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SECURITY CONSTRAINED OPTIMAL POWER DISPATCH USING ANT COLONY OPTIMIZATION ALGORITHM

A. A. Abou El-Ela [1] A. M. Kinawy [1] R. A. El-Sehiemy[2] M. T. Mouwafi [1]

1) Electrical Engineering Department, Faculty of Engineering, Shebin El-Kom, Minoufiya University, Egypt
2) Electrical Engineering Department, Faculty of Engineering, Kafrelsehiekh University, Egypt

ABSTRACT

This paper proposes a procedure for solving a security constrained optimal power dispatch (SCOPD) problem under normal and emergency conditions using ant colony optimization (ACO) algorithm. The objective function is to minimize the non-linear generation cost function by optimizing the control variables of the generators real power under equality and inequality constraints.

The ACO algorithm is applied to 5- bus system, the IEEE standard 14-bus and 30-bus systems. In addition, an application of the proposed algorithm to a real power system at the west Delta network (WDN) as a part of the Unified Egyptian Network (UEN) considering the valve-points effects has been demonstrated. The results obtained are compared with those obtained using a conventional linear programming (LP), the fuzzy linear programming (FLP) technique and genetic algorithm (GA). Simulation results show that the proposed ACO algorithm for the SCOPD is more accurate and efficient, especially with increasing the system size.

يقدم هذا البحث طريقة مقترحة لحل مشكلة التوزيع الأمثل للقدرة الكهربية، مع تحقيق الحدود الأمنة، فى حالات التشغيل العادية والطارئة للنظم الكهربية باستخدام خوارزم مستعمرة النمل (ACO). تم إعتبار دالة تكاليف وحدات التوليد الغير خطية كدالة هدف حيث تم ايجاد القيم المثلى للقدرات الفعالة لوحدات التوليد مع الأخذ فى الإعتبار الحدود القصوى والصغرى لهذه الوحدات بالاضافة الى الأخذ فى الإعتبار حد الوفاء بتغذية الأحمال.

تم تطبيق خوارزم مستعمرة النمل على العديد من الأنظمة القياسية والحقيقية وهى نظام 5 قضبان، 14 قضيب، 30 قضيب. بالاضافة الى التطبيق على منظومة شبكة غرب الدلتا (WDN) لنظام حقيقى داخل الشبكة الموحدة لجمهورية مصر العربية مع الأخذ فى الإعتبار تأثيرات فتحة الصمام لوحدات التوليد. تم مقارنة نتائج الطريقة المقترحة مع نتائج بعض الطرق الأخرى مثل طريقة البرمجة الخطية التقليدية وطريقة المنطق الغيمى للبرمجة الخطية وطريقة الخوارزميات الجينية. حيث أوضحت النتائج أن أسلوب خوارزم مستعمرة النمل أكثر دقة وكفاءة فى حل مشكلة التوزيع الأمثل للقدرة الفعالة الكهربية خاصة عند زيادة حجم المنظومات الكهربية.

Keywords: Optimal power dispatch, Security, Ant colony optimization algorithm, Valve-points

1. INTRODUCTION

Security constrained optimal power dispatch (SCOPD) is one of the optimization problems in power systems that optimally allocate the power demand among committed generators in the most economical manner while satisfying system security constraints. The problem becomes more complicated due to the non-linear nature of the objective function and constraints of real life problems. The objective function may be convex or nonconvex based on the characteristic of the supply. The next paragraph presents the different optimization methods that can be used for solving the economic dispatch (ED) problem.

