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Genetic Algorithm-Particle Swarm Optimization (GA-PSO) for Economic Load Dispatch

***Abstract**. This paper presents a method for Economic Load Dispatch (ELD). Economic dispatch problem is basically an optimization problem where objective function may be highly nonlinear, non-convex, and no differentiable and may have multiple local minima. Therefore classical optimization methods may be trapped to any local minima and may not be able to reach the global minima. The solution to this problem was presented by the application of heuristics methods such as genetic algorithms unfortunately the long execution time and non-guaranteed in convergence to the global optimal solution contribute the main disadvantages of GAs. In this paper provides a solution to this problem through a hybrid method Genetic algorithm - Particle Swarm Optimization (GA-PSO)*

***Streszczenie.** Problem ekonomicznego rozsyłu energii ELD jest trudny do optymalizacji. Jedną z metod jest zastosowanie algorytmu genetycznego. Niestety algorytm ten jest czasochłonny i nie zawsze gwarantujący optymalne rozwiązanie. W pracy zaproponowano hybrydową metodę złożona z algorytmu genetycznego i algorytmu mrówkowego. (**Hybrydowy algorytm genetyczny/mrówkowy jako metoda optymalizacji ekonomicznego rozsyłu energii**)*

Keywords: economic load dispatch, genetic algorithm, particle swarm optimization.
Słowa kluczowe: ekonomiczny rozsył energii, algorytm genetyczny, algorytm rówkowy.

Introduction

Economic Load Dispatch (ELD) are designed and operated to meet the continuous variation of power demand. The power demand is shared among the generating units and economic of operation is the main consideration in assigning the power to be generated by each generating units. Therefore, Economic load Dispatch (ELD) is implemented in order to ensure for economic operation of a power system. Economic Dispatch problem is an optimization problem that determines the optimal output of online generating units so as to meet the load demand with an objective to minimize the total generation cost [1].

Various mathematical methods and optimization techniques have been employed to solve for ELD problems. Among the methods that were previously employed include genetic algorithms (GAs), and evolutionary algorithm (EA) have been increasingly used to solve for power system optimization problems [2].

Since its introduction in late 1980’s, GAs has been used to solve many power system optimization problems. It has been successfully employed to solve for economic load dispatch problem due its ability to model any kind of constraints using various chromosome-coding schemes according to specific problem. On the other hand, long execution time and non-guaranteed in convergence to the global optimal solution contribute the main disadvantages of GAs. However, its long execution time posed its main disadvantage [3].

In this paper, a new method for solving ELD problem based on the hybrid genetic algorithm – PSO method. The hybrid approach executes the two systems simultaneously and selects P individuals from each system for exchanging after the designated N iterations. The individual with larger fitness has more opportunities of being selected.

The feasibility study of the proposed technique was conducted on a practical system having 5 generating units. Several loading scenarios with a number of equality and in equality constraints were tested in order to demonstrate the effectiveness of the proposed technique. The results obtained from the proposed technique were also compared with those obtained from the GA optimization methods in order to assess the solution quality and computational efficiency.

Optimal power flow formulation

Consider an ELD problem with i generators. The ELD problem is to find the optimal combination of power generation that minimizes the total cost while satisfying the total demand. The cost function of ELD problem is defined as follows [4, 5]:

$$\min f(P_G) = \sum_{i=1}^{N} f_i(P_{Gi}) \tag{1}$$

In Eq. (1), the generation cost function $f_i(P_{Gi})$ in \$/h is usually expressed as a quadratic polynomial [6, 7].

$$f_i(P_{Gi}) = a_i P_{Gi}^2 + b_i P_{Gi} + c_i \tag{2}$$

where: $f(P_G)$ – total production cost (\$/h), $f_i(P_{Gi})$ – the cost of the ith generator in \$/h, P_{Gi} – the power output of generator i in MW, a_i, b_i, c_i – the cost coefficients of the i *th* generator.

When minimizing the total production cost, the equality constraint (power balance) and inequality constraint (power limits) should be satisfied.

Equality constraint

$$\sum_{i=1}^{N} P_{Gi} - P_D - P_L = 0 \tag{3}$$

where: P_D –power demand, P_{Gj} – active power generation of generator i, P_L – active power losses, N – number of generators.

