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Load margin expansion for sustainable power system operation

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Abstract

An efficient reactive power management is important in providing secured operation for a power system in terms of maintaining its stability condition. Lack of safe operating margin and reactive power support were known to cause a system to operate in an unstable voltage condition. Hence, voltage stability improvement must be planned properly so that the likeliness to instability event could be determined before the more severe event of blackout could occur in a system. For that reason, the application of the developed a new optimization technique namely Adaptive Tumbling Bacterial Foraging (ATBO) was to obtain the most possible optimal Reactive Power Planning (RPP) solution. The objective of RPP problem was not only to minimize the total power losses in a system but was also extended in terms of voltage stability and now termed as security constrained RPP (SCRPP). In order to ensure maximum benefit while ensuring secure operating condition and minimum impact to environment, the proposed ATBFO and Multi objective ATBFO (MOATBFO) were utilized to solve for the single and multi-objective for SCRPP issues. The performance of the proposed techniques were comprehensive analyzed between two other familiar optimization methods known as original Bacterial Foraging Optimization (BFO) algorithm and Meta heuristic Evolutionary Programming (Meta-EP) for standard IEEE 57 bus system. From the results it shows that the multi objective ATBFO optimization is able to give better overall improvement among all objective functions of SCRPP.

Keywords: RPP; SCRPP; ATBFO; MOATBFO

1. Introduction

Many countries have claimed that millions of dollars was lost due to voltage collapse events. The voltage instability may occur in a network if sufficient reactive power support is not given to the stressed busses [1]. Major countermeasures correspond to voltage stability control are categorized into preventive and corrective actions. The corrective methods involve adjustment of on load transformer tap change, capacitor switching, active and reactive power rescheduling and load shedding. While, the preventive control measures involve reactive power planning or centralized voltage and reactive energy control methods.

Large voltage stability margin could be obtained through shunt connected reactive power support and hence granting in higher system security. Various voltage stability analysis methods were explained in Ref. [2]. This reference organized those methods into two important categories as static and dynamic methods. It was proven that the load margin assessment is important to measure closeness to voltage collapse [3]. Most literature agreed that maximum loadability and VSM depend

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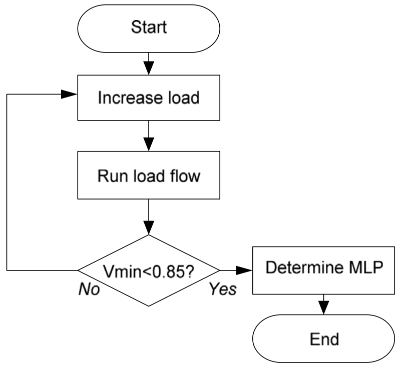

Fig. 1. Calculation of MLP.

on the solvability of load flow [4]. An approach called direct interior algorithm was discussed in Ref. [5] for determining maximum loadability of a power system. This algorithm is much faster than the conventional simplex method and suitable for enormous linear programming solution [6]. Subsequently, the Continuation Power Flow (CPF) was developed and used to identify load margin by calculating the solution path [7]. During dynamic analysis, a power system is represented by a set of algebraic differential equations and time domain simulation was performed [8]. Normally this technique needs extensive computation schemes. Therefore, Quasi Steady State (QSS) methods that integrated from static and dynamic approaches were introduced largely to speed up the computation [9]. Generally, the studies on and the computation of load margin are more concentrated on static voltage analysis as compared to dynamic conditions since it required less computational time with reliable solution [10]. Recently, the application of Artificial Intelligence (AI) techniques has been employed which aimed for faster searching results during load margin estimation [4,11]. Many research have been conducted in improving the load margin to meet the growing in load demand. Many published papers presented fuzzy set theory to determine the optimal operating point [12]. The author from Ref. [13] has introduced Genetic Algorithm (GA) to search for the active and reactive power dispatch in multi-objectives Economic Dispatch (ED) problem and utilized the fuzzy set theory decision making methodology in determining the fitness of the strings which represent the participating objectives. On the other hand, the researcher in Ref. [14] has recommended to use of EA to find the Pareto Optimal Solution. In this paper, the author has shown that the multiple Pareto Optimal solution can be found in a single run. The RPP optimization problem was finally solved using an enhanced simulated annealing (SA) optimization technique.

