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ORPP with MAIEP Based Technique for Loadability Enhancement

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Abstract**—**One of the factors to maintain system survivability is the adequate reactive power support to the system. Lack of reactive power support may cause undesirable voltage decay leading to total system instability. Thus, appropriate reactive power support scheme should be arranged in order to maintain system stability. The strength of a system capacity is normally denoted as system loadability. This paper presents the enhancement of system loadability through optimal reactive power planning technique using a newly developed optimization technique, termed as Multiagent Immune Evolutionary Programming (MAIEP). The concept of MAIEP is developed based on the combination of Multiagent System (MAS), Artificial Immune System (AIS) and Evolutionary Programming (EP). In realizing the effectiveness of the proposed technique, validation is conducted on the IEEE-26-Bus Reliability Test System. The results obtained from pre-optimization and post-optimization process were compared which eventually revealed the merit of MAIEP.

Keywords**—**Load margin, MAIEP, Maximum loading point, ORPP.

I. Introduction

NUMEROUS voltage collapse (VC) occurrences resulted a great loss to the nation. Therefore, various research efforts have been conducted to identify the voltage instability events and to determine optimal system operation state or limit before it becomes unstable. It is also meant to develop efficient control strategies to ensure that the system operation is away from voltage instability events.

Load margin analysis has been profoundly identified as one of the fundamental measurement in VC or voltage stability studies. In load margin assessment, the VC condition is predicted to occur when the load is increased exceeding the maximum loading point (MLP) and subsequently the system starts to lose its equilibriums.

Various studies have been conducted to address this problem. Generally, maximum loading determination can be achieved by 2 techniques namely direct method and continuation power flow (CPF) method. Both techniques involved computation of repetitive load flow along with the increment of the loading. Nonetheless, the CPF approach put in place the corrector-predictor scheme in order to forecast the bifurcation point (nose point) of PV or QV curve [1, 2]. This identified the maximum loading point (MLP) of the system.

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The study on the load margin also involved the estimation of MLP of a system which was discussed in detailed in [3]-[5]. The MLP is essential to be known in advance to ensure that proper control action can be taken before VC happen. For instance, Fast Voltage Stability Index (FVSI) has been used in [3] and [4] as the index to identify the system condition. However, each paper is different in the optimization technique employed. In [3], Ant Colony optimization technique has been used while in [4], it utilized the Evolutionary Programming (EP). In other study, Amgad A. *et. al.* [5] compares the MLP obtained using Hybrid Particle Swarm optimization technique with the results from CPF technique.

The studies on system loadability are not only restricted on the methods and techniques to determine the secure operation of a system but emphasized also on loading margin improvement. This study is very crucial since the electrical utilities can fully utilized the power system to cater for increasing load demand. Among the popular approaches to enhance the load margin are the reconfiguration of distribution system [6], control of generation direction [7, 8], installation of FACTS devices [9, 10], reactive power scheduling [11-14], load shedding [15] and etc.

Researches conducted on reactive power scheduling show that the proposed control strategy were not only capable to improve the load margin, but, it also managed to minimize the system's loss and operational cost. In this approach, the reactive power injections at generators and/or load buses were optimized using various optimization techniques. In [11] the Optimal Power Flow (OPF) scheme which comprises of Reactive Power Planning (RPP), Reactive Power Dispatch (RPD) and Compensating Capacitor Placement (CP) has been employed with EP technique to achieve the above results. Modification on EP technique was then introduced in [12] combining the EP technique with Gradient Method to increase convergence speed. Both studies [12] and [13] applied the active participation factor approach (APF) to indicate which generators should be stimulated to inject reactive power in increasing the loadability of the system. B. Venkatesh *et. al.* [14] implemented newly developed Successive Multi-objective Fuzzy LP method to solve the optimal reactive power scheduling problem.

This paper presents MAIEP technique for loading margin improvement. The study involved the development of optimization engine implementing EP, AIS, and MAS techniques in hybrid form. Validation of the proposed technique through various experiments on the IEEE 26-bus

RTS indicated the feasibility of this technique for further implementations in other systems.

II. BACKGROUND STUDIES

A. Optimal Reactive Power Planning (ORPP)

ORPP is a sub-problem of OPF solution which has been widely used in power system operation and planning. This scheme aims to determine the optimal values of the control parameter to optimize the desired objective function while satisfying a set of system constraints. In RPP; the optimal values of the transformer tap setting and the injection of reactive power at generator bus would be the most suitable values of the control parameters to achieve the optimal solution. Since the OPF approach is commonly implemented with the security and economic operation of power system, thus economic dispatch (ED) is adopted in RPP scheme.