The transmission loss can be represented by the B-coefficient method [8, 9] as:

$$P_L = \sum_i \sum_j P_{Gi} B_{ij} P_{Gj} \tag{4}$$

where: B_{ij} – the transmission loss coefficient, P_i, P_j – the power generation of ith and jth units. The B-coefficients are found through the Z-bus calculation technique.

Inequality constraint

The generation capacity of each generator has some limits and it can be expressed as

$$P_{Gi}^{\min} \le P_{Gi} \le P_{Gi}^{\max} \tag{5}$$

where: $P_{Gi}^{\min}, P_{Gi}^{\max}$ – Lower and upper limit of active power generation at bus i.

Description of Particle Swarm Optimization method

The particle swarm optimization works by adjusting trajectories through manipulation of each coordinate of a particle. Let x_i and v_i denote the positions and the corresponding flight speed (velocity) of the particle *i* in a continuous search space, respectively [6,7]. The particles are manipulated according to the following equations.

$$v_i^{(t+1)} = wv_i^{(t)} + c_1 r_1 (x_{gbest}^{(t)} - x_i^{(t)}) + c_2 r_2 (x_{ipbest}^{(t)} - x_i^{(t)})$$

$$x_i^{(t+1)} = x_i^{(t)} + v_i^{(t+1)}$$

where: t – pointer of iterations (generations), w – inertia weight factor, c_1, c_2 – acceleration constant, r_1, r_2 – uniform random value in the range (0,1), $v_i^{(t)}$ – velocity of particle *i* at iteration t, $x_i^{(t)}$ – current position of particle i at iteration t, $x_{ipbest}^{(t)}$ – previous best position of particle *i* at iteration *t*, $x_{gbest}^{(t)}$ – best position among all individuals in the population at iteration *t*, $v_i^{(t+1)}$ – new velocity of particle *i*, $x_i^{(t+1)}$ – new position of particle i.

Algorithm

1. Initialize the population - positions and velocities
2. Evaluate the fitness of the individual particle (*pbest*)
3. Keep track of the individuals highest fitness (*gbest*)
4. Modify velocities based on *pbest* and *gbest* position
5. Update he particles position
6. Terminate if the condition is met
7. Go to Step 2

Genetic algorithm

The genetic algorithm is a search algorithm based on the mechanics of natural selection and natural genetics [8]. As summarized by Tomassini [9], the main idea is that in order for a population of individuals to adapt to some environment, it should behave like a natural system. This means that survival and reproduction of an individual is promoted by the elimination of useless or harmful traits and by rewarding useful behavior. The genetic algorithm belongs to the family of evolutionary algorithms, along with genetic programming, evolution strategies, and evolutionary programming. Evolutionary algorithms can be considered as a broad class of stochastic optimization techniques. An evolutionary algorithm maintains a population of candidate solutions for the problem at hand. The population is then evolved by the iterative application of a set of stochastic operators. The set of operators usually consists of mutation, recombination, and selection or something very similar.

Globally satisfactory, if sub-optimal, solutions to the problem are found in much the same way as populations in nature adapt to their surrounding environment.

Using Tomassini's terms, genetic algorithms (GAs) consider an optimization problem as the environment where feasible solutions are the individuals living in that environment.

The degree of adaptation of an individual to its environment is the counterpart of the fitness function evaluated on a solution. Similarly, a set of feasible solutions takes the place of a population of organisms. An individual is a string of binary digits or some other set of symbols drawn from a finite set. Each encoded individual in the population may be viewed as a representation of a particular solution to a problem. In general, a genetic algorithm begins with a randomly generated set of individuals. Once the initial population has been created, the genetic algorithm enters a loop [9]. At the end of each iteration, a new population has been produced by applying a certain number of stochastic operators to the previous population. Each such iteration is known as a generation. The evolutionary cycle can be summarized as follows [9]:

> generation = 0
> seed population
> **while** not (termination condition) **do**
> generation = generation + 1
> calculate fitness
> selection
> crossover
> mutation
> **end while**

Genetic Algorithms Assisted by Particle Swarm Optimization

PSO incorporates swarming behaviors observed in flocks of birds, schools of fish, or swarms of bees, and even human social behavior, from which the idea is emerged [10, 11, 12, 13].