Madrigal and Quintana [1] presented an analytical solution to the classic economic dispatch problem using duality theory to derive an expression to compute both the exact primal (dispatches) and dual (marginal cost) solution to the problem without the need for numerical iterative optimization algorithms. No conflict of interest is caused if the (ED) model is used as an optimization-based electricity auction. C. Chen and N. Chen [2] solved the economic dispatch problem considering transmission capacity constraints using direct search method (DSM) to handle a number of inequality and equality constraints and units with any kind of fuel cost functions. For improving the performance of direct search procedure, a novel strategy with multi-level convergence is incorporated in the DSM to minimize the number of total iterations in the searching process. Pathom *et al*. [3] presented a methodology for solving the dynamic economic dispatch (DED) problem using evolutionary programming (EP) combined with sequential quadratic programming (SQP) that consists of two parts. The first part employed the property of EP which can provide a near global search region at the beginning. When the specified termination criteria of EP are reached, the local search SQP is applied to tune the control variables to obtain the final optimal solution. Xia and Song [4] proposed a novel approach based on the analysis of the process of solution of ED problem by Lagrangian Relaxation, called dynamic queuing (DQ) algorithm. Yan and Quintana [5] presented an improving an interior-point based OPF by a predictor-corrector primal-dual log-barrier (PCPDLB) method as a sequence of linearized sub-problems. Jabr *et al*. [6] presented a homogeneous interior point (HIP) method for the ED problem by approximating the network constraints through the DC load flow, and the transmission losses through the B-matrix loss formula. Liu *et al*. [7] analyzed the mixed integer OPF based on the interior point cutting plane method (IPCPM). Also, they presented a new base identification method based on the improvement of IPCPM to solve the problems of degenerate solutions and convex combination solutions that depends on the difference between nonzero element number of optimal solution and rank of coefficient matrix. Vlaisavljevic *et al*. [8] demonstrated the feasibility of using a fuzzy expert system, based on interactive fuzzy linear programming (FLP) to optimal power system rescheduling problem, incorporating the preventive redispatch. Their aim was to explore the feasibility of creating an intelligent power system rescheduling system. Pathom *et al*. [9] proposed the fuzzy-optimization approach for solving the (DED) under an uncertain deregulated power system. Amjady and Nasiri- Red [10] presented a RCGA with arithmetic-average-bound crossover (AABX) and hybrid mutation (HM) to solve the nonconvex ED problem. Through few recent years, ACO algorithms are employed to solve optimization problems in different fields with more accurate and efficiently solution compared with conventional and other modern optimization algorithms.

In this paper, an approach is proposed to solve the nonsmooth ED problem using the ACO algorithm, which based on the behavior of real ants for searching the shortest route between the colony and the souce of food based on the indirect communication media, called pheromone. The minimization of the total fuel generation costs is considered as an objective function with equality and inequality constraints. This paper is organized as; Section II formulates the considered ED problem that shows the objective function and constraints. Section III is divided into two parts. Part 1 shows the description of real ants for searching the shortest route between nest and food source. Part 2 introduces the mathematical model of ACO algorithm that based on the probabilistic transition rule and the pheromone updates. In Section IV, the ACO algorithm is implemented to the ED problem. Section V contains the results obtained by the application of the ACO algorithm to the 5-bus, IEEE-14 and 30 bus test systems under normal and emergency conditions which are compared with the results obtained using the conventional LP, fuzzy linear programming (FLP) and GA. Also, the ACO algorithm is applied to a real power system at the WDN system as a part of the Unified Egyptian Network (UEN). The results show that, the proposed algorithm is more accurate and efficient in solving the ED problem.

2. PROBLEM FORMULATION

The SCOPD problem can express as a constrained optimization problem as:

$$\text{Min } f(x) \tag{1}$$

$$\text{s. t.:} \quad \left.\begin{aligned} g(x) &= 0 \\ h(x) &\le 0 \end{aligned}\right\} \tag{2}$$

where, *f(x)* is the objective function such as generators fuel costs, transmission line losses,...etc, *g(x)* represents the equality constraints, *h(x)* represents the inequality constraints, and *x* is the vector of the control variables that may be generator real power outputs, generator voltages, switchable reactive power and transformer tap setting. In this paper, the objective function is the non-linear fuel cost of generators with the valve-point effects that appears in a rectified sinusoidal function introduce ripples in the heat-rate curves, that's a function in the generator real power output, which are defined, as:

$$MinF_t = \sum_{i=1}^{NG} f_i\left(PG_i\right) = \sum_{i=1}^{NG} a_i + b_i PG_i + c_i PG_i{}^2 + \left|e_i \times \sin\left(f_i \times \left(PG_i^{\min} - PG_i\right)\right)\right| \tag{3}$$

where,

F_t : is the non-linear objective function of power generation cost.

a_i, b_i and c_i are the coefficients of power generation cost function.

e_i and f_i are the fuel cost coefficients of the *i*th unit with valve-points effects.

NG : is the number of generation buses.

The objective function (3) is subjected to the following constraints:

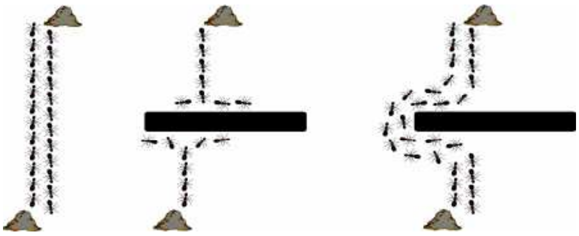
a) Equality constraints

- Power balance constraint

The generators real power output should be equal to the total load demand and transmission line losses as:

$$\sum_{i=1}^{NG} PG_i = \sum_{j=1}^{NL} PD_j + P_{losses} \tag{4}$$

where, PG_i is the power generation at bus i, PD_j is the load demand at load bus j, NL is the number of load buses, and P_{losses} is the total power losses in the system.



a. b. c.

