Maximum Loadability Enhancement with a Hybrid Optimization Method

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ABSTRACT

Nowadays, a power system is operating in a stressed condition due to the increase in demand in addition to constraint in building new power plants. The economics and environmental constraints to build new power plants and transmission lines have led the system to operate very close to its stability limits. Hence, more researches are required to study the important requirements to maintain stable voltage condition and hence develop new techniques in order to address the voltage stability problem. As an action, most Reactive Power Planning (RPP) objective is to minimize the cost of new reactive resources while satisfying the voltage stability constraints and labeled as Secured Reactive Power Planning (SCRPP). The new alternative optimization technique called Adaptive Tumbling Bacterial Foraging (ATBFO) was introduced to solve the RPP problems in the IEEE 57 bus system. The comparison common optimization Meta-Heuristic Evolutionary Programming and original Bacterial Foraging techniques were chosen to verify the performance using the proposed ATBFO method. As a result, the ATBFO method is confirmed as the best suitable solution in solving the identified RPP objective functions.

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1. INTRODUCTION

Many countries have reported that millions of dollars were lost due to voltage collapse incidents. Failure to progress above the specific voltage magnitude leads to voltage collapse [1]. In other words, voltage collapse is due to voltage instability that refers to the inability of a power system to keep the steady state voltages at all buses [2]. Besides that, failure in congestion management may results in blackout of the whole or parts of power system. This situation is verified by a report which stated that an outage of a 345kV transmission line has caused blackout in Canada and U.S in August 2003 because the system is unable to sustain the additional load [3]. Therefore, efficient RPP planning would be able to avoid the occurrence of voltage collapse. Several objective functions were implemented in SCRPP in order to improve the voltage stability condition of a power system such as minimizing voltage deviation from specified operating points and maximizing static stability margin (SM) [4].

In order to obtain optimal solution to SCRPP, the efficient and reliable optimization technique has become necessary. These advanced and efficient solutions are able to overcome the weakness of the existing classical methods which are not capable to solve non convex, non-continuous and highly nonlinear solution such as in SCRPP problems [5]. Thus, today meta-heuristic optimization approaches such as Particle Swarming Optimization (PSO), Evolutionary Programming (EP), Genetic Algorithm (GA) and Bacterial Foraging Algorithm (BFA) with advanced search techniques make the problems possible to be solved. These techniques offered global optimal solutions, however, at the expense of computational time [6]. Therefore, recent researches are inspired to merge conventional methods and advanced optimization techniques for better and faster optimization approaches.

This study intended to introduce 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 to solve the single objective SCRPP problems. Finally, the performances of the newly developed technique ATBFO were compared with that provided by the EP and the basic BFO. The best solutions were identified based on the smallest total system losses and maximum loading point that the system can withstand. In addition, the aggregate function method was applied to confirm the outperformed method among them. The lowest total aggregate value is declared as the excellent approach for the SCRRP problem.

2. SECURED REACTIVE POWER PLANNING

RPP is also known as VAR planning in which reactive power sources are managed and planned optimally [7]. Reactive power can either inductive or capacitive in nature [8]. RPP is normally solved by using optimization methods. Various factors and objectives are taken into account in solving RPP in order to ensure for optimal power flow solution. The main objective of RPP is normally minimization of cost functions such as variable VAR cost, fixed VAR cost, real power losses and also fuel cost [9]. The authors in this reference also have explained on the deviation of the operating voltage from a specified voltage schedule and hence utilized Voltage Stability Margin (VSM). In Secured Reactive Power Planning (SCRPP), voltage stability criteria are normally treated as the constraints. Therefore, the importance of Load Margin (LM) assessment is used as a tool to indicate the maximum loading point in order to provide secure operating margin in power system operation.

2.1. Load Margin Assessment

Load Margin (LM) is broadly accepted in analyzing the closeness of the operating condition of a power system to its voltage collapse. The LM is defined as the quantity of load increment allowable before a power system reaches the unsecure voltage condition. The load margin was determined by gradually increase the load until the load flow failed to give solution.

The relationship between reactive power reserve and Voltage Stability Margin (VSM) was investigated by researchers in reference [10]. The authors in [11] proposed for re-dispatch of reactive power in order to improve the voltage stability condition of the power system. However, the total active power losses were not measured because they believed that the solution is not the optimum one. For that reason, many researchers have given attention to enhance voltage stability condition by sustaining the reactive power in a power system [12].

The important steps for load margin estimation that involved the load margin analysis and enhancement were discussed. Thus, load margin assessment can be classified into two categories in which the first is to forecast the MLP while the second one is to enhance the voltage stability margin for better stability condition.

