

Multi Objective Adaptive Tumbling Bacterial Foraging in VAR Solutions for Sustainable Power System Operation

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ABSTRACT

The application of the developed optimization technique Multi Objective Adaptive Tumbling Bacterial Foraging (MOATBFO) was introduced to solve the multi objective Reactive Power Planning (RPP) problems. The objective of conventional RPP problems is to minimize the total power losses in a system. However, in this study, the aspect of security was also taken into consideration in terms of voltage stability condition in solving RPP problems. Hence, the RPP problem is now termed as security constrained RPP (SCRPP) and generalized into a multi objective function via weighted sum method that labeled as MOSCRPP. The best minimum voltage solution for the network is aimed in ensuring the sustainable power system operation. In order to verify the performance of the proposed technique were used for MOSCRPP in the IEEE 57 bus system thus the comprehensive analyses were also conducted with other multi objective Meta heuristic Evolutionary Programming (Meta-EP). From the results it shows that the multi objective ATBFO optimization is able to give better overall improvement in the objective functions for SCRPP problems.

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1. INTRODUCTION

In modern development, Reactive Power Planning becomes one of the most vital study areas in power system [1]. Thus, they found that reactive power support is critical and vital to sustain voltage and regulate power factor in electric power systems. In recent years, numerous blackouts in the world have been occurred, such as 2003 North American caused by poor planning and managing of reactive power in US power system [2]. As a consequence, several objectives functions are suggested from researchers in this field in order adequate Reactive Power Planning (RPP). As referred to [3], their approach was first dealt with an objective to minimize the real power losses hence reducing operational cost while improving the voltage profile. Other considerations are minimizing deviation of given voltage profile, Voltage Stability Margin (VSM) improvement and also combinations of different single objective functions to form multi-objective functions. Reactive power planning is one of the most challenging problem for efficient and source operation of an interconnected power network [4]. RPP can also be combined with Optimal Power Flow (OPF) in which cost minimization has become one of the considerations in the optimization. The cost reductions obtained through both OPF were compared with the total system costs during Base Case.

The principle of SCRPP is to optimize the power system control variables so as to achieve the optimal objective function value or fitness value, while at the same time satisfying the nonlinear operational constraints. The equality constraint is developed from the nodal power balance equation whereas the edge of

all control or state variables representing the inequality limitations. The merging of optimality and security contribute to the complexity of SCRPP problem since it is necessary to treat all components simultaneously. The control variables considered are voltage variation, capacitor or reactor switching, transformer tap changing, active power of generator, FACTs and STATCOMs switching [5] to facilitate the requirement of SCRPP.

Throughout years, numerous conventional techniques offered solutions to RPP or VAR sources planning problem included LP [6], NLP, MINLP and Non Linear Interior Point Method (NIPM) [7]. However, it frequently resulted in local optima rather than giving a solution of global optima. It also caused divergence in solution when trying to optimize two objective functions simultaneously. Consequently, new advanced optimization methods were introduced which exhibit some artificial intelligence behaviors such as Simulated Annealing (SA), Evolutionary Algorithms (EA), Genetic Algorithm (GA) and Tabu Search (TS) [8]-[11]. These techniques offered global optimal solutions, however, at the expense of computational time [12]. Therefore, recent researches are inspired to merge conventional methods and advanced optimization techniques for better and faster optimization approaches.

This study introduced a new Adaptive Tumbling Bacterial Foraging Optimization (ATBFO) algorithm which is an improvement to the basic Bacterial Foraging Optimization (BFO) algorithm. The proposed technique was implemented for RPP multi-objective functions. Several identified objective functions were generalized into single objective function via the weighted sum method then known as the multi-objectives function. For that reason, the ATBFO for multi-objectives function is named as the multi-objective Adaptive Tumbling Bacterial Foraging algorithm (MOATBFO). Finally, the performances of the newly developed technique MOATBFO were compared with that provided by the multi objective Meta-EP method. The smallest total system losses and larger maximum loading point that the system can withstand are declared as the best solutions.