Fig. 1 Illustration of real ant behavior

b) Inequality constraints

- The generator real power output must be within the feasible limits as:

$$PG_i^{\min} \le PG_i \le PG_i^{\max} \tag{5}$$

where, PG_i^{max} and PG_i^{min} are the maximum and minimum limits of power generation at bus i, respectively.

- Power flow constraints

The power flow in each transmission must be less than the maximum limit of power flow in that line as:

$$|PF_k| = |D_{k,i} PG_i| \prec PF_k^{\max} \tag{6}$$

where, PF_k is the power flow in line k, PF_k^{max} is the maximum power flow in line k and $D_{k,i}$ is the sensitivity parameters of the power flows related to the power generations.

3. ACO ALGORITHM

ACO algorithms were first proposed by Dorigo [11] and his related future work [12-13].

3.1. Description of real ants

ACO algorithms are based on the behavior of real ants that are members of a family of social insects. However, a group of explorer ants leave the colony for finding the food source in a randomly directions where they marked their routes by laying a chemical substance on the ground. Other ants attractive to the route that has the largest amount of pheromone that decays with time. So that, a shorter route will be found that has a largest amount of pheromone than a longer route. Hence, they are found the shortest route between the nest and food source by indirect communication media that called *pheromone* that laid on the ground as a guide for another ants. Fig. 1 shows how the real ants can find the shortest path between nest or colony and food source. In Fig. 1-a, there are no obstacles between nest and food source. However, the shortest route is the straight line. If an obstacle is located on the route of ants to become two routes around the obstacle, some of ants choose the left side around the obstacle and the other will choose the right side as shown in Fig. 1-b. The pheromone laid on the left side will be concentrated than right side of obstacle because ants in the shortest path takes minimum time in leaving and returning for nest where they moves in the same speed. So, they will be laid a largest amount of pheromone than other ants on the other route. While, the other ants attractive to the shortest route. Hence, all ants in the colony will take the shortest route around the obstacle as shown in Fig. 1-c.

3. 2. Mathematical Model of ACO Algorithm

A random amount of pheromone is deposited in each rout after each ant completes its tour, anther antes attract to the shortest route according to the probabilistic transition rule that depends on the amount of pheromone deposited and a heuristic guide function as equal to the inverse of the distance between beginning and ending of each route. The probabilistic transition rule of ant k to go from city i to city j can be expressed as in Traveling Salesman Problem (TSP) [13] as:

$$P_{ij}^k(t) = \frac{[\tau_{ij}(t)]^\alpha [\eta_{ij}(t)]^\beta}{\sum_q [\tau_{iq}(t)]^\alpha [\eta_{iq}(t)]^\beta};\ j,q \in N_i^k \tag{7}$$

where, τ_{ij} is the pheromone trail deposited between city i and j by ant k; η_{ij} is the visibility or sight and equal to the inverse of the distance or the transition cost between city i and j ($\eta_{ij} = 1/d_{ij}$). α and β are two parameters that influence the relative weight of pheromone trail and heuristic guide function, respectively. If α=0, the closest cities are more likely to be selected that corresponding to a classical greedy algorithm. On the contrary, if β=0, the probability will be depend on the pheromone trial only. These two parameters should be tuned with each other, Dorigo in [11] found experimentally the good values of α and β are 1 and 5, respectively, q is the cities that will be visited after city i. While, N_r^k is a tabu list in memory of ant that recodes the cities are visited to avoid stagnations. After each tour is completed, a *local pheromone update* is determined by each ant depending on the route of each ant as in equation (8). After all ants attractive to the shortest route, a *global pheromone update* is considered to show the influence of the new addition deposits by the other ants that attractive to the best tour as shown in equation (9).

$$\tau_{ij}(t+1) = (1-\rho)\tau_{ij}(t) + \rho\tau_\circ \tag{8}$$

$$\tau_{ij}(t+1) = (1-\rho)\tau_{ij}(t) + \varepsilon\Delta\tau_{ij}(t) \tag{9}$$

where, τ_{ij} *(t+1)* is the pheromone after one tour or iteration. ρ is the pheromone evaporation constant equals to 0.5 as a good value by Dorigo in [11]. ε is the elite path weighting constant. $\tau_o = 1 / d_{ij}$ is the incremental value of pheromone of each ant. While, $\Delta\tau_{ij}$ is the amount of pheromone for elite path as:

$$\Delta\tau_{ij}(t) = 1/d_{best} \tag{10}$$

where, d_{best} is the shortest tour distance found as in TSP.