2.2. Objective Functions for SCRPP

The consideration to be an objective function based on Maximum Loadability Point (MLP) improvement for all load busses in solving SCRPP and also at the improvement of MLP at the critical bus [13].

2.2.1. Maximizing MLP

MLP for a power networks is the maximum amount of load that could be sustained before it reached the unstable operating point. As referred to references [14], the LM or also called as VSM could be defined as the distance from the base case, λ_0 load to the maximum loading limit, λ_{max} prior to its imbalance point as shown in Figure 1. During the assessment, the weakest bus among the network and maximum load that it can sustain can also be determined. The bus with the smallest margin is identified as the weak or critical bus. This figure also illustrates the comparison between the MLP before optimizing the reactive power sources through RPP i.e point A and the MLP after the reactive sources are optimized i.e point B.



Figure 1. The comparison graph between pre and post SCRPP implementation

2.2.2. Minimizing Total System Losses

The objective function for total loss minimization is given by Equation 1.

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

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

$$Q_{Gi_{min}} \leq Q_{Gi} \leq Q_{Gi_{Max}} i \in \{N_{PV}, n_s\}$$
(1)

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.

2.2.3. The Important Control Variables

The control variables considered are capacitor or reactor switching transformer tap changing [15] and active power of generator, to facilitate the requirement of SCRPP.

3. METHODOLOGY

3.1. New Adaptive Bacterial Foraging Optimization (ATBFO) Algorithm

This recent Bacterial Foraging Optimization (BFO) searching algorithm invented by K.M. Passino, is supported by the fact that natural selection tends to eliminate animals with poor foraging strategies against those with attractive foraging [16]. These poor hunters will be either eliminated or sometimes reshaped to good ones through a repeated generation process. Several processes of E. coli foraging that are present in our intestines are called chemotaxis, swarming, reproduction and elimination and dispersal [17]. 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 2 to 4 in ATBFO algorithm.

$$\theta^{i}(j+1,k,l) = \theta^{i}(j,k,l) + C(i)\emptyset(i)$$
⁽²⁾

Hence: $\emptyset(i) = \frac{\Delta(i)}{\sqrt{\Delta^T(i)\Delta(i)}}$, 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 2.

$$\phi' i(j) = \phi(j) \exp \tau' N(0,1) + \tau N i(0,1)$$
(3)

$$P'i(j) = Pi(j) + \emptyset'i(j)Nj(0,1)$$
(4)

where $\tau = \sqrt{\frac{1}{\sqrt{2n}}}$, $\tau' = \frac{1}{\sqrt{2n}}$, P'i(j), Pi(j), $\emptyset'i(j)$ and $\emptyset(j)$ 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*.

3.2. A New ATBFO Algorithm for Single Objective Function SCRPP

An intelligence heuristic technique named as ATBFO algorithm was implemented as an optimization mechanism for solving SCRPP problems with single objective solution. This single objective is either to maximize the Maximum Loadability Point (MLP) or minimize system losses while satisfying the operational constraints. The corresponding objective function is calculated while the value of the other is observed. The simulations were tested under tested on the IEEE 57 bus system for unstressed and stressed conditions as illustrated in Figure 2. The task also covered all possibilities of load increments as following:

- a. Reactive load increment or Q increment
- b. Real load increment or P increment and
- c. Reactive and Real load increment or Q and P load increased simultaneously.

In addition, the ATBFO method was also executed on identified critical load bus growth called as Case 1. While, in Case 2 was when the load at all busses were increased simultaneously. During the implementation, different sizes of control variables were determined, such as Reactive Power Dispatch (RPD) Q_{gs} , Capacitor Placement (CP), Q_{inj} and Transformer Tap Change Setting (TTCS), X_{mer} . The solution in searching for optimal sizes of control variables were also categories into different group of RPP techniques such as X_{mer} , Q_{inj} , $Q_{gs} \& X_{mer}$, $Q_{inj} \& X_{mer}$, $Q_{inj} \& X_{mer}$ or Q_{inj} , $Q_{gs} \& X_{mer}$ as RPP technique respectively as referred in [32, 33]. The overall implementations of the structure covered throughout the contribution were explained in depth by the subsequent Figure 2.



Figure 2. Flowchart of ATBFO process for SCRPP for stressed and unstressed condition

The proposed ATBFO was tested on the IEEE 57 bus system for each Single Objective SCRPP functions as the following:

- a. SOSCRPP1=maximum MLP
- b. SOSCRPP2=minimum total losses

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The similar optimization process using this ATBFO method which to minimize the total system losses SOSCRPP2 solutions were also obtained from Case 1 and Case 2 i.e during unstressed and stressed situations.