ORPP is a nonlinear programming problem which can be presented by the following mathematical formulation:

Maximize or minimize

$$f(\mathbf{x}, \mathbf{u}) \tag{1}$$

subject to

$$g(\mathbf{x}, \mathbf{u}) = 0 \tag{2}$$

$$h_{min} \leq h(\mathbf{x}, \mathbf{u}) \leq h_{max} \tag{3}$$

where $\mathbf{u}$ is the vector of control variables (these include generator active/reactive power/voltage levels and transformer tap setting); $\mathbf{x}$ is the vector of dependent variables (load node voltages, generator reactive power); $f(\mathbf{x}, \mathbf{u})$ is the objective function; $g(\mathbf{x}, \mathbf{u})$ is nodal power constraints and $h_{min} \leq h(\mathbf{x}, \mathbf{u}) \leq h_{max}$ are the inequality constraints of the dependent and independent variables.

B. Load Margin

Loading margin is defined as the amount of additional load in a specific pattern of load increase that would cause a voltage collapse [16]. Fig. 1 demonstrates load margin in graphical form where λ_o denotes the load at base case while λ_{max} represents the MLP value.

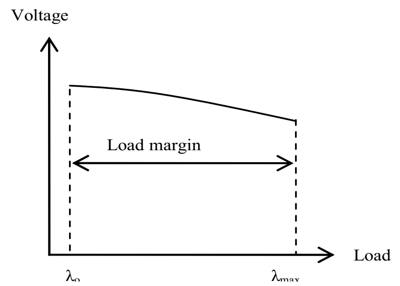

Fig. 1. Voltage profile with respect to load variation

From the load margin values for several selected load buses, critical bus of a system can be identified. A bus is considered as the critical bus if it has the lowest load margin in the system. Fig. 2 presents the voltage profile and the load margin with and without the implementation of optimization process. The comparisons between pre and post optimization are indicated by point A and point B. Point A represents the MLP obtained from pre-optimization. For post optimization, the loss and cost of the system at this point are measured to monitor the improvement of the system compared to the pre-optimization condition. Point B signifies the MLP achieved during post optimization.

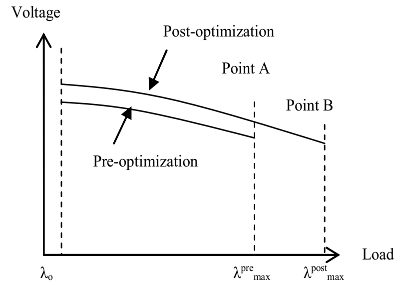

Fig. 2. Voltage profile and load margin with without the implementation of ORPP.

C. Evolutionary Programming

EP is one of the popular techniques which falls under the Evolutionary Computation in Artificial Intelligence (AI) hierarchy and has been increasingly applied for solving power system optimization problem in recent years. It is a stochastic optimization strategy, which is based on the mechanics of natural selections-mutation, competition and evolution. This technique stressed on the behavioral linkage between parents and their offspring. In general, EP consists of 3 major steps which have been briefly discussed in [17-18]:

i. Initialization

The initial population of μ individuals consists of ($\mathbf{x}_i$, η_i), $\forall i \in \{1, 2,\ldots\mu\}$ are generated randomly based on its limit. $\mathbf{x}_i$ denotes the control variable/s and η_i is the strategic parameter/s for each x_i. The fitness is calculated for each individual based on its objective function, $f(\mathbf{x}_i)$.

ii. Mutation

Each parent ($\mathbf{x}_i$, η_i), i=1,…, μ, creates a single offspring ($\mathbf{x}'_i$, η'_i), j=1,…, n, where x'_i and η_i are given by:

$$x'_i(j) = x_i(j) + \eta'_i(j)\, \mathrm{N}j\,(0, 1) \tag{4}$$

$$\eta'_i(j) = \eta_i(j) \exp(\tau' \,\mathrm{N}(0, 1) + \tau\, \mathrm{N}_j(0, 1)) \tag{5}$$

and

$$\tau = ((2(n)^{½})^{½})^{-1} \tag{6}$$

$$\tau' = ((2n)^{½})^{-1} \tag{7}$$

$x_i(j)$, $x'_i(j)$, $\eta_i(j)$ and $\eta'_i(j)$ are the j-th component of the vectors $\mathbf{x}_i$, $\mathbf{x}'_i$, η_i and η'_i respectively. N(0, 1) represents a normally distributed one-dimensional random number with mean of zero and standard deviation of 1.Nj(0, 1) denotes that the random number is generated anew for each value of j. The fitness is calculated for each offspring.

