COMBINED HEAT AND POWER ECONOMIC DISPATCH BY A FISH SCHOOL SEARCH ALGORITHM

Leonardo Trigueiro dos Santos, leo.trigueiro@hotmail.com
Marsil de Athayde Costa e Silva, marsil@ymail.com
Undergraduate in Mechatronics Engineering, Pontifical Catholic University of Parana
Imaculada Conceição, 1155, Zip code 80215-901, Curitiba, Parana, Brazil

Leandro dos Santos Coelho, leandro.coelho@pucpr.br
Industrial and Systems Engineering Graduate Program, PPGEPS, Pontifical Catholic University of Parana
Imaculada Conceição, 1155, Zip code 80215-901, Curitiba, Parana, Brazil

Abstract. *The conversion of primary fossil fuels, such as coal and gas, to electricity is a relatively inefficient process. Even the most modern combined cycle plants can only achieve efficiencies of between 50-60%. A great portion of the energy wasted in this conversion process is released to the environment as waste heat. The principle of combined heat and power, also known as cogeneration, is to recover and make beneficial use of this heat, significantly raising the overall efficiency of the conversion process. However, the optimal utilization of multiple combined heat and power systems is a complicated problem which needs powerful methods to solve. This paper presents a fish school search (FSS) algorithm to solve the combined heat and power economic dispatch problem. FSS is a novel approach recently proposed to perform search in complex optimization problems. Some simulations presented in the literature indicated that FSS can outperform many bio-inspired algorithms, mainly in multimodal functions. The search process in FSS is carried out by a population of limited-memory individuals – the fishes. Each fish represents a possible solution to the problem. Similarly to particle swarm optimization or genetic algorithm, search guidance in FSS is driven by the success of some individual members of the population. A four-unit system proposed recently which is a benchmark case in the power systems field has been validated as a case study in this paper.*

Keywords*: optimization, heat and power economic dispatch, metaheuristics, fish school search.*

1. INTRODUCTION

Several biological and natural processes have been strongly influencing the methodologies in science and technology in the last years. Nature inspired intelligence becomes increasingly popular through the development and utilization of intelligent paradigms in engineering design. In this context, the evolutionary mechanisms discovered by Darwin and described in *The Theory of Natural Evolution* (Darwin, 1858) inspired several research fields, such as evolutionary computation and swarm intelligence, wherein, to solve a desired problem, it is not necessary previous knowledge of the way for achieve the solution.

Evolutionary algorithms are stochastic search that uses the principles of evolution of nature to drive the search towards optimal solution. Compared to traditional optimization methods, evolutionary algorithms are robust, global, and may be applied generally without a prior knowledge about the problem to be optimized.

On the other hand, swarm intelligence is a recent research field, which has recently gained a wide popularity. Algorithms belonging to this field, draw inspiration from the collective intelligence emerging from the behavior of a group of social insects (like bees, termites and wasps). Many optimization approaches have been used in the last years such as Particle Swarm Optimization (PSO) (Kennedy and Eberhart, 1995; Eberhart and Kennedy, 1995), Ant Colony Optimizations (ACO) (Dorigo and Stützle, 2004), Artificial Bee Colony (ABC) (Karaboga and Akay, 2009), among others.

As the other mentioned swarm intelligence techniques based on swarms, metaheuristics based on fish swarm have been proposed in the recent literature, such as the fish swarm algorithm (Xiaolei et al., 2002), the fish school search (Bastos Filho et al., 2008), and the fish swarm algorithm based on chaos search (Ma and Wang, 2009).

In Fish School Search (FSS) proposed in Bastos Filho et al. (2008), the fish school creation phenomenon can be viewed under two distinct aspects: mutual protection and synergy in collectively executing tasks. The fish school decreases the probability of success of the predator guarantying the survival of great number of individuals. The synergy is related with the ease in finding food for all fishes in the school.

In the search process in the FSS algorithm each fish represents a possible solution for the problem, as the particles in PSO algorithm and the individuals in Genetic Algorithms. In order to explain the FSS, some initial concepts need to be defined: the aquarium is the search space wherein the fishes are positioned and able to move. The food density is related to the objective function to be optimized in the sense that as the food density decreases, the value of the objective function becomes worse.

In this paper, the FSS is used to solve an economic load dispatch problem, which is an important problem in electrical power systems. The thermoelectric plants are often used to supply the demand of power mainly where is impracticable to construct a hydroelectric plant. However convert natural gas in electrical energy is an in-efficient process. The most modern plants have an efficiency of 50-60% in this conversion (Vasebi et al., 2007).