3.3. Aggregate Function Method

The aggregate function is introduced in this study as an alternative to describe the results obtained from optimization methods to meaningful evaluation and conclusion. From the results obtained, the least answers bring the smallest aggregate value among others objective functions and vice versa. At the end, the total aggregates are calculated and the smallest sum value as the finest solution.

4. RESULTS AND DISCUSSION

This section discusses the comparison between two individual objective functions namely SOSCRPP1 and SOSCRPP2 which are to maximize the MLP and to minimize the total losses. Table 1 shows the improved voltages and their corresponding losses after the implementation SCRPP by optimizing RPD+TTCS+CP using ATBFO (Point A'). Similarly, the less total loss was determined from SOSCRPP1 as compared to SOSCRPP2 at the same Point A'. Initially, the Pre-SCRPP (Point A) has 0.849V (Vmin), 30.4575MW (Losses) and 195% (MLP).

Table 1. Comparison between SOSCRPP1 and SOSCRPP2 at Point A' (After the Implementation of SCRPP) for Case 1

	Single objective of SCRPP for Case 1 using (RPD+TTCS+CP) technique at Point A'						
Ħ	Objective function	SOSCRPP 1	SOSCRPP 2	SOSCRPP 1	SOSCRPP 2		
nei		Minimum	Minimum	Losses	Losses		
crei		Voltage, (p.u)	Voltage, (p.u)	(MW)	(MW)		
.ii	P load-unstressed condition	0.957	0.877	31.2383	31.9231		
ad	P load-stressed condition	0.940	0.912	30.9819	31.8038		
flc	Q load-unstressed condition	0.971	0.866	28.2897	28.6808		
so	Q load-stressed condition	0.973	0.942	27.9983	27.9994		
ype	Q & P load-unstressed condition	0.948	0.885	29.5578	30.1719		
Ĥ.	Q & P load-stressed condition	0.951	0.885	29.2530	30.1169		

Table 1 highlights that SOSCRPP 1 resulted in the highest minimum voltage improvement for all types of load increments at the critical load bus 31. The SOSCRPP1 is solved through the improved ATBFO which optimized the RPD+RPP+CP with minimizing total losses and maximizing MLP as objective functions.

While in case 2, the results obtained from SOSCRPP1 (objective function: maximizing MLP) and SOSCRPP2 (objective function: minimizing total losses) for P load, Q load and Q with P load increments during the unstressed and stressed situations are compared as shown in Table 2. The table also tabulates the minimum voltages after of the implementation of SCRPP.

Table 2. Comparison between SOSCRPP1 and SOSCRPP2 at Point A' (post optimization)fc	r Case 2
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	Single objective of SCRP	P for Case 2 usin	g (RPD+TTCS+C	CP) technique	
ent	Objective function	SOSCRPP1	SOSCRPP2	SOSCRPP1	SOSCRPP2
ů.		Minimum	Minimum	Losses	Losses
ICLE		Voltage, (p.u)	Voltage, (p.u)	(MW)	(MW)
1 in	P load-unstressed condition	0.931	0.906	70.6513	71.6664
oat	P load-stressed condition	0.935	0.898	66.4320	67.7000
ofl	Q load-unstressed condition	0.932	0.919	29.3769	29.7674
es	Q load-stressed condition	0.924	0.913	29.9849	29.7363
q	Q & P load-unstressed condition	0.925	0.899	48.2148	48.5307
	Q & P load-stressed condition	0.939	0.887	46.4769	46.6924

The results gained from SOSCRPP1 show higher minimum voltage as compared to that obtained by SOSCRPP2. In addition, SOSCRPP 1 also leads to lower total losses. Hence, SOSCRPP1 is better in performance as compared to SOSCRPP2 for Case 1 and Case 2.

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4.1. Comparison of Single Objective Function in SCRPP among Optimization Techniques

The single objective results for maximizing MLP obtained by ATBFO were compared with those obtained from the original BFO and Meta-EP approaches. Thus, Table 3 highlights the comparison of the results obtained after solving SCRPP using the above approaches i.e at Point A' and Point B.

Aggregate function was introduced in the comparative study in order to identify the technique which gives the best optimization performance as in Table 4. At Point A', the observed performances are the minimum voltage improvement and total losses minimization. While at point B, MLP enhancement is observed.

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. From this table, it shows that ATBFO always resulted in the best overall performance. Hence, it can be concluded that ATBFO outperformed the other two optimization technique. This conclusion is summarized in Table 5.

Therefore, the outstanding optimization computational tool is recorded by the new ATBFO, followed by Meta-EP and finally the original BFO algorithm.