A hybrid genetic algorithm–PSO method is proposed. The hybrid approach executes the two systems simultaneously and selects *P* individuals from each system for exchanging after the designated *N* iterations. The individual with larger fitness has more opportunities of being selected. The main steps of the hybrid approach are as below:

1. Initialize GA and PSO subsystems.
2. Execute GA and PSO simultaneously.
3. Memorize the best solution as the final solution and stop if the best individual in one of the two subsystems satisfies the termination criterion.
4. Perform the hybrid process if generations could be divided exactly by the designated number of iterations *N*. Select *P* individuals from both sub-systems randomly according to their fitness and exchange. Go to step 3.

Simulation Results

In this study, the standard IEEE 25-bus 5-generator test system is considered to investigate the effectiveness of the proposed approach. The IEEE 25 bus system [14]. The values of fuel cost coefficients are given in Table 1, total load demand of the system is 730 (MW), and 5 generators should satisfy this load demand economically. The result obtained from the classical optimization technique of Broyden-Fletcher-Goldfarb-Shanno (BFGS), a binary-coded genetic algorithm (BCGAs) method [14], a practical real-coded genetic algorithms (RCGAs) [15] and the proposed method are shown in Tables 2, 3 and 4. This method has been tested 25 times.

Three test cases are considered, specifically, the first test case ignores the transmission losses. The second test case differs from the first in that it incorporates the transmission losses. The transmission line losses are calculated and maintained constant (*PL* = 41.4487 MW).

Finally, in the third test case, we consider the variable losses according to each method.

First Variant

Ignores the transmission losses (*PL* = 0.00 MW), table 2, figure 1.

Second Variant

Transmission line losses are calculated and maintained constant (*PL* =41,4487 MW),), table 3, figure 2.

Third Variant

We consider the variable losses according to each method, table 4, figure 3.

Table 1. Generator operating limits and quadratic cost function coefficients.

Bus No	Real Power Limit (MW)		Cost Coefficients c_i, b_i , a_i		
	Min	Max			
1	100	300	0.0015	1.8	40
2	80	150	0.0030	1.7	60
3	80	200	0.0012	2.1	100
4	20	100	0.0080	2.0	25
5	100	300	0.0010	1.9	120

Table 2. Results of GA-PSO compared with Classical methods (BFGS), BCGAs and PSO for the IEEE 25-bus system, with the constant losses =0,00.

Variable	BFGS	BCGAs	PSO	GA-PSO
P1 (MW)	211.74	147.32	153.228963	196.673190
P2 (MW)	111.23	129.13	106.986301	117.808219
P3 (MW)	194.41	171.02	147.866928	132.602740
P4 (MW)	39.42	38.13	21.722114	27.514677
P5 (MW)	173.58	244.51	298.825832	253.033268
Total fuel cost ($/h)	1927.03	1919.09	1914.227075	1907.186844
PL (MW)	0.00	0.00	0.00	0.00
Time (sec)	0.0	3.25	2.85	0.19

Table 3. Results of GA-PSO compared with Classical methods (BFGS), BCGAs and PSO for the IEEE 25-bus system. with the constant losses =41,4487

Variable	BFGS	BCGAs	RCGAs	PSO	GA-PSO
P1 (MW)	211.30	206.72	213.68	197.45	211.54
P2 (MW)	126.30	121.64	127.46	114.93	122.46
P3 (MW)	151.29	151.82	141.93	168.29	140.117
P4 (MW)	71.24	33.21	29.53	29.08	27.358
P5 (MW)	211.31	258.05	258.86	259.29	267.514
Total cost ($/h)	2029.3	2011.0	2010.8	2009.00	2007.440
PL (MW)	41,4487	41,4487	41,4487	41,4487	41,4487
Time (sec)	0.0	4.78	1.60	3.21	0.45

Table4. Results of GA-PSO compared with Classical methods (BFGS) , BCGAs and PSO for the IEEE 25-bus system. with the variable losses.

