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Improved Adaptive Tumbling Bacterial Foraging Optimization (ATBFO) for Emission Constrained Economic Dispatch Problem

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Abstract — **This paper highlights the improved Adaptive Tumbling Bacterial Foraging Optimization (ATBFO) to grant better solution particularly in emission economic power dispatch issue. The proposed methodology simply takes care in solving non-convex power system issues along maintaining the requirement of all equipped constraints for healthy power delivery operation. The performances are evaluated with different recent computational routine identified as the faster Evolutionary Programming (Meta-EP) in order to choose a leader in getting the minimal single objective function. The receiving answer defines the robustness and reliability of proposed optimization technique among other mentioned existing method.**

Index Terms* – *Adaptive Tumbling Bacterial Foraging Optimization; Economic power dispatch; Evolutionary Programming

I. Introduction

Traditionally, economic dispatch (ED) plays an important role in order to allocate a combination of generation levels to the generating units so that the demand system could be supplied entirely and most economically [1].

In today's environment the quality requirement of economic dispatch is not only to schedule the least cost but also to consider the other performance factors in order to optimize the power flow. The obligation of social attentions have influenced in reducing the energy conservation and pollution emission produced by power plants. The researchers in [2] claimed that a single objective function which to minimize the total fuel cost can no longer be considered alone.

ED issues must also subject to the operational constraints and security criteria in order to provide a secure and economical dispatch [3]. Due to large complex power system, an economic operation, minimal impact on environments, security and reliability are typical objectives to be considered [4]. Therefore, a classical method such as Gradient based technique; Newton Methods, linear programming and quadratic programming are no longer proper solution for a non-convex, non-continuous and highly non-linear solution gap [5-8].

Throughout the years, many attempts were made to improve weaknesses of primitive techniques especially from intelligent computational expertise. Several methods were employed namely Artificial Neural network (ANN) [9], Genetic Algorithm (GA) [4, 5, 10-12], Particle Swarm Optimization (PSO) [13-17], Evolutionary Programming (EP) [18], Simulated Annealing (SA)[19] and Ant Colony Optimization (ACO) [20] to meet the demand with minimum objective function.

Today's efforts also include the new immunity based algorithm, known as Artificial Immune System (AIS) to be an essential tool to minimize fuel cost generation with constraints consideration for optimal solutions [21]. Most recent, new algorithm based on the foraging behavior of Escherichia coli Bacteria in human intestine known as Bacteria Foraging Algorithm (BFA) was introduced. This new algorithm with the help of fuzzy satisfying method is used to optimize two conflicting objectives; cost and emission [21].

This paper proposed a methodology using Bacterial Foraging Optimization Algorithm (BFOA) to satisfy the optimal power flow solution. Alterations in tumbling strategy are completed to develop low cost and more steadily BFOA optimization strategy. An iteration routine called Meta EP is also selected for evaluation tournament.

II. Problem Description

The primary concern in economic dispatch issues is to determine minimum objective function as described below.

A. Minimum Total Fuel Cost

This the main objective function corresponding to production fuel cost which approximately to quadratic cost function of generating units in the network [22]. The related function can be formulated as in (1)

$$Minimise, F_{Total} = \sum_{i=1}^{N_G} a_i P_i^2 + b_i P_i + c_i \quad (\$/MWh) \qquad (1)$$

where

i=1,2,3,…,N_G are the number of generating units
a_i ,b_i ,c_i are corresponding cost coefficient
P_i is the real power output (MW) of ith generator.

B. Minimum total emission function

The next important objective function is finding the total emission released at thermal generator during system operation. Mathematically, this overall emission function is represented by equation as (2) that given in [21]

$$Minimise, E_{Total} = \sum_{i=1}^{NG} (\gamma_i P_i^2 + \beta_i P_i + \alpha_i) * (10^{-2}) + \zeta_i \exp(\lambda_i P_{gi}) \quad (ton/h) \qquad (2)$$

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where

α_i , β_i , γ_i , ε_i, λ_i are corresponding emission coefficient of *i*th generator

C. Equality and inequality constraints

The deployment equality and inequality variables that must be serious mind for network security. This equality constraint based upon equilibrium total system generation and total losses of the system that are symbolized as equation (3)

$$T_{loss} = \sum_{i=1}^{N_g} P_{gi} - P_{load} \tag{3}$$

where

T_{Loss} = total system losses;
P_{load} = system demand and
N_g = number of generating units