iii. Combination and Selection

In the combination stage, the union of parents and offspring are ranked in ascending or descending order according to its fitness. For example, if the objective function is to determine the maximum value of load, the union is ranked in descending order. Then, in the selection process, the highest individuals of μ are selected to be the parents for the next generation.

The process of mutation, combination and selection are repeated until the stopping criterion is met. In this paper, the stopping criterion is defined as the difference between the maximum and minimum value of the fitness.

D. Artificial Immune System

Artificial Immune System (AIS) is also one of the optimization techniques used extensively in Power System studies. The principles and processes of AIS are inspired by the natural vertebrate immune system. Generally, the basic algorithm of AIS involves initialization, cloning, mutation and selection [19]. Cloning stage is a stage whereby the best individual of the population is reproduced to ensure that only the best result will be processed.

E. Multiagent System

Research on Multiagent System (MAS) has been carried out under AI; and the area of study is rapidly expanding. An agent in MAS represents a candidate solution to the optimization problem. In order to achieve the optimal solution, an agent interacts or works together with other agents in the environment. Generally, each agent has the following characteristics [20, 21];

1. It is able to live and act in the environment (global).
2. It is able to sense its local environment.
3. It is driven by certain purposes.
4. It is able to respond to changes that occur in it, based on its learning capability.

Thus, it is very crucial to identify the above criteria before solving a problem involving MAS.

III. MULTIAGENT-BASED IMMMUNE EVOLUTIONARY PROGRAMMING

MAIEP integrates all the above optimization techniques; EP, AIS and MAS to optimize the desired objective function. The proposed technique is quite general and the engine can be later utilized for solving other optimization problem. Initially, the characteristic of an agent is specified as follows:

A. Definition of Global Environment

All agents in MAIEP are arranged in the form of lattice-like environment. It is also identified as the global environment, L. The size of L is L_{size} x L_{size}, where L_{size} is an integer. Fig. 3 shows the structure of the global environment.

Each circle in the above model represents an agent in MAIEP and the data it carries represents the coordinate in the lattice. Indirectly, each agent also contains certain fitness value and a set of control variables of the optimization problem which in this approach, it is generated during initialization procedure in the EP.

B. Definition of Local Environment

An agent is only capable to interact and to share information with its own neighbors or local environment. From Fig. 3, neighbors of an agent are chosen if there is a line connecting them. For instance, if an agent located at (i, j) is represented by $L_{i,j}$, $i, j = 1, 2,\ldots, L_{size}$, then the neighbors are defined as follows [20]:

$$N_{i,j} = \{L_{i',j}, L_{i,j'}, L_{i'',j}, L_{i,j''}\} \quad (8)$$

where

$$i' = \begin{cases} i-1 & i \neq 1 \\ L_{size} & i = 1 \end{cases} \qquad j' = \begin{cases} j-1 & j \neq 1 \\ L_{size} & j = 1 \end{cases}$$

$$i'' = \begin{cases} i+1 & i \neq L_{size} \\ 1 & i = L_{size} \end{cases} \qquad j'' = \begin{cases} j+1 & j \neq L_{size} \\ 1 & j = L_{size} \end{cases}$$

Generally, each agent has only four neighbors and the information is spread in the local environment before it diffused to the global environment.

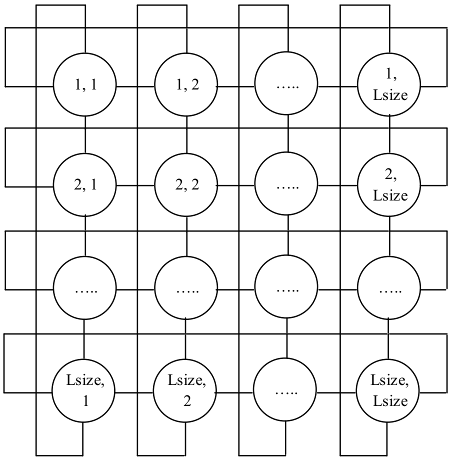

Fig. 3. Model of the agent lattice [20].

