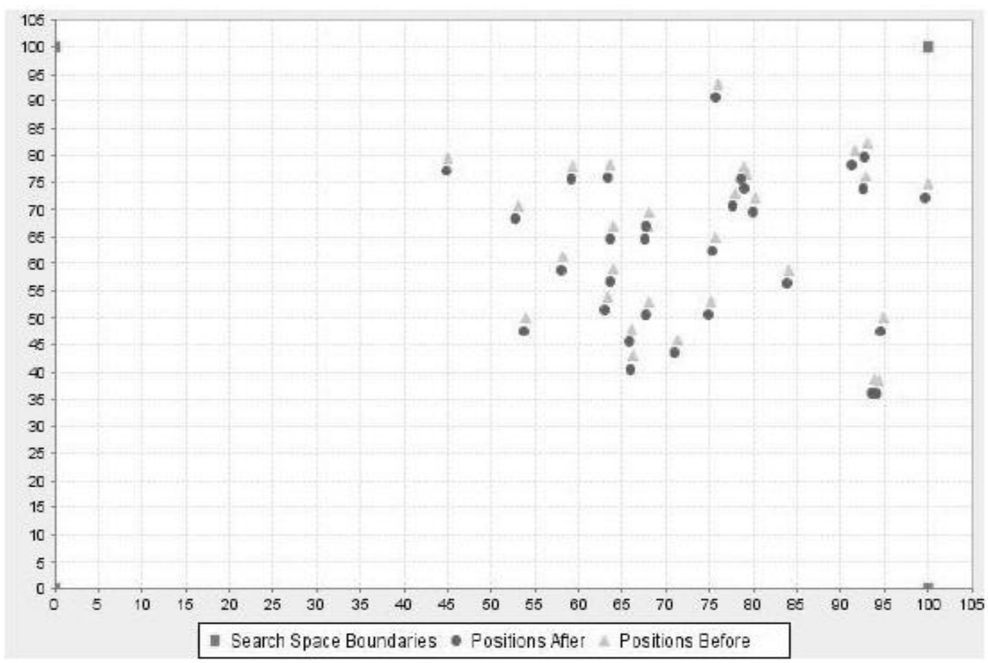

Fig. 2 Collective-instinctive movement is illustrated here before and after its occurrence; circular dots are fish positions after and triangular dots are the same fish before collective-instinctive movement

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G.Collective-Volitive Movement

After individual and collective-instinctive movements are performed, one additional positional adjustment is still necessary for all fish in the school: the collective-volitive movement. This movement is devised as an overall success/failure evaluation based on the incremental weight variation of the whole fish school. In other words, this last movement will be based on the overall performance of the fish school. The rationale is as follows: if the fish school is putting on weight (meaning the search has been successful), the radius of the school should contract; if not, it should dilate. This operator is deemed to help greatly in enhancing the exploration abilities in FSS.

This phenomenon might also occur in real swarms, but the reasons are as yet unknown. The fish-school dilation or contraction is applied as a small step drift to every fish position with regard to the school's barycenter. The fish-school's barycenter is obtained by considering all fish positions and their weights, as shown in 3. Collective-volitive movement will be inwards or outwards (in relation to the fish-school's barycenter), according to whether the previously recorded overall weight of the school has increased or decreased in relation to the new overall weight observed at the end of the current FSS cycle.

$$\mathrm{Bari}\ (t) = \frac{\sum_{i=1}^{N} X_i(t) W_i\,(t)}{\sum_{i=1}^{N} W_i\,(t)} \qquad (26)$$

For this movement, we also define a parameter called volitive step (stepvol). We evaluate the new position as in (27) if the overall weight of the school increases in the FSS cycle; if the overall weight decreases, we use (28).

$$X_i(t+1)=X_i\,(t) - step_{vol\,.}\, rand.[X_i(t) - Bari\ (t)] \qquad (27)$$

$$X_i(t+1)=X_i\,(t) + step_{vol\,.}\, rand.[X_i(t) - Bari\ (t)] \qquad (28)$$

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where rand is a random number uniformly generated in the interval [0,1]. We also decreased the linear stepvol along the iterations. Fig. 3 shows the influence of the collective-volitive movement in the example presented in Fig. 1 after individual and collective-instintive movements. In this case, asthe overall weight of the school had increased, the radius of the school diminished.