2. MULTI OBJECTIVE SECURED REACTIVE POWER PLANNING

The multi-objective SCRPP or named as MOSCRPP aimed to maximize the MLP and minimize the total system losses simultaneously. Both objective functions are combined to be one objective function using the weighted sum method and applied to the new MOATBFO technique.

2.1. Maximizing MLP objective function

Load margin analysis has known to be one of the significant parameters for voltage stability studies. In maximum load ability limit evaluation, the load was increased until the occurrence voltage collapse, that when the system begins to lose its equilibrium as in Figure 1. Graphically, the load margin is portrayed by the range between λ_0 or the loading for base case and λ_{max} , or identified as the maximum loading position [13]. During the assessment, the weakest or critical bus among the network and maximum load that it can sustain can also be determined.

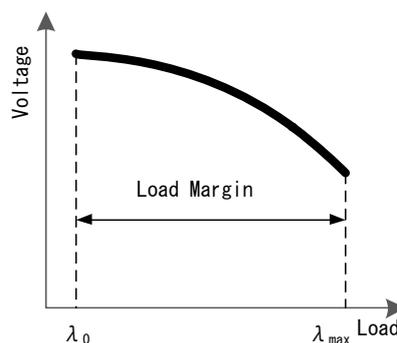


Figure 1. Load Margin Assessment

The load margin is determined by an increment of load at 0.05 or 5% repeatedly from the overall load. In the approach, minimum voltage, V_{min} has been set at 0.85V as the cutoff point for the voltage limit and the system is assumed to operate in stress situation when reaching this value [14]. The flowchart as in Figure 2 is presented the calculation of objective function MLP.

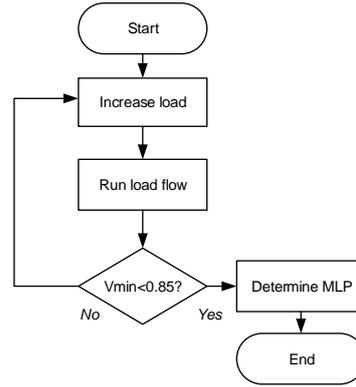


Figure 2. Flow Chart to get MLP

2.2. Minimizing total system losses objective Function

The objective function for total loss minimization is given by equation (1).

$$\min f_Q = \sum_{k \in N_G} P_{kLoss},(v, \theta) = \sum_{\substack{k \in N_G \\ k=(i,j)}} g_k (V_i^2 + V_j^2 - 2V_i V_j \cos \theta_{ij}) \text{ MW} \tag{1}$$

$$V_{i_{min}} \leq V_i \leq V_{i_{max}} \quad i \in N_B$$

$$Q_{Gi_{min}} \leq Q_{Gi} \leq Q_{Gi_{Max}} \quad i \in \{N_{PV}, n_s\}$$

where, Q_i and Q_j are reactive power at sending and receiving buses respectively, Q_{Gi} is generated reactive power of bus i , V_i and V_j are voltage magnitude at sending and receiving buses respectively. P_{kLoss} , is total active power loss over the network, N_B is load bus, N_{PV} is voltage controlled bus and n_s is reference (slack) bus.

2.3. The weighted sum method

The approach that used to formulate two or more objective functions and represents into one general mathematical formula as described in equation (2).

$$F_T = \sum_{i=1}^k (\alpha_i \times f_{mi}) \tag{2}$$

where $\sum_{i=1}^k \alpha_i = 1$ and $f_{ni} = \frac{\max(f_i) - f_i}{\max(f_i) - \min(f_i)}$ k is numbers of objective function, α_i is weighting factor for i^{th} objective function and f_{ni} is normalised value for i^{th} objective function.

3. METHODOLOGY

3.1. Bacterial Foraging Optimization Algorithm

Bacterial Foraging Optimization (BFO) algorithm is motivated through the foraging activities of the Escherichia coli (E.coli) bacteria. The details on the biological aspects, regarding to their hunting strategies, considered their motile behavior for decision-making mechanism, is explained in [15]. Several process of E. coli foraging that are present in our intestines are called chemotaxis, swarming, reproduction and elimination and dispersal [16].