The thermoelectric generation, as well as other power generation processes, causes environmental impacts and contributes to the global warming. The natural gas burning produces pollutants and also uses fossil fuel, nonrenewable fuel source, as input.

Considering these aspects of power generation from fossil fuel, many efforts in the sense of optimize the generation and distribution of energy have been carried out. One of the main focus of study in power generation systems is the economic dispatch (ED). The aim of the ED problem in a traditional thermoelectric plant is to find the optimal operation point that supplies the demand while minimizes the fuel cost (Subbaraj et al., 2009).

The rest of this paper organized as follows: section 2 explains the concepts of the FSS algorithm, in the section 3 are the description of the test problem, section 4 shows the result of the simulations and finally a conclusion is made in the last section.

2. FUNDAMENTALS OF FISH-SCHOOL SEARCH ALGORITHM

Several studies related to fish schools have been presented in the literature, such as Niwa (1996), Hubbard et al. (2004), Zheng et al. (2005), Viscido et al. (2005, 2007), and Adioui et al. (2003).

The main characteristics observed in a fish school were incorporated to the search process of the FSS algorithm. They can be divided into two groups: feeding and swimming. The feeding process consists, inspired in the natural instinct of each fish, of finding food to guarantee its own survival (note that the food is a metaphor for the candidate's value in the search process). The swimming process can be divided in three different stages: the first is the mimetism, where individuals move collectively in the direction of most increasing in the food density found in the previous stage of the search, the second is the individual stage, where each fish makes, randomly, a movement with small amplitude, and the last is the expansion and contraction of the swarm, the function of this behavior, despite its proved existence, is not explained in the real fish schools, but, in the algorithm, aid to avoid local minima.

The FSS simulates the behavior of fish schools by executing these steps: (i) a first individual move, where each fish executes a small randomly movement, which is limited due the fact of to be in a fish school; (ii) an instinctive movement in the direction of the food, motivated by the better efficiency of the other fishes in the previous stage; and (iii) the last movement described as the collective-volitive movement of the fish school, given by the continuation of the movement in the direction of the food. Figure 1 shows the overall procedure of FSS.

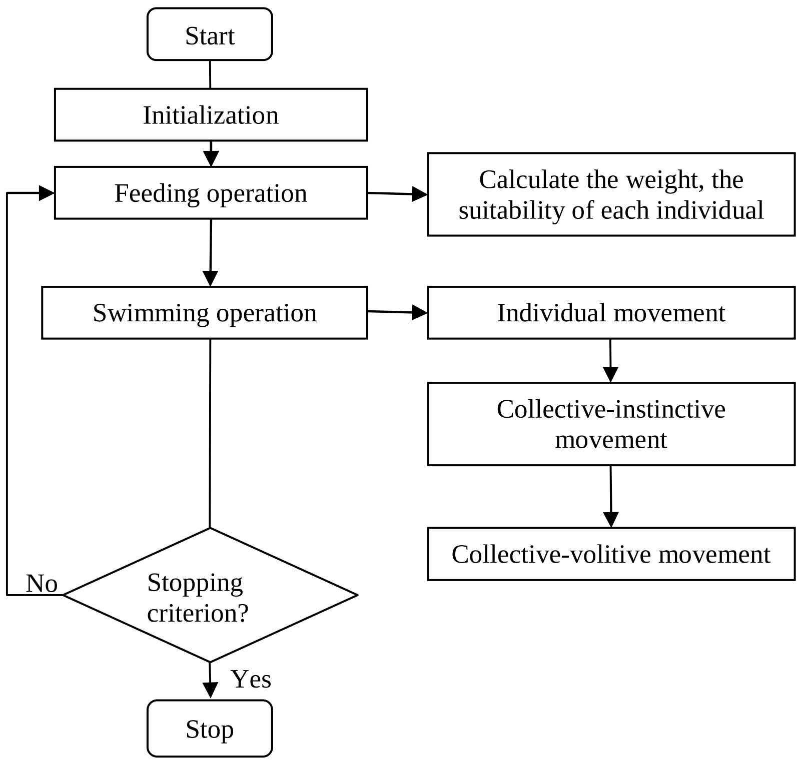

Figure 1. Overall procedure of FSS.

The feeding operation is used in order to evaluate whether the fish is in a good place or not. This is modeled by assigning for each fish its weight, i.e., if a fish is in a good place (good solution) then its weight is larger and if the fish is in a poor place then its weight is fewer. Equation (1) mathematically describes this step of the fish-school. This equation is given by

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

where $x_i(t)$ is the position of fish i at time t and $f[x_i(t)]$ is the amount of food in position $x_i(t)$.