This research introduced newly optimization methods namely ATBFO and MOATBFO to solve the individual and multi objective SCRPP problems respectively. In order to verify the best performance method thus two other optimization methods called Meta-EP and original BFO were selected as the comparison methods. The improvement on overall multi objectives solution was found from MOATBFO hence declared as the excellent optimization for SCRPP solution.

2. Methodology

2.1. Objective functions

In order to solve for SCRPP, two significant objective functions were used such as load margin enhancement and real power losses.

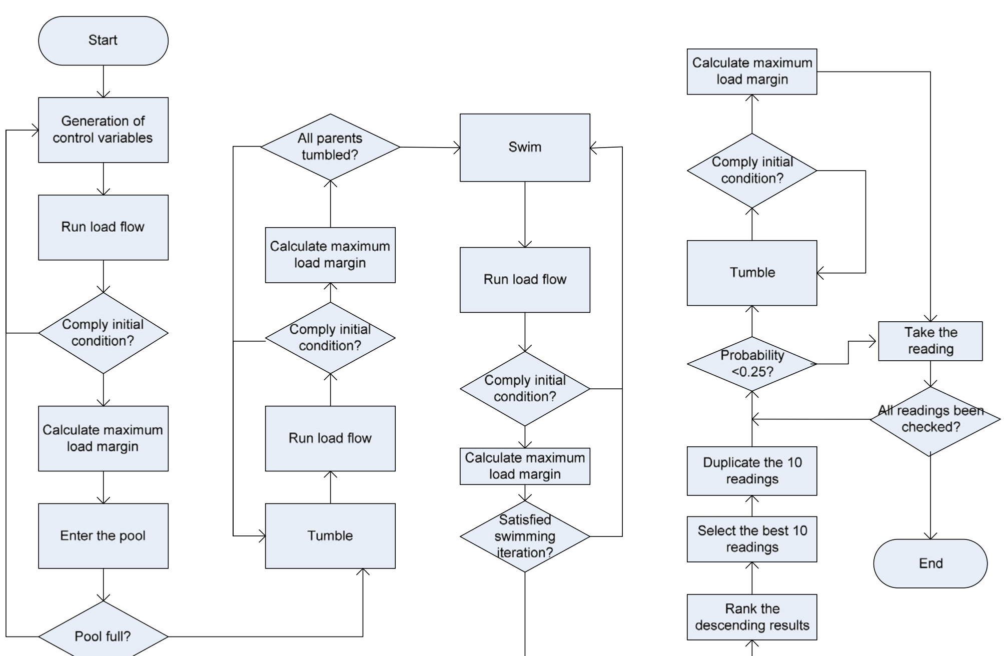

Fig. 2a. Flow chart of ATBFO for single objective SCRPP.

2.1.1. Load Margin Maximization

During maximum loadability limit evaluation, the load was increased until the occurrence voltage collapses that when the system begins to lose its equilibrium. The maximum load margin or Maximum Loadability Point (MLP) 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 0.85 V as the cutoff point for the voltage limit and the system is assumed to operate in stress situation when reaching this value. The flowchart as in Fig. 1 is presented the calculation of objective function MLP.

2.1.2. Real Power Losses Minimization

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

$$\min f_Q = \sum_{k\in N_G} P_{kLoss,}\,(v,\vartheta) = \sum_{\substack{k\in N_G\\ k=(i,j)}} g_k\left(V_i^2+V_j^2 - 2V_iV_j\cos\vartheta_{ij}\right) \tag{1}$$

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

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

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.

2.2. Weighted sum method

This study implemented both as single objective functions and combining them as a multi-objective function using the weighted sum approach as Eq. (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 number of objective function, α_i is weighting factor for ith objective function and f_{ni} is normalized value for ith objective function.

2.3. Adaptive tumbling bacterial foraging

The algorithm is motivated through the foraging activities of the Escherichia coli (E. coli) bacteria introduced by K.M. Passino. Several processes of E. coli foraging that are present in our intestines are called chemotaxis, swarming, reproduction and elimination and dispersal [15,16]. While, another popular numerical optimization solution namely Meta-Heuristic Evolutionary Programming (Meta-EP) was reported capable in obtaining the global optimum solution through the mutation strength strategy. For that reason, 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 equations (3) to (5) in ATBFO algorithm. The important steps describe the process flow of Adaptive Tumbling Bacterial Foraging Optimization (ATBFO) algorithm for single objective and multi objective SCRPP as in Figs. 2a and 2b respectively.