Variable	BFGS	BCGAs	PSO	GA-PSO
P1 (MW)	184.06	214.05	245.988258	196.673190
P2 (MW)	139.27	82.049	102.739726	123.013699
P3 (MW)	168.09	161.87	152.798434	149.275930
P4 (MW)	73.387	28.73	38.943249	29.236791
P5 (MW)	202.71	281.04	225.636008	266.731898
Total cost ($/h)	2028.50	2008.09	2004.734642	1998.961492
Time (sec)	0.0	4.11	3.51	0.85

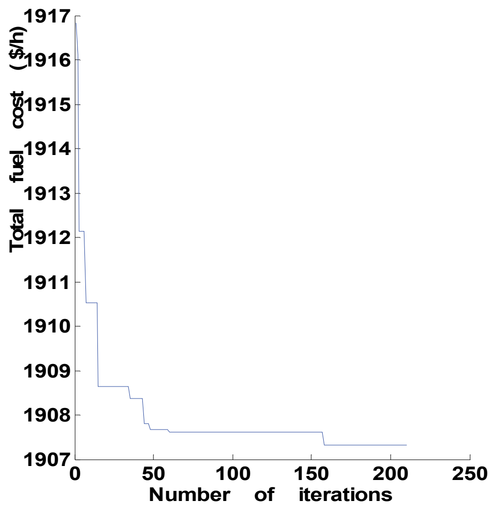

Fig.1. The generation cost evolution during The iterative procedure with the losses=0.00

For the First Variant and the Third Variant, as shown in Table 2, fig 1 and Table 4, fig 3, although classical optimization technique of BFGS [14] can give a solution within a short computational time, the solution is only a local optimal which depends on a starting point. The result obtained from BCGA is better, but it takes longer computational time.

It can be seen from results that the result obtained from the proposed GA-PSO is better in terms of convergence time and total production cost.

For the Second Variant, as illustrated in Table 3, the proposed GA-PSO method is also compared with the real-coded genetic algorithm (RCGA) of the references [14]. A comparison between the GA-PSO method, the RCGAs methods and BCGAs in term of the generated active powers as well as the costs and computational time.

From these results, it can be seen that the advantage of the proposed GA-PSO method was very obvious, and it could obtain both the fastest computation efficiency and the minimum total generation cost.

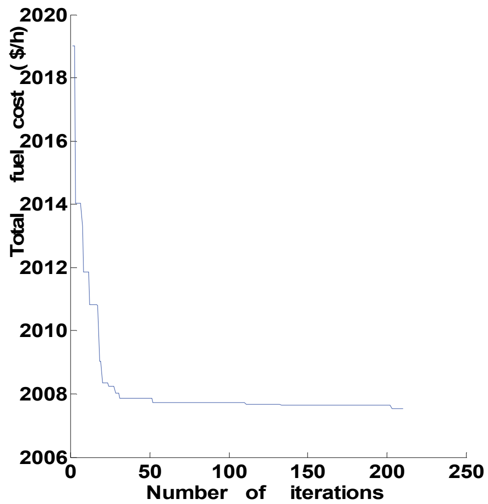

Fig.2. The generation cost evolution during the iterative procedure, with the constant losses=41,4487

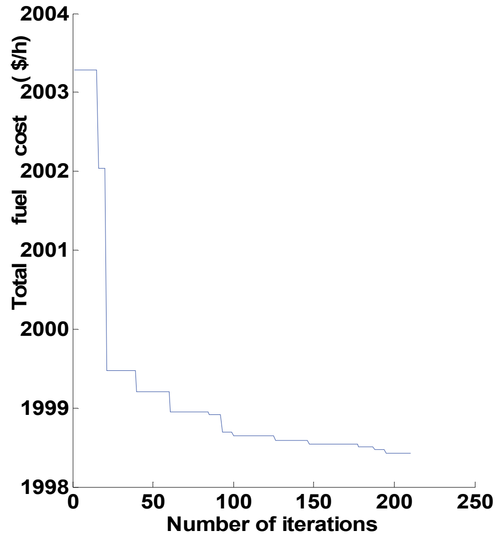

Fig.3.The generation cost evolution during The iterative Procedure with the variable losses

Conclusion

PSO is a relatively recent heuristic search method that is based on the idea of collaborative behavior and swarming in biological populations. PSO is similar to GA in the sense that they are both population-based search approaches and that they both depend on information sharing among their population members to enhance their search processes using probabilistic rules.

The objective of this research is the combination of these two methods to improve their effectiveness (solution quality),

The feasibility of the proposed algorithm is demonstrated on an IEEE 25-bus system. The results show that the proposed algorithm is applicable and effective in the solution of ELD problems that consider nonlinear characteristics of power systems. GA-PSO can generate an efficiently high quality solution and with more stable convergence.

The advantage of GA-PSO over other method is modelling flexibility, sure and fast convergence, less computational time than other methods.

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