Table 3. Comparison between ATBFO and Others Optimization Techniques for SOSCRP	'P1
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RPP technique -(RPD+TTCS+CP)									
		Point B (Post-optimization) Point A' (Post-optimization			imization)				
	Optimization	Vmin	Vmax	Losses	MLP	Vmin	Vmax	Losses	MLP
	techniques	(p.u)	(p.u)	(MW)	(%)	(p.u)	(p.u)	(MW)	(%)
				Case1					
Dlast	ATBFO	0.855	1.064	43.439	705	0.957	1.092	31.238	325
P load -	BFO	0.847	1.067	41.241	600	0.916	1.067	32.409	325
unstressed	Meta-EP	0.847	1.066	41.278	635	0.929	1.077	31.387	325
D1 1	ATBFO	0.852	1.096	41.550	570	0.940	1.100	30.982	285
P load -	BFO	0.855	1.076	38.865	495	0.917	1.073	31.685	285
stressed	Meta-EP	0.846	1.071	40.250	535	0.937	1.071	31.237	285
0.11	ATBFO	0.853	1.075	32.362	905	0.971	1.099	28.290	350
Q load-	BFO	0.850	1.051	31.083	765	0.925	1.067	28.423	350
unstressed	Meta-EP	0.849	1.075	30.893	795	0.959	1.074	27.977	350
01 1	ATBFO	0.850	1.086	31.615	765	0.973	1.100	27.998	305
Q load -	BFO	0.848	1.069	30.768	655	0.958	1.077	28.335	305
stressed	Meta-EP	0.849	1.098	31.285	655	0.946	1.070	28.628	305
0001 1	ATBFO	0.846	1.082	36.297	455	0.948	1.099	29.558	225
Q&P load-	BFO	0.850	1.065	35.737	425	0.940	1.070	29.961	225
unstressed	Meta-EP	0.846	1.075	34.493	405	0.947	1.053	29.566	225
0001 1	ATBFO	0.856	1.091	35.755	390	0.951	1.095	29.253	195
Q&P load -	BFO	0.844	1.046	34.510	335	0.909	1.048	30.010	195
stressed	Meta-EP	0.843	1.069	35.346	365	0.938	1.068	29.769	195
				Case2					
Dlast	ATBFO	0.843	1.074	159.430	235	0.931	1.089	70.651	165
P load-	BFO	0.847	1.040	89.111	180	0.855	1.040	73.946	165
unstressed	Meta-EP	0.850	1.056	122.053	210	0.907	1.051	66.686	165
D1 1	ATBFO	0.840	1.066	159.298	205	0.935	1.097	66.432	140
P load -	BFO	0.844	1.040	80.660	150	0.846	1.040	69.740	140
stressed	Meta-EP	0.847	1.069	126.100	185	0.906	1.054	67.641	140
0.11	ATBFO	0.855	1.045	35.709	265	0.932	1.100	29.377	160
Q load-	BFO	0.843	1.040	33.404	205	0.881	1.040	31.287	160
unstressed	Meta-EP	0.844	1.040	36.000	260	0.924	1.058	29.728	160
0.11	ATBFO	0.858	1.040	35.020	245	0.924	1.053	29.985	140
Q load -	BFO	0.852	1.040	33.003	165	0.866	1.040	31.759	140
stressed	Meta-EP	0.840	1.040	35.945	215	0.913	1.043	30.498	140
0001 1	ATBFO	0.842	1.044	91.411	180	0.925	1.085	48.215	135
Q&P load-	BFO	0.848	1.040	67.629	155	0.878	1.040	50.383	135
unstressed	Meta-EP	0.844	1.049	80.010	170	0.905	1.060	48.383	135
0001 1	ATBFO	0.857	1.095	89.123	155	0.939	1.100	46.477	115
Q&P load -	BFO	0.841	1.040	63.136	130	0.867	1.040	48.992	115
stressed	Meta-EP	0.835	1.070	77.541	145	0.902	1.060	47.225	115