While, the upper and lower bound of output power for each generating unit is called inequality constraints. Approximately, these variables can be expressed as in (4) below. Generating capacity limits

$$P_{min} \leq P_{g_i} \leq P_m \tag{4}$$

where

P_{min} and P_{max} is the minimum and maximum real power generation of unit *i* respectively

III. Overview of Evolutionary Programming (EP) and Bacterial Foraging Optimization (BFO) Strategy

A. Evolutionary Programming (EP)

Initially, the EP was proposed for the evolution of finite-state machines as prediction tool by David B.Fogel in 1960's [23, 24]. The evolution process is starting from initial generation population solution ranging over their upper and lower limits. The next practice named mutation often concerned on adding a random number or vector from Gaussian distribution to parent in the classical EP. The degree of mutation deviation is controlled through standard deviation or strategy parameter.

As stated earlier, the selected EP in this paper will be Meta-EP, which implemented the self-adaptation parameters during mutation process. The results obtained in mutation called offspring to be used for competition in recombination with parent. Upon completion the tournament process then this selected population with corresponding fitness value will reproduced for next generation until meet the convergence accuracy.

B. Bacterial Foraging Optimization (BFO)

BFO algorithm is motivated through the foraging activities of the Escherichia coli E.coli) bacteria. The details on the biological aspects of their hunting strategies considered their motile behavior for decision-making mechanism is explained in [25, 26]. This recent BFO searching invented from K.M.Passino supported on the truth that natural selection tends to eliminate animals with poor foraging strategies against those with the attractive foraging [27]. Several process of E. coli foraging that present in our intestines are called chemotaxis, swarming, reproduction and elimination and dispersal process [25].

The chemotaxis provides a tumbling and swimming activities depending on the rotation of the flagella in each bacterium. The involved bacterium spends their entire life between these two modes alternatively. The swarming case invites the bacteria with optimum path of food able to attract others and assemble into groups. Then, the performed group can move as concentric patterns with high bacterial density.

The least healthy bacteria depart this life during reproduction process while the healthiest bacteria divide to become two numbers of bacteria and placed in same location. At the end, the consistent number of bacteria is produced. The final phase named elimination and dispersal events occupied the changes population of bacteria either by consumption of nutrients or suddenly due to some other influence. In addition, this process helps from being trapped in premature solution point or local optima [27].

IV. An Improved Adaptive Tumbling Bacterial Foraging Optimization (ATBFO)

This paper is concerned to solve the non convex and complexity of solving economic dispatch issues. Therefore, the modification in tumbling strategy of bacteria foraging method is to accelerate the convergence as well as finding the least fitness value. The improved BFO is named as ATBFO with an ignoring on swarming case is discussed briefly as below.

Step 1: Initialization variables:

The following parameters are initialized

i. Number of bacteria (S) to be used in searching space
ii. The number of random values corresponding to generating units to be optimized,*p*
iii. Swimming length, N_s
iv. The number of chemotactic steps, N_c where ($N_c > N_s$)
v. The number of reproduction, N_{re}
vi. The number of elimination and dispersal events, N_{ed}
vii. The probability of elimination and dispersal

Step 2: Iterative algorithm for optimization

This section describes the bacterial population chemotaxis, reproduction and elimination and dispersal events. At beginning, j=k=*l*=0.

i. Elimination-dispersal loop: *l*=*l*+1
ii. Reproduction loop: k=k+1
iii. Chemotaxis loop: j=j+1
   a) For each i=1,2,…S, calculate the objective function or fitness value (either cost or emission)
   b) For each i=1,2,…S, take tumbling or swimming decision
   c) Go to the next bacterium (*i* +1). If *i*≠S , go to b)
iv. If j<N_c, go to step 3. Repeat the chemotaxis loop over the life of bacteria
v. Reproduction

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a) For a stated k and l for each i=1,2,…S, let the health of bacterium,i is

$$J^{i}_{health} = \min_{j \in \{1 \ldots N_c\}} \{J_{sw}(i,j,k,l)\} \quad (9)$$

Then, the bacteria are sorted according to ascending objective function J_{health} described that higher fitness values mean lower health.

b) The $S_r = \frac{S}{2}$ bacteria with highest J_{health} values eliminate and other S_r bacteria the healthiest value split and copies to the same location with previous generation

vi. If $k<N_{re}$ then go to 2) to reprocess the chemotaxis iteration for the second generation of bacteria population

vii. Elimination and dispersal events for *i*=1,2,…S, with probability, P_{ed} whether eliminate or disperse each bacterium the constant number of bacteria population.