3.2. New Adaptive Tumbling Bacterial Foraging Optimization Algorithm

Using the E.coli foraging strategy as in BFO, the global searching space is improved by modifying the tumbling approach by adapting the mutation technique applied in Meta-EP into tumbling expression implemented in basic BFO thus represented by new equation (3) to (5) in ATBFO algorithm. The important steps describe through the process flow of Adaptive Tumbling Bacterial Foraging Optimization (ATBFO) algorithm in Figure 3.

$$\theta^i(j + 1, k, l) = \theta^i(j, k, l) + C(i)\emptyset(i) \tag{3}$$

Hence $\phi(i) = \frac{\Delta(i)}{\sqrt{\Delta^T(i)\Delta(i)}}$, where $\Delta(i)$ = random vector for each bacterium, $\Delta^T(i)$ = transpose of random vector for each bacterium. Then, mutate the new position of $Jlast$ by using given by equation (3).

$$\phi'i(j) = \phi(j) \exp \tau'N(0,1) + \tau Ni(0,1) \tag{4}$$

$$P'i(j) = Pi(j) + \phi'i(j)Nj(0,1) \tag{5}$$

where $\tau = \sqrt{\frac{1}{2n}}$, $\tau' = \frac{1}{\sqrt{2n}}$, $P'i(j), Pi(j), \phi'i(j)$ and $\phi(j)$ is a i^{th} component of respective vector. $Ni(0,1)$ is normally distributed one dimensional random number with mean 0 and 1. $Nj(0,1)$ Indicates the random number will be new for each value of j .

3.3. New MOATBFO algorithm for the multi-objective function for SCRPP optimization solution

A new MOATBFO algorithm was developed with multi-objective function in solving the SCRPP problems in power system. The multi-objective functions would minimize the total system losses and maximize the MLP at the same time. The related objective functions were combined and formulated into a single objective function via the weighted sum method as in equation (2) before implemented into MOATBFO algorithm.

The solution search for optimal sizes of control variables which was classified into a group of X_{mer} , Q_{inj} , Q_{gs} & Q_{inj} , Q_{gs} & X_{mer} , Q_{inj} & X_{mer} or Q_{inj} , Q_{gs} & X_{mer} as RPP technique respectively. The MOATBFO implementation was conducted on IEEE - 57 bus system under unstressed and stressed conditions at identified Case 1 and Case 2 as illustrated in Figure 3.

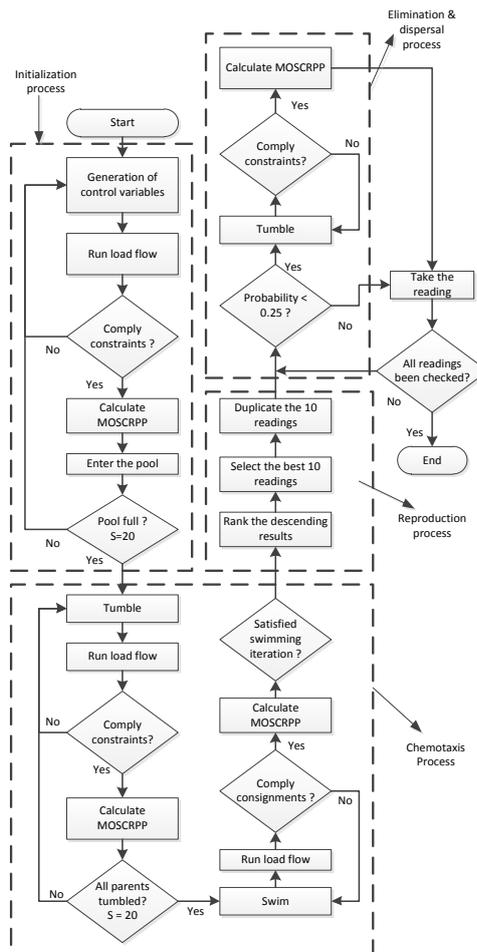


Figure 3. The Flowchart of MOATBFO Process for MOSCRPP for Case 1 and Case 2 During Unstressed and Stressed Condition