The swimming operator mathematically describes the three steps observed, previously described, in the fish school movement. The individual movement is a random movement, allowing a complete scan of the search space. The collective-instinct can be described as when a better food source is found, the school instinct is to move in that direction (equation 2). Mathematically speaking, the fish school moves in the direction of the weight's average of the school. Fishes that find more food become heavier. So the center of mass of the school trend to the places with more food.

$$x_i(t+1) = x_i(t) + \frac{\sum_{i=1}^{N} \Delta x_{ind\ i}\{ f[x_i(t+1)] - f[x_i(t)]\}}{\sum_{i=1}^{N} \{ f[x_i(t+1)] - f[x_i(t)]\}} \tag{2}$$

where $\Delta x_{ind\ i}$ represents the average of the individual movements made in the previous iteration. This representation is only valid for the restriction that if the movement of a fish leads to a worse position than the previous or to an infeasible position then the movement is discarded. The collective volitive movement is a small movement after the collective-instinct, the desire of the school in achieving the food, and can be a contraction or expansion movement. If the average of the weight increases, i.e. the fishes have improved their objective function values, then the fish school contract (equation 4), otherwise expands (equation 5) in order to scan a bigger area looking for food. In this case, the equations are given by

$$Bary(t) = \frac{\sum_{i=1}^{N} x_i(t) W_i(t)}{\sum_{i=1}^{N} W_i(t)} \tag{3}$$

$$x_i(t+1) = x_i(t) - step_{vol} \cdot rand \cdot [x_i(t) - Bary(t)] \tag{4}$$

$$x_i(t+1) = x_i(t) + step_{vol} \cdot rand \cdot [x_i(t) - BarY(t)] \tag{5}$$

where $step_{vol}$ is the volitive step, $Bary$ is the fish-school's barycenter (center of mass) and $rand$ is a uniformly distributed number in the range [0,1].

3. FORMULATION OF OPTIMIZATION PROBLEM

One of the types of the ED problems is the combined heat and power economic dispatch (CHPED), which is the case studied in this work. The objective of the CHPED problem is to minimize the cost of production subject to the demand supply, heat and power demand, with technological and physical constraints for each generation unit considering dependent production.

The benchmark study of CHPED evaluated in this paper was originally proposed in Guo (1996). Many techniques have been proposed in the literature to solve this problem: Lagrangean relaxation (Guo, 1996), genetic algorithms (Song and Xuan, 1998; Sudhakaran and Slochanal, 2003; Subbaraj et al., 2009), ant colony (Song et al., 1999), and harmonic search (Vasebi et al., 2007).

The test system consists of a plant of electricity generation, two plants of co-generation and a plant of heat generation. The objective is to find the minimum cost to achieve the heat and power demands while satisfying constraints imposed by the problem optimizing 6 decision variables. In figures 2 and 3 are presented the constrained region for the co-generation plants, respectively.

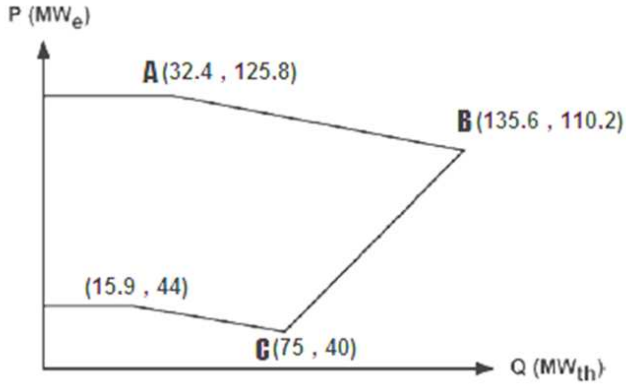

Figure 2. Feasible region for the second unit of the study case (Vasebi et al., 2007).

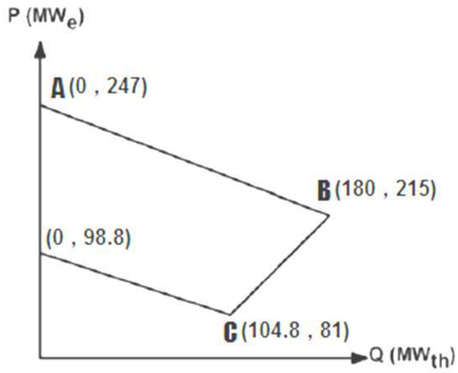

Figure 3. Feasible region for the third unit of the study case (Vasebi et al., 2007).