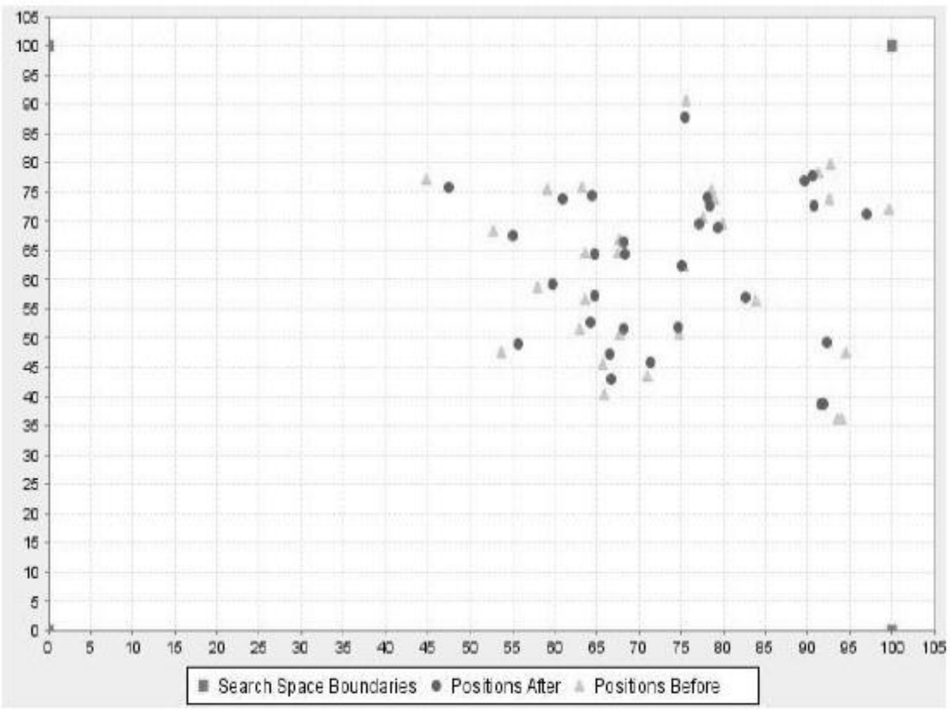

Fig. 3 Collective-volitive movement is illustrated here before and after its occurrence; circular dots are fish positions after and triangular dots are the same fish before collective-volitive movement

H.F SS Cycle and Stop Conditions

The FSS algorithm starts by randomly generating a fish school according to parameters that control fish sizes and their initial positions. Regarding dynamics, the central idea of FSS

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is that all bio-inspired operators perform independently of each other across the three conceived classes. The search process (i.e. FSS at work) is enclosed in a loop, where invocations of the previously presented operators will occur until at least one stop condition is met. As of now, stop conditions conceived for FSS are as follows: limitation of the number of cycles (the stopping condition of all experiments in this chapter), time limit, maximum school radius, minimum school weight and maximum fish number.

V. SIMULATION RESULTS

The validity of the proposed Algorithm technique is demonstrated on IEEE-30 bus system. The IEEE-30 bus system has 6 generator buses, 24 load buses and 41 transmission lines of which four branches are (6-9), (6-10) , (4-12) and (28-27) - are with the tap setting transformers. The real power settings are taken from [1]. The lower voltage magnitude limits at all buses are 0.95 p.u. and the upper limits are 1.1 for all the PV buses and 1.05 p.u. for all the PQ buses and the reference bus.

TABLE I: Voltage Stability under Contingency State

Sl. No	Contigency	ORPD Setting	Vscrpd Setting
1	28-27	0.1400	0.1422
2	4-12	0.1658	0.1662
3	1-3	0.1784	0.1754
4	2-4	0.2012	0.2032

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TABLE II: Limit Violation Checking of State Variables

State variables	limits		ORPD	VSCRPD
	Lower	upper		
Q1	-20	152	1.3422	-1.3269
Q2	-20	61	8.9900	9.8232
Q5	-15	49.92	25.920	26.001
Q8	-10	63.52	38.8200	40.802
Q11	-15	42	2.9300	5.002
Q13	-15	48	8.1025	6.033
V3	0.95	1.05	1.0372	1.0392
V4	0.95	1.05	1.0307	1.0328
V6	0.95	1.05	1.0282	1.0298
V7	0.95	1.05	1.0101	1.0152
V9	0.95	1.05	1.0462	1.0412
V10	0.95	1.05	1.0482	1.0498
V12	0.95	1.05	1.0400	1.0466
V14	0.95	1.05	1.0474	1.0443
V15	0.95	1.05	1.0457	1.0413
V16	0.95	1.05	1.0426	1.0405
V17	0.95	1.05	1.0382	1.0396
V18	0.95	1.05	1.0392	1.0400

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V19	0.95	1.05	1.0381	1.0394
V20	0.95	1.05	1.0112	1.0194
V21	0.95	1.05	1.0435	1.0243
V22	0.95	1.05	1.0448	1.0396
V23	0.95	1.05	1.0472	1.0372
V24	0.95	1.05	1.0484	1.0372
V25	0.95	1.05	1.0142	1.0192
V26	0.95	1.05	1.0494	1.0422
V27	0.95	1.05	1.0472	1.0452
V28	0.95	1.05	1.0243	1.0283
V29	0.95	1.05	1.0439	1.0419
V30	0.95	1.05	1.0418	1.0397

TABLE III: COMPARISON OF REAL POWER LOSS

Method	Minimum loss
Evolutionary programming[16]	5.0159
Genetic algorithm[17]	4.665
Real coded GA with Lindex as SVSM[18]	4.568
Real coded genetic algorithm[19]	4.5015
Proposed FSS method	4.3008

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CONCLUSION

In this paper a novel approach FSS algorithm used to solve optimal reactive power dispatch problem, considering various generator constraints, has been successfully applied. The proposed method formulates reactive power dispatch problem as a mixed integer non-linear optimization problem and determines control strategy with continuous and discrete control variables such as generator bus voltage, reactive power generation of capacitor banks and on load tap changing transformer tap position. To handle the mixed variables a flexible representation scheme was proposed. The performance of the proposed algorithm demonstrated through its voltage stability assessment by modal analysis is effective at various instants following system contingencies. Also this method has a good performance for voltage stability Enhancement of large, complex power system networks. The effectiveness of the proposed method is demonstrated on IEEE 30-bus system

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