4. RESULT AND DISCUSSION

4.1. Result for multi-objective of SCRPP

Initially, the increase in the MLP before and after the implementation of multi objective SCRPP on the critical bus during Case 1 and overall load busses in Case 2 are discussed here. Firstly, the comparison between pre-SCRPP with post-SCRPP is analyzed through the two identified points called as Point A and B respectively as in Figure 4 for both unstressed and stressed condition. As referred to the graph, Point A indicates the MLP before the implementation of SCRPP. On the other hand, Point B indicates the MLP after the implementation of SCRPP. The difference between Point A and Point B is identified as MLP enhancement. The voltage profile and total system losses were also recorded for different RPP technique with different objective function.

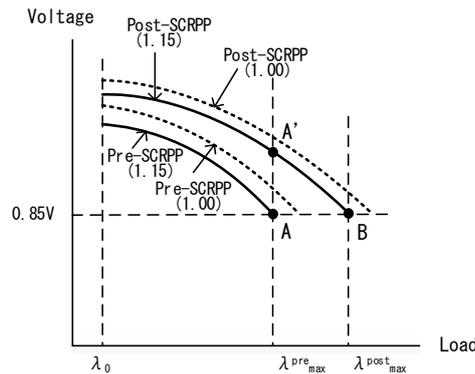


Figure 4. Graph to Depict the Point A (before the implementation of SCRPP) and Point B (after the implementation of SCRPP)

This section details on study of multi-objective function, MOSCRPP. The findings concluded that the best suitable optimization solution performed by RPP+TTCS+CP technique that have been simplified Table 1 below, during Case 1 (load increment at critical bus).

Table 1. Results of MOSCRPP at Point A' in Case 1

MOSCRPP for Case 1 using (RPD+TTCS+CP) technique			
Types of load increment	Objective function	MOSCRPP Minimum Voltage, (p.u)	MOSCRPP Losses (MW)
		P load - unstressed condition	0.946
	P load - stressed condition	0.955	30.7151
	Q load - unstressed condition	0.971	27.9527
	Q load - stressed condition	0.955	27.8475
	Q & P load - unstressed condition	0.954	29.2781
	Q & P load - stressed condition	0.944	29.1790

Overall, MOSCRPP shows that the enhancement in voltage profile. On the other hand, MOSCRPP approach resulted in the lowest total losses minimization. While, the following Table 2 shows the results of MOSCRPP for Case 2 (load increment at all load busses) under unstressed and stressed conditions.

Table 2. Results of MOSCRPP at Point A' in Case 2

MOSCRPP for Case 2 using (RPD+TTCS+CP) technique			
Types of load increment	Objective function	MOSCRPP Minimum Voltage, (p.u)	MOSCRPP Losses (MW)
		P load - unstressed condition	0.907
	P load - stressed condition	0.917	66.4184
	Q load - unstressed condition	0.925	29.1839
	Q load - stressed condition	0.921	29.0200
	Q & P load - unstressed condition	0.911	47.9662
	Q & P load - stressed condition	0.911	46.1958

4.2. Comparison among others optimization techniques

The solutions for multi-objective solutions from MOATBFO were also compared with that obtained from MOBFO and MOMeta-EP in order to identify the best solutions for MOSCRPP as simplified in Table 3.

Table 3. Comparison between MOTBFO and others optimization techniques for MOSCRPP