C. Purpose of Agents

In this paper, each agent is assigned to find the maximum value of MLP in order to improve the loading margin.

D. Agent's Behaviour

All agents have some distinctive behaviors to respond to changes that occur in the environment. In order to obtain optimal solution quickly, each agent competes and cooperates with their neighbors to diffuse the information using competition and cooperation operator, use the evolution mechanism (EP operator) as its knowledge in the competition and use the self learning operator as the learning capability to solve the problem. The description on these 3 operators is briefly discussed as follow:

i. Competition and Cooperation Operator

The main function of this operator is to compare the fitness of the selected agent with its neighbors' fitness. Agent which has the best fitness value is chosen to replace or maintain the selected agent's location in the lattice. Suppose that this operator is performed on agent $L_{i,j} = (l_1, l_2,\ldots, l_n)$ and $M = Max_{i,j} = (m_1, m_2,\ldots, m_n)$ is the agent with maximum fitness (depending on the objective function) value among the neighbors of $L_{i,j}$; if agent $L_{i,j}$ satisfies (9) it is a winner, otherwise it is a loser.

$$f(L_{i,j}) > f(Max_{i,j}) \quad (9)$$

If the agent is a winner, it can maintain its position in the lattice. However, if it is a loser, the agent must be eliminated and its position is replaced by $Max_{i,j}$. $l_1, l_2, \ldots, l_n$ and $m_1, m_2, \ldots, m_n$ are the set of control variables represented by agent $L_{i,j}$ and $Max_{i,j}$ respectively.

ii. EP Operator

Work conducted in [17] and [18] proved that EP technique is capable to offer global optimal solution. Based on this idea, the EP operator is utilized to ensure that generated new individuals are capable to provide robust and reliable results. Generally, EP operator makes use of the evolution mechanism of EP. The process consists of mutation, competition and selection procedures as discussed in section II.

iii. Self learning Operator

Self learning operator is opted to realize the behavior of using knowledge. Here, new approach in self learning operator is introduced based on clone operation in AIS technique. The best agent produced after the execution of the first stage of EP operator is cloned before it goes through the second stage of EP operator operation.

IV. IMPLEMENTATION OF MAIEP FOR LOAD MARGIN IMPROVEMENT

The methodology of ORPP for load margin improvement using MAIEP is depicted in Fig. 4 and Fig. 5 as follow:

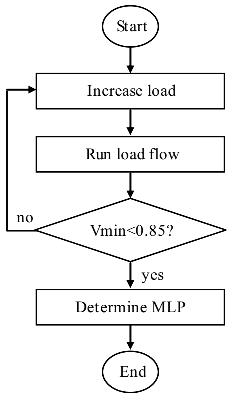

Fig. 4. Flowchart for calculation of MLP

Fig. 4 shows the flowchart for the calculation of MLP which is employed at the 5th step in Fig. 5. In the approach, V_{min} has been set at 0.85p.u as the cut-off point for the voltage limit and the system is assumed to operate in stress condition when reach this value. The initial condition in Fig. 5 implies the restriction for initial loss value, voltage limit, operation limit of active power at generator 1 and initial operation cost.

V. RESULTS AND DISCUSSION

The proposed algorithm has been tested on the IEEE 26-bus system. The clone value is set to 10 and the L_{size} is set to 3 or 4. The programming code of the proposed technique is written in Matlab (7.0) using Pentium (R) D 2.8 G computers.

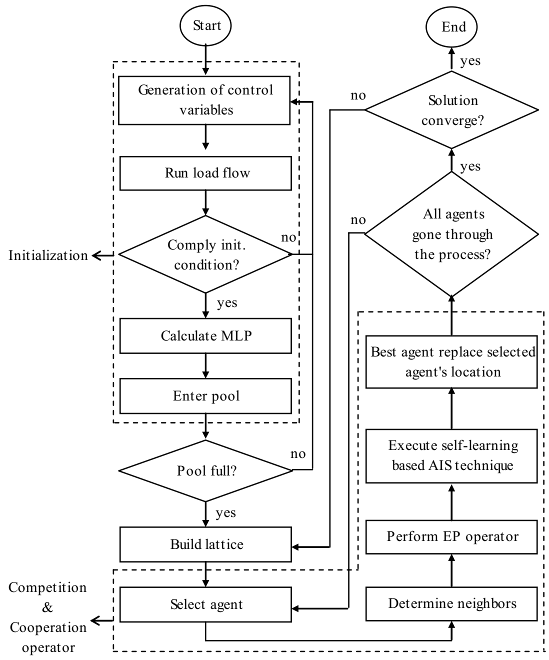

Fig. 5. Flowchart for the overall procedure of load margin improvement using MAIEP