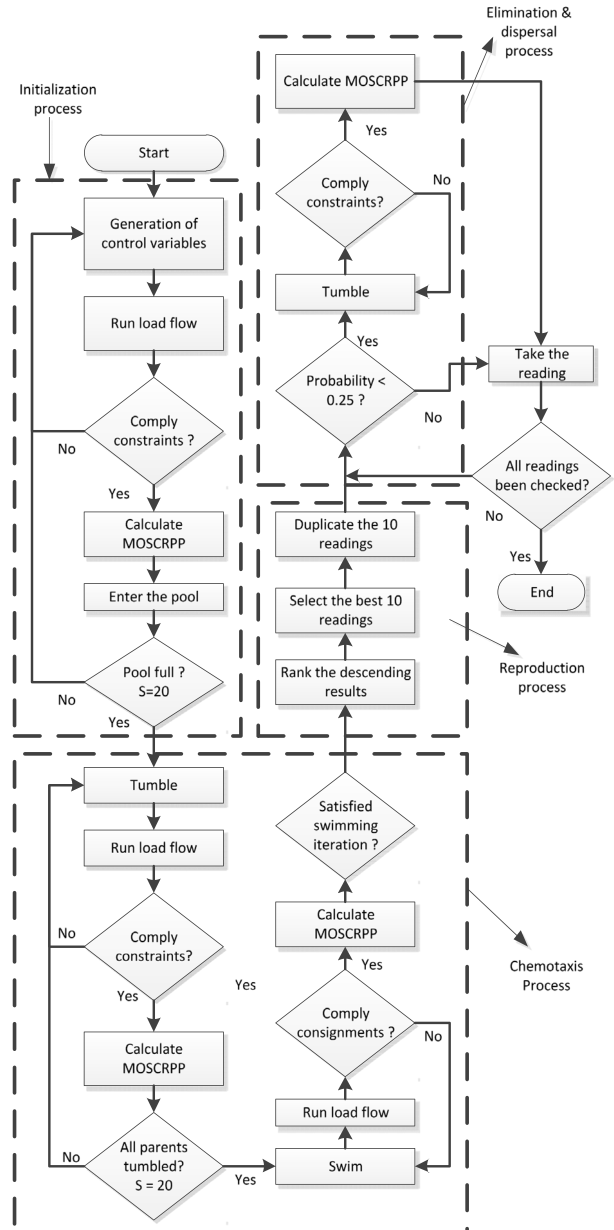

Fig. 2b. Flow chart of ATBFO for multi objective SCRPP.

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

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 Eq. (3).

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

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

Table 1
Comparison between SOSCRPP1 and MOSCRPP at Point A′ when all load busses increased.

SOSCRPP and MOSCRPP using (RPD + TTCS + CP) technique					
	Objective function	SOSCRPP1	MOSCRPP	SOSCRPP1	MOSCRPP
		Minimum Voltage (P.U)	Minimum Voltage (P.U)	Losses (MW)	Losses (MW)
Types of load increment	P load-unstressed	0.931	0.907	70.6513	70.3994
	P load-stressed	0.935	0.917	66.4320	66.4184
	Q load-unstressed	0.932	0.925	29.3769	29.1839
	Q load-stressed	0.924	0.921	29.9849	29.0200
	$Q\&P$ load-unstressed	0.925	0.911	48.2148	47.9662
	$Q\&P$ load-stressed	0.939	0.911	46.4769	46.1958

Table 2
Comparison between MOTBFO and others optimization techniques for MOSCRPP using RPP technique—(RPD + TTCS + CP).