Optimization techniques		RPP technique - (RPD+TTCS+CP)							
		Point B (Post-optimization)				Point A' (Post-optimization)			
		Vmin (p.u)	Vmax (p.u)	Losses (MW)	MLP (%)	Vmin (p.u)	Vmax (p.u)	Losses (MW)	MLP (%)
		Case1							
P load - unstressed	MOATBFO	0.846	1.081	41.900	600	0.946	1.089	31.194	325
	MOBFO	0.849	1.065	37.558	500	0.913	1.065	31.858	325
	MOMeta-EP	0.848	1.054	37.822	540	0.923	1.056	31.684	325
P load -stressed	MOATBFO	0.847	1.073	39.761	535	0.955	1.080	30.715	285
	MOBFO	0.846	1.075	35.910	410	0.880	1.072	31.827	285
	MOMeta-EP	0.847	1.073	38.452	480	0.920	1.051	31.860	285
Q load- unstressed	MOATBFO	0.853	1.072	31.421	865	0.971	1.097	27.953	350
	MOBFO	0.850	1.057	31.330	725	0.895	1.060	29.041	350
	MOMeta-EP	0.849	1.064	30.060	630	0.917	1.060	28.679	350
Q load -stressed	MOATBFO	0.852	1.085	30.901	710	0.955	1.086	27.848	305
	MOBFO	0.848	1.083	29.694	555	0.914	1.080	28.124	305
	MOMeta-EP	0.848	1.082	30.567	595	0.929	1.056	28.667	305
Q&P load-unstressed	MOATBFO	0.846	1.082	36.297	455	0.948	1.099	29.558	225
	MOBFO	0.854	1.081	33.561	355	0.918	1.077	29.992	225
	MOMeta-EP	0.850	1.086	33.990	385	0.934	1.074	29.749	225
Q&P load -stressed	MOATBFO	0.849	1.089	34.280	360	0.944	1.100	29.179	195
	MOBFO	0.854	1.089	33.657	320	0.928	1.086	29.790	195
	MOMeta-EP	0.845	1.099	34.434	340	0.940	1.071	29.812	195
		Case2							
P load-unstressed	MOATBFO	0.844	1.068	135.127	220	0.907	1.086	70.399	165
	MOBFO	0.849	1.047	81.887	175	0.854	1.047	72.532	165
	MOMeta-EP	0.845	1.043	122.524	210	0.896	1.053	71.393	165
P load -stressed	MOATBFO	0.851	1.086	132.656	190	0.917	1.093	66.418	140
	MOBFO	0.852	1.059	57.172	125	0.851	1.062	69.586	140
	MOMeta-EP	0.844	1.076	126.219	185	0.906	1.060	67.605	140
Q load-unstressed	MOATBFO	0.846	1.059	34.231	250	0.925	1.067	29.184	160
	MOBFO	0.845	1.044	32.452	210	0.842	1.052	30.597	160
	MOMeta-EP	0.842	1.060	33.552	230	0.912	1.055	29.983	160
Q load -stressed	MOATBFO	0.848	1.065	33.527	210	0.921	1.077	29.020	140
	MOBFO	0.851	1.057	32.220	175	0.875	1.058	30.795	140
	MOMeta-EP	0.849	1.060	34.367	200	0.904	1.055	30.481	140
Q&P load-unstressed	MOATBFO	0.842	1.073	84.551	175	0.911	1.097	47.966	135
	MOBFO	0.844	1.064	70.319	160	0.883	1.064	49.084	135
	MOMeta-EP	0.842	1.067	69.672	160	0.888	1.066	48.479	135
Q&P load -stressed	MOATBFO	0.839	1.056	82.702	150	0.911	1.068	46.196	115
	MOBFO	0.831	1.056	67.229	135	0.869	1.043	47.987	115
	MOMeta-EP	0.841	1.063	82.666	145	0.912	1.066	46.428	115

In Table 4, the performance of each optimization technique is ranked and value 1 is given to the best result, while value 3 is given to the worst. The least total aggregate indicates the best performance overall. Results in Table 4 shows that MOATBFO always resulted in the best overall performance. This conclusion is summarized in Table 5. Therefore, the outstanding optimization computational tool is recorded by the new MOATBFO, followed by MOMeta-EP and finally the original MOBFO algorithm. As a conclusion, the MOATBFO technique provided the best results in solving multi-objective SCRPP problem or MOSCRPP.