The objective function C to be minimized is given by:

$$C = \sum_{i=1}^{4} c_i, \quad i = 1,...,4 \tag{6}$$

where

$$c_1 = 50 p_1 \tag{7}$$

$$c_2 = 2650 + 14.5 p_2 + 0.0345 p_2^2 + 4.2 h_2 + 0.031 p_2 h_2 \tag{8}$$

$$c_3 = 1250 + 36 p_3 + 0.0435 p_3^2 + 0.6 h_3 + 0.027 h_3^2 + 0.011 p_3 h_3 \tag{9}$$

$$c_4 = 23.4 h_4 \tag{10}$$

The following constraints are adopted:

$$0 \le p_1, p_2, p_3 \le 150 \quad MW \tag{11}$$

$$0 \le h_2, h_3, h_4 \le 2695.2 \quad MWth \tag{12}$$

$$P_D = p_1 + p_2 + p_3 \tag{13}$$

$$H_D = h_2 + h_3 + h_4 , \tag{14}$$

where p_i and h_i are the power and the heat outputs, respectively, of the i-th unit. The heat demand is 115 MWth and the power demand is 200 MW. In this paper, a penalty function is adopted to handle the constraints given by equations (11)-(14). In this way, deviation from the constraint is added to the objective function such that each unfeasible solution is penalized by a large penalty term proportional to the deviation.

4. SIMULATION RESULTS

The FSS approach was implemented in MATLAB (MathWorks). To illustrate the effectiveness of the FSS approach 30 runs were performed. The parameters for the FSS were set empirically, i.e., for each algorithm a number of tests with different parameter settings were carried out and the results were compared. The best settings were chosen, as shown in

Table 1. Also, FSS is compared to the canonical genetic algorithm (GA). The GA settings were adjusted to the following values: crossover rate was 0.8, population size was 30 individuals, stopping criteria was 1000 generations and the adopted mutation operator was the Gaussian. In terms of constraint handing strategy, a penalty parameter based method presented in Subbaraj et al. (2009) to penalize infeasible solutions was used.

Table 1. Settings of control parameters in FSS approach.

Parameter	Value
Number of iterations (generations)	1000
Population size	30
Initial individual step	5
Final individual step	0.01
Initial collective step	1
Final collective step	0.01

Table 2 presents the results of FSS and GA approaches in terms of convergence (30 runs). FSS obtained superior performance than the GA in terms of minimum and mean cost. The best results using FSS is equal to the results presented in Subbaraj et al. (2009) using self adaptive real-coded genetic algorithm (SARGA) in terms of minimum cost (see Table 3). On other hand, SARGA presented better convergence rate than the FSS and GA approaches presented in this paper.

However, the optimal solution of cost function C added to the penalties depends on penalty parameter tuning. Users usually have to try different values of penalties values to find which value would steer the search towards the feasible region. In this paper, the procedure to obtain feasible solutions using FSS in terms of inequality and equality constraints was a very time consuming task and hard to converge towards near-optimal solution presented in Vasebi et al. (2007) and Subbaraj et al. (2009).

Table 2. Results of optimization after 1000 iterations (generations) in 30 runs.

Method	Minimum cost ($)	Maximum cost ($)	Mean cost ($)	Standard deviation of cost
FSS	9257.07	11451.23	11084.72	21.05
GA	11567.40	11687.14	11663.85	24.17

Table 3. Best configuration of the units using FSS.

Decision Variables	Representation	FSS	SARGA
p_1	x_1	0.00	0.00
p_2	x_2	159.99	159.99
p_3	x_3	40.01	40.01
h_2	x_4	39.99	39.99
h_3	x_5	75.00	75.00
h_4	x_6	0.00	0.00
Objective function	C	9257.07	9257.07

5. CONCLUSION

The use of optimization algorithms in several applications in almost all areas is growing due the necessity of increase profit, minimize costs and wastes. Also, in the energy sector, exists the importance of minimize the environmental impact caused by the power and heat generation in thermoelectric plants.

The low computational cost and the capability of adapt to complex search spaces is the main characteristics of natural computing algorithms as the swarm-based algorithms. The particularities presented in the FSS make it a good option to solve complex problems as the CHPED problem.

The proposed FSS evaluated in this paper presented promising results to a CHPED. In future works, modifications in FSS can be useful for a balance between exploration and exploitation of the search space. Also, methods of adaptive tuning of FSS control parameters can be used to maintain the diversity of fish swarm.

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