Aggragate Function							
	Aggregater	Point B					
	Optimization techniques	Vmin	Losses	MIP	Total Aggregates		
	Optimization teeninques	1	LUSSUS	WILA	Total Aggregates		
	ATREO	1	1.0	1.0	3.0		
D load unstrassed	BEO	3.0	3.0	3.0	9.0		
1 load-unstressed	Meta-EP	2.0	2.0	2.0	5.0 6.0		
	ATREO	1.0	1.0	1.0	3.0		
P load -stressed	BEO	3.0	3.0	3.0	9.0		
i ioud stressed	Meta-FP	2.0	2.0	2.0	6.0		
	ATBEO	1.0	2.0	1.0	4.0		
O load- unstressed	BEO	3.0	3.0	3.0	9.0		
Q loud unstressed	Meta-FP	2.0	1.0	2.0	5.0		
	ATBEO	1.0	1.0	1.0	3.0		
O load -stressed	BEO	2.0	2.0	2.0	6.0		
Q loud shessed	Meta-EP	3.0	3.0	3.0	9.0		
	ATBFO	1.0	2.0	1.0	4.0		
O&P load-unstressed	BFO	3.0	3.0	2.0	8.0		
C	Meta-EP	2.0	1.0	3.0	6.0		
	ATBFO	1.0	1.0	1.0	3.0		
O&P load -stressed	BFO	3.0	3.0	3.0	9.0		
(Meta-EP	2.0	2.0	2.0	6.0		
Case2							
	ATBFO	1.0	2.0	1.0	4.0		
P load-unstressed	BFO	3.0	3.0	3.0	9.0		
	Meta-EP	2.0	1.0	2.0	5.0		
	ATBFO	1.0	1.0	1.0	3.0		
P load -stressed	BFO	3.0	3.0	3.0	9.0		
	Meta-EP	2.0	2.0	2.0	6.0		
	ATBFO	1.0	1.0	1.0	3.0		
Q load-unstressed	BFO	3.0	3.0	3.0	9.0		
-	Meta-EP	2.0	2.0	2.0	6.0		
	ATBFO	1.0	1.0	1.0	3.0		
Q load -stressed	BFO	3.0	3.0	3.0	9.0		
-	Meta-EP	2.0	2.0	2.0	6.0		
	ATBFO	1.0	1.0	1.0	3.0		
Q&P load-unstressed	BFO	3.0	3.0	3.0	9.0		
	Meta-EP	2.0	2.0	2.0	6.0		
	ATBFO	1.0	1.0	1.0	3.0		
Q&P load -stressed	BFO	3.0	3.0	3.0	9.0		
	Meta-EP	2.0	2.0	2.0	6.0		

Table 4. Comparison between ATBFO and Others Optimization Techniques for SOSCRPP1 Using Aggregate Performance

Table 5. Comparison between ATBFO and Others Optimization Techniques for SOSCRPP1 for Overall Performance

renormance						
ATBFO	BFO	MetaEP				
Case1						
3.0	9.0	6.0				
3.0	9.0	6.0				
4.0	9.0	5.0				
3.0	6.0	9.0				
4.0	8.0	6.0				
3.0	9.0	6.0				
Case2						
4.0	9.0	5.0				
3.0	9.0	6.0				
3.0	9.0	6.0				
3.0	9.0	6.0				
3.0	9.0	6.0				
3.0	9.0	6.0				
39.0	104.0	73.0				
	ATBFO Case1 3.0 4.0 3.0 4.0 3.0 4.0 3.0 4.0 3.0 4.0 3.0 3.0 3.0 3.0 3.0 3.0 3.0 3.0 3.0 3.0 3.0 3.0 3.0 3.0 3.0 3.0	ATBFO BFO Case1 3.0 9.0 3.0 9.0 4.0 9.0 3.0 9.0 4.0 9.0 3.0 6.0 4.0 8.0 3.0 9.0 3.0 9.0 3.0 9.0 3.0 9.0 3.0 9.0 3.0 9.0 3.0 9.0 3.0 9.0 3.0 9.0 3.0 9.0 3.0 9.0 3.0 9.0 3.0 9.0 3.0 9.0 3.0 9.0 3.0 9.0 3.0 9.0 3.0 9.0 3.0 9.0 3.0 9.0 3.0 9.0 3.0 9.0				

5. CONCLUSION

The objective of SCRPP was to maximize the MLP. In other words, the system has the capability to support extra loads before going into the voltage instability point. Hence, the number of voltage collapse events could be reduced. The MLP considered in the study were P, Q and P & Q load increases, while two cases were analyzed, which were MLP at the critical bus (case 1) and MLP for all load buses simultaneously (case 2). Single objective functions namely, total losses minimization and MLP improvement were

implemented and analyzed in solving the SCRPP problems. Several RPP approaches were studied and it was found that optimizing RPD, CP and TTCS simultaneously gave the best results. Hence, ATBFO was utilized in SCRPP in order to optimize the RPD, CP and TTCS simultaneously so that the required optimal results would be obtained. The performance ATBFO was compared with that obtained by BFO and Meta-EP. Based on the analysis, it was found that ATBFO performed better in terms of MLP improvement, minimum voltage improvement and total losses minimization.

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