Table 4. Comparison between MOATBFO and others optimization techniques for MOSCRPP using aggregate performance

Optimization techniques	Aggregate Function			Total Aggregates	
	Point A'		Point B		
	Vmin	Losses	MLP		
Case1					
P load - unstressed	MOATBFO	1.0	1.0	1.0	3.0
	MOBFO	3.0	3.0	3.0	9.0
	MOMeta-EP	2.0	2.0	2.0	6.0
P load -stressed	MOATBFO	1.0	1.0	1.0	3.0
	MOBFO	3.0	2.0	3.0	8.0
	MOMeta-EP	2.0	3.0	2.0	7.0
Q load- unstressed	MOATBFO	1.0	1.0	1.0	3.0
	MOBFO	3.0	3.0	2.0	8.0
	MOMeta-EP	2.0	2.0	3.0	7.0
Q load -stressed	MOATBFO	1.0	1.0	1.0	3.0
	MOBFO	3.0	2.0	3.0	8.0
	MOMeta-EP	2.0	3.0	2.0	7.0
Q&P load-unstressed	MOATBFO	1.0	1.0	1.0	3.0
	MOBFO	3.0	3.0	3.0	9.0
	MOMeta-EP	2.0	2.0	2.0	6.0
Q&P load -stressed	MOATBFO	1.0	1.0	1.0	3.0
	MOBFO	3.0	2.0	3.0	8.0
	MOMeta-EP	2.0	3.0	2.0	7.0
Case2					
P load-unstressed	MOATBFO	1.0	1.0	1.0	3.0
	MOBFO	3.0	3.0	3.0	9.0
	MOMeta-EP	2.0	2.0	2.0	6.0
P load -stressed	MOATBFO	1.0	1.0	1.0	3.0
	MOBFO	3.0	3.0	3.0	9.0
	MOMeta-EP	2.0	2.0	2.0	6.0
Q load-unstressed	MOATBFO	1.0	1.0	1.0	3.0
	MOBFO	3.0	3.0	3.0	9.0
	MOMeta-EP	2.0	2.0	2.0	6.0
Q load -stressed	MOATBFO	1.0	1.0	1.0	3.0
	MOBFO	3.0	3.0	3.0	9.0
	MOMeta-EP	2.0	2.0	2.0	6.0
Q&P load-unstressed	MOATBFO	1.0	1.0	1.0	3.0
	MOBFO	3.0	3.0	3.0	9.0
	MOMeta-EP	2.0	2.0	2.0	6.0
Q&P load -stressed	MOATBFO	2.0	1.0	1.0	4.0
	MOBFO	3.0	3.0	3.0	9.0
	MOMeta-EP	1.0	2.0	2.0	5.0

Table 5. Comparison between MOATBFO and others optimization techniques for MOSCRPP for overall performance

Optimization Techniques	MOATBFO	MOBFO	MOMetaEP
Case1			
P load - unstressed	3.0	9.0	6.0
P load -stressed	3.0	8.0	7.0
Q load- unstressed	3.0	8.0	7.0
Q load -stressed	3.0	8.0	7.0
Q&P load-unstressed	3.0	9.0	6.0
Q&P load -stressed	3.0	8.0	7.0
Case2			
P load - unstressed	3.0	9.0	6.0
P load -stressed	3.0	9.0	6.0
Q load- unstressed	3.0	9.0	6.0
Q load -stressed	3.0	9.0	6.0
Q&P load-unstressed	3.0	9.0	6.0
Q&P load -stressed	4.0	9.0	5.0
Overall Aggregates	37.0	104.0	75.0

5. CONCLUSION

Mainly the multi objective SCRPP aiming to maximize the MLP so that the number of voltage collapse events could be reduced. Hence, the study conducted for P, Q and P & Q load increases, while two cases MLP at the critical bus (case 1) and MLP for all load buses simultaneously (case 2) were analyzed. Several significant objective functions were developed and implemented in the MOATBFO optimization technique in order to overcome the problems in solving the SCRPP problems. Individual objective functions

namely, total losses minimization and MLP improvement were combined to form the multi-objective function using the weighted sum method. Besides, all identified RPP approaches were studied and it was found that optimizing RPD, CP and TTCS simultaneously obtained the best results. Thus, MOATBFO was utilized in MOSCRPP in order to optimize the RPD, CP and TTCS simultaneously so that the optimal results would be provided. The performance of MOATBFO was compared with that of MOBFO and MOMeta-EP. Throughout the analysis, the MOATBFO shows the best achievement in terms of MLP improvement, minimum voltage improvement as well in total losses minimization.

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