A. Pre optimization Study

During pre-optimization stage, the system's condition is determined. The critical bus was also identified based on load margin evaluation as discussed in section II. There are 2 cases of load increment were considered which are load increased at a single bus (Case 1) and at the overall load buses (Case 2). In Case 1, the assessment on the load margin improvement is monitored at the critical bus. However, no critical bus is selected for Case 2 because all loads are subjected to uniform rate of load increased (5%). Thus, the MLP of the system is monitored at the overall buses and the increment is portrayed in terms of percentage value which measured with respect to its initial or base case value. In this paper, both P and Q loads are assumed increased concurrently in each case mentioned above.

Table I tabulates the result of load margin calculation given by the lowest 3 load buses in the system for Case 1.

TABLE I
LOAD MARGIN CALCULATION FOR CASE 1

Bus No	23		24		25	
Load	P (MW)	Q (MVar)	P (MW)	Q (MVar)	P (MW)	Q (MVar)
Base case Load	25.00	12.00	54.00	27.00	28.00	13.00
Max. Load	197.50	94.80	232.20	116.10	135.80	63.05
Load Margin	172.50	82.80	178.20	89.10	107.80	50.00

From the table, the lowest P&Q margin value among the load buses is 107.80 MW and 50.00 MVar which offered by bus 25. Therefore, bus 25 is chosen as the critical bus for the increment of P&Q load for Case 1. For Case 2, the system can only withstand 80.00% of load increment from base case value when P&Q load is increased concurrently at all load buses. Table II and III show the summary of pre-optimization results for Case 1 and Case 2 respectively.

TABLE II
SUMMARY OF PRE-OPTIMIZATION RESULTS FOR CASE 1

		MLP (MW/Mvar)	Loss (MW)	Cost ($K/h)	V_{min} (p.u)	V_{max} (p.u)
Case 1 (Bus 25)	P_{load}	135.8000	32.0003	18.9905	0.8516	1.0450
	Q_{load}	63.0500				

TABLE III
SUMMARY OF PRE-OPTIMIZATION RESULTS FOR CASE 2

		Sustainable load (MW/Mvar-%)	Loss (MW)	Cost ($K/h)	V_{min} (p.u)	V_{max} (p.u)
Case2	P_{load} Q_{load}	80.00%	62.5985	42.6429	0.8530	1.0250

The results for maximum load, total system losses, total generation cost and voltage profile obtained during pre-optimization stage will be taken as reference for comparison with post-optimization condition. These results are actually the results obtained during pre-optimization at point A (refer to Fig. 2).

B. Post-optimization study: MLP enhancement for Case1

In this section, the ORPP technique is utilized with MAIEP technique to improve the load margin. The load margin is improved when the MLP of the critical bus (Case 1) is extended from the value obtained during pre-optimization. Besides, the results for total system losses, total generation cost and voltage profile obtained during pre and post optimization are also compared.

Table IV compares the performance between pre-optimization and post-optimization at point A as well as the MLP obtained at post-optimization stage.

TABLE IV
COMPARISON OF RESULTS BETWEEN PRE AND POST OPTIMIZATION FOR INCREMENT OF P AND Q LOADS FOR CASE 1

	Comparison at point A (P_{load} = 135.80 MW, Q_{load} = 63.05 MVar)				MLP at point B (MW/MVar)
	Loss (MW)	Cost ($K/h)	Vmin (p.u)	Vmax (p.u)	
Pre-optimization	32.0003	18.9905	0.8516	1.0450	-
Post-optimizatio	26.2199	17.1912	0.9352	1.0829	P = 196.91 Q = 91.42

The above table shows that the overall result achieved during post-optimization stage is capable to improve the system's loadability, reduce the total system losses and generation cost as well as enhancing the system's voltage profile compared to pre-optimization condition. The ORPP utilizing MAIEP technique manages to stimulate the system to withstand 45.00% more loads as compared to pre-optimization value. The total losses and generation cost are reduced to 18.06% and 9.47% respectively. Table V tabulates the optimized values of the control variables for Case 1.