V. RESULTS AND ANALYSIS

Thoroughly, the improved ATBFOA accomplished the initial standard parameters that give the least cost function which are N_c=100, N_s=50, swimming length, c =0.3, N_{re}=2, N_{ed}=2 taken as the optimized model.

A. Comparison Results for Objective Function As Minimum Cost Function With Observation on Emission Over IEEE 118 Bus Case System.

As stated earlier, the chosen variables representation will be applied to find the minimum total cost function with scrutiny on total emission drawn out during system operation. In order to maintain the consistency of the required fitness, the whole iteration process is reserved to repeat for 5 times running loop. As a result, Table I registers the values of corresponding generating units from the improved ATBFO and Meta EP respectively.

The important objective between the improved ATBFO tool and Meta EP is to attain the lowest amount total cost operational execution. All essential data which regards to the fitness values with observation on total emissions for both optimization routines is recorded into Table II.

From Table II, it is clearly seen that the fitness value for the improved ATBFO outperformed Meta EP. The total cost is 113448.8908 dollar/MWh as well as fewer emissions disappeared. The deviation for the crucial function is about 26131.84336 dollar/MWatt in hourly which comparable in spending 228914947.8 dollar/MWatt over a year to the system. Besides, ATBFO is also faster in convergence time as compared to self-adaptation EP. Thus, the new improved ATBFO is verified as best solution for desired total cost function among them.

B. Comparison Result for Objective Function As Minimum Emission With Observation on Cost Function over IEEE 118 Bus Case System.

The new improved ATBFO is then applied to the following fitness that is looking for a minimum total emission occurred. Similarly, all required parameters remain unchanged for the entire process. The procedure to target goal is similar as optimization loop described above. The corresponding results are depicted in Table III and IV below which obtained after 5 running times for both defined methods

Table IV compared the fitness function for both techniques. The third row stated the monitoring total cost function emerged from the contributed emission. Again, the tabulated data confirmed the improved ATBFO as an efficient and quicker learning technique at 92978.05879 ton/h with only 92.79584395 minutes acquired time.

In summary, there is a strong bonding between cost functions with evaporated emission. Even though only one of them is taken as fitness function but higher emission also causes more money in operational cost.

TABLE I

Technique	Improved ATBFO	Meta EP	Pg Max
Pg10	490	483	550
Pg12	127	140	185
Pg25	286	236	320
Pg26	338	348	414
Pg31	8	15	107
Pg46	97	92	119
Pg49	242	220	304
Pg54	90	98	148
Pg59	201	217	255
Pg61	204	169	260
Pg65	395	430	491
Pg66	364	428	492
Pg80	477	484	577
Pg87	8	13	104
Pg89	609	618	707
Pg100	255	269	352
Pg103	45	114	140
Pg111	87	64	136

TABLE II

Technique	Improved ATBFO	Meta EP
Total cost (dollar/MWh)	(Fitness) 113448.8908	(Fitness) 139580.7342
Total emission (ton/h)	(Observation) 98755.47347	(Observation) 102643.9452
Average Time (minutes)	81.57092962	777.6944033

TABLE III

Technique	ATBFOA	Meta EP	Pg Max
Pg10	450	463	550
Pg12	121	168	185
Pg25	221	292	320
Pg26	394	314	414
Pg31	73	87	107
Pg46	88	94	119
Pg49	206	220	304
Pg54	51	52	148
Pg59	157	175	255
Pg61	178	191	260
Pg65	391	419	491
Pg66	394	395	492
Pg80	480	519	577
Pg87	8	6	104
Pg89	609	628	707
Pg100	255	273	352
Pg103	45	88	140
Pg111	87	64	136

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TABLE IV

Technique	Improved ATBFO	Meta EP
Total emission (ton/h)	Fitness 92978.05879	Fitness 101660.2283
Total cost (dollar/MWh)	Observation 143184.356	Observation 141493.5053
Average Time (minutes)	92.79584395	1071.367941

VI. CONCLUSIONS

Over the years, the proper optimization solutions are indeed focused to overcome complexity economic dispatch issues. Regarding the matter, this study brings the new improved ATBFO as an essential tool to realize preferred objective functions. The deployment is examined alternately in both cases using similar variables for 5 time's complete loop to ensure the quality results. At the same time, Meta EP is chosen to challenge the capability of proposed method.

As a conclusion, based upon the obtained results, it guarantees that the new approach improved ATBFO performed the lowest fitness function and fastest practice.

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