	Optimization techniques	Point B (Post-optimization)			Point A′ (Post-optimization)			
		Vmin (P.U)	Losses (MW)	MLP (%)	Vmin (P.U)	Vmax (P.U)	Losses (MW)	MLP (%)
P load-unstressed	**MOATBFO**	**0.844**	**135.127**	**220**	**0.907**	**1.086**	**70.399**	**165**
	MOBFO	0.849	81.887	175	0.854	1.047	72.532	165
	MOMeta-EP	0.845	122.524	210	0.896	1.053	71.393	165
P load-stressed	**MOATBFO**	**0.851**	**132.656**	**190**	**0.917**	**1.093**	**66.418**	**140**
	MOBFO	0.852	57.172	125	0.851	1.062	69.586	140
	MOMeta-EP	0.844	126.219	185	0.906	1.060	67.605	140
Q load-unstressed	**MOATBFO**	**0.846**	**34.231**	**250**	**0.925**	**1.067**	**29.184**	**160**
	MOBFO	0.845	32.452	210	0.842	1.052	30.597	160
	MOMeta-EP	0.842	33.552	230	0.912	1.055	29.983	160
Q load-stressed	**MOATBFO**	**0.848**	**33.527**	**210**	**0.921**	**1.077**	**29.020**	**140**
	MOBFO	0.851	32.220	175	0.875	1.058	30.795	140
	MOMeta-EP	0.849	34.367	200	0.904	1.055	30.481	140
$Q\&P$ load-unstressed	**MOATBFO**	**0.842**	**84.551**	**175**	**0.911**	**1.097**	**47.966**	**135**
	MOBFO	0.844	70.319	160	0.883	1.064	49.084	135
	MOMeta-EP	0.842	69.672	160	0.888	1.066	48.479	135
$Q\&P$ load-stressed	**MOATBFO**	**0.839**	**82.702**	**150**	**0.911**	**1.068**	**46.196**	**115**
	MOBFO	1.067	67.229	135	0.869	1.043	47.987	115
	MOMeta-EP	0.841	82.666	145	0.912	1.066	46.428	115

where $\tau = \sqrt{\frac{1}{\sqrt{2n}}}$, $\tau' = \frac{1}{\sqrt{2n}}$, $P'i\,(j)$, $Pi\,(j)$, $\emptyset' i(j)$ and $\emptyset\,(j)$ is an ith 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. Result and discussion

3.1. Results for single and multi objective SCRPP

The simulations were tested under the IEEE 57 bus system when all load busses increased that covered all possibilities of load increments as following:

i. Reactive load increment or Q increment

ii. Real load increment or P increment and

iii. Reactive and Real load increments or Q and P load increased simultaneously.

for all load busses increment at all respective points i.e. Point A, Point A’ and Point B as in Fig. 3 during unstressed and stressed conditions.

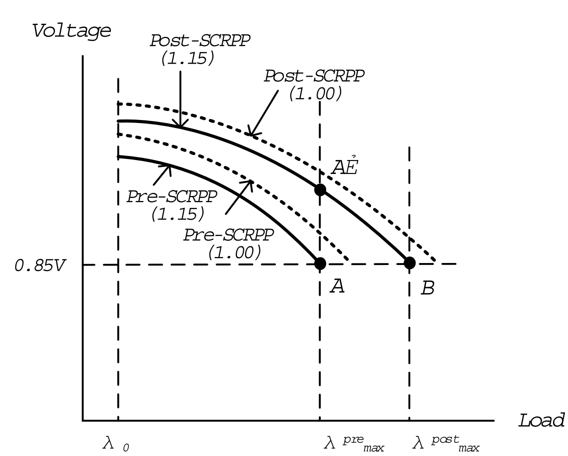

Fig. 3. The pre-SCRPP and post-SCRPP MLP.

Table 1 compares the results from SOSCRPP and MOSCRPP for all load busses increment. Although SOSCRPP

Table 3
Comparison between MOATBFO and others optimization techniques for MOSCRPP using aggregate performance.

	Optimization techniques	Aggregate function			
		Point A′	Point B		Total aggregates
		Vmin	Losses	MLP	
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 4
Comparison between ATBFO and others optimization techniques for MOSCRPP for overall performance.

Optimization techniques	MOATBFO	MOBFO	MOMetaEP
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

resulted in better minimum voltage improvement as compared to MOSCRPP, the considerations in determining the best performance overall must take into account the total losses minimization. Based on the lowest total losses, the solutions from optimizing RPD+TTCS+CP via MOATBFO show the best performance and hence are considered to be the best overall since the difference in the minimum voltage is only small as compared to that given by SOSCRPP.

Table 2 tabulates the results obtained from MOATBFO, MOBFO and MOMeta-EP optimization techniques in solving the MOSCRPP problems.

Further in Table 3, 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 3 show that MOATBFO always resulted in the best overall performance. This conclusion is summarized in Table 4. 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.

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Conflicts of interest

The authors declare that there is no conflict of interest in this paper.

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