TABLE V
VALUES OF CONTROL VARIABLES FOR LOAD MARGIN IMPROVEMENT UTILIZING MAIEP & ORPP TECHNIQUES FOR CASE 1 CONSIDERING P&Q LOAD INCREASED

Variables					
T_1	T_2	T_3	T_4	T_5	T_6
0.9103	0.9089	1.0133	0.9558	0.9285	0.9059
T_7	P_{g2}	P_{g3}	P_{g4}	P_{g5}	P_{g26}
0.9174	153.0689	230.3152	145.4525	187.7926	104.6184
Q_{g2}	Q_{g3}	Q_{g4}	Q_{g5}	Q_{g26}	Q_{inj6}
158.3261	142.2862	67.1354	41.4072	32.9159	9.0689
Q_{inj9}	Q_{inj11}	Q_{inj12}	Q_{inj15}	Q_{inj19}	
44.8762	43.4073	37.5279	10.7683	34.7733	

T_1, T_2, T_3, T_4, T_5, T_6 and T_7 represent the transformer tap setting at lines 3, 6, 8, 9, 10, 15 and 18. On the other hand, P_{g2}, P_{g3}, P_{g4}, P_{g5} and P_{g26} signify generator active power, Q_{g2}, Q_{g3}, Q_{g4}, Q_{g5} and Q_{g26} denote generator reactive power and Q_{inj6}, Q_{inj9}, Q_{inj11}, Q_{inj12}, Q_{inj15}, Q_{inj19} represent capacitor placement at bus 6, 9, 11, 12, 15 and 19 respectively. These representations are applicable to the same variables in other tables.

C. Post-optimization study: MLP enhancement for Case2

TABLE VI
COMPARISON OF RESULTS BETWEEN PRE AND POST OPTIMIZATION FOR INCREMENT OF P AND Q LOADS FOR CASE 2

	Sustainable load at Point A 80.00%				Sustainable load at Point B
	Loss (MW)	Cost ($K/h)	Vmin (p.u)	Vmax (p.u)	
Pre-optimization	62.5985	42.6429	0.8530	1.0250	-
Post-optimizatio	50.5359	37.3405	0.9662	1.0750	161.00%

Same with Case 1, the measurement of performance during post-optimization is compared with the pre-optimization condition at point A. The system's loadability is considered improved if the system manages to withstand higher percentage of load compared to pre-optimization value. Table VI summarizes the results obtained when P&Q load are assumed to increase simultaneously.

TABLE VII
VALUES OF CONTROL VARIABLES FOR LOAD MARGIN IMPROVEMENT UTILIZING MAIEP & ORPP TECHNIQUES FOR CASE 2 CONSIDERING P&Q LOAD INCREASED

Variables					
T_1	T_2	T_3	T_4	T_5	T_6
0.9026	0.9649	1.0078	0.9091	0.9326	0.9045
T_7	P_{g2}	P_{g3}	P_{g4}	P_{g5}	P_{g26}
0.9260	163.1952	233.1357	128.6611	165.2526	119.0179
Q_{g2}	Q_{g3}	Q_{g4}	Q_{g5}	Q_{g26}	Q_{inj6}
56.2082	118.0930	51.0797	60.2303	38.9305	35.2451
Q_{inj9}	Q_{inj11}	Q_{inj12}	Q_{inj15}	Q_{inj19}	
12.922	29.8548	20.4501	44.4438	22.6603	

Table VI reveals that the loadability of the system is improved to 161.00% of P and Q load with respect to its base case value, measured at point B. At point A, the resulted loss and cost are also reduced to 19.27% and 12.43% respectively. Table VII tabulates the value of the optimized control variables for the above improvement.

VI. CONCLUSION

In this paper, MAIEP has been developed and utilized with ORPP in order to improve the load margin of a system. In the proposed optimization technique, the concept of MAS is employed to increase the convergence speed and the characteristic of EP is opted in the approach to ensure that the results fall on global optimal region. Slightly different with other MAS approach, the self learning process in MAIEP uses the clone concept from AIS technique instead of constructing the local searchers. From the results, it is revealed that the proposed technique offers the most significant improvement on maximizing the loading point of a system considering P&Q loads are increased simultaneously. The resulted system's losses, generation cost and voltage profile are also improved accordingly.

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