4. ACO ALGORITHM FOR SCOPD PROBLEM

ACO algorithm is applied to solve the SCOPD problem as an optimization technique with equality and inequality constraints where artificial ants travels in search space to find the shortest route that having the strongest pheromone trail and a minimum cost function. Our objective in this paper is to minimize the total cost of generation real output power as described in (3) with equality constraint (4) and inequality constraints in (5) and (6). So, heuristic guide function is the inverse of the individual cost of each ant that positioned in the reasonable limit of the control variable to the visibility of each ant. While, heuristic guide function of the problem is the inverse of the total costs at iteration *t+1* as:

$$\eta(t+1) = 1/\sum_{i=1}^{NG} f_i(PG_i) \tag{11}$$

In GA, a chromosome is subdivided into genes, each gene represents a variable, consists of a binary string with length that depends on the boundary of the corresponding variable. While, in particle swarm optimization (PSO), a swarm consists of particles or populations that corresponding to the control variables. In ACO algorithm, a search space creates with dimensions of stages on number of control variables and states or the randomly distributed values of control variables with in a reasonable threshold. Artificial ants leaves colony to search randomly in the search space based on the probability in (7) to complete a tour matrix that consists of the positions of ants with the same dimension of the search space. Then, tour matrix is applied on the objective function to find a heuristic guide function to find the best solution and update local and global pheromone to begin a next iteration. System parameters are adjusted by trail and error to find the best values of theses parameters.

The ACO algorithm can be applied to solve the SCOPD problem using the following steps:

Step 1: Initialization

Insert the lower and upper boundaries of each control variable (PG^{min}, PG^{max}), system parameters and create a search space with a dimensions of number of control variables (PG) and the length of randomly distributed values with the same dimension of the initial pheromone that contains elements with very small equal values to give all ants with the same chance of searching.

Step 2: Provide first position

Each ant is positioned on the initial state randomly with in the reasonable range of each control variable in a search space with one ant in each control variable in the length of randomly distributed values.

Step 3: Transition rule

Each ant decide to visit a next position in the range of other control variables according to the probability transition rule in equation (7) that depends on the amount of pheromone deposited and the visibility that is the inverse of objective function (11). Where, the effect of pheromone and visibility on each other depends on the two parameters α and β.

Step 4: Local pheromone updating

Local updating pheromone is different from ant to other because each ant takes a different route. The initial pheromone of each ant is locally updated as in equation (8).

Step 5: Fitness function

After all ants attractive to the shortest path that having a strongest pheromone, the best solution of the objective function is obtained

Step 6: Global pheromone updating

Amount of pheromone on the best tour becomes the strongest due to attractive of ants for this path. Moreover, the pheromone on the other paths is evaporated in time.

Step 7: Program termination

The program will be terminated when the maximum iteration is reached or the best solution is obtained without the ants stagnations.

5. APPLICATIONS

5. 1. Test Systems

Three standard test systems and a real power system are used to study the proposed technique for SCOPD using an ACO algorithm. The first test system contains 5 buses and 7 transmission lines [14]. The second system is IEEE 14-bus test system [15], while the third is IEEE 30-bus test system [15]. The critical lines are number 1 in all test systems. The maximum power flow ratings of these critical lines are equal to 45, 150 and 65 MW for the three systems, respectively. However the ratings of the other lines in the three systems are below their security limits. The results that obtained are compared with those obtained in a previous work using a conventional linear programming (LP), the fuzzy linear programming (FLP) and the genetic algorithm (GA) technique [14]. The real power system is the WDN system (Fig. 2) as a part of the Unified Egyptian Network (UEN) [16]. The best values of ACO algorithm parameters are α =1, β=8, ρ=0.5 and ε=5

Two different operation conditions are considered to obtain the SCOPD, which are normal and emergency conditions.

The emergency conditions that may occur in the three test systems are:

a) Sudden increase in load demand.

b) Unexpected outage of one line.

c) Unexpected outage of units inside the generation plant.

5. 2. Results and Comments

The results are obtained using ACO algorithm that processed using MatLab code version 7.1 that setup on a Pentium 4, 3.0 GHz PC, 0.99 GB of ram.

5.2.1 Normal conditions

Tables 1, 2 and 3 show a comparison between the results obtained using ACO algorithm and the previous results using conventional LP, the FLP and GA [14]. In theses tables, the ACO algorithm has the minimum generation cost compared with other techniques.

Table 4 shows a comparison between the results obtained using ACO algorithm and the results using conventional LP, the FLP and GA for WDN system with valve-point effects are taken into account. In this table, the ACO algorithm has the minimum generation cost compared with other techniques. The computation time using ACO algorithm dependent on the system size and related to the number of control variables in tables 1-4, the computation time is 2.1, 2.25, 2.28 and 2.344 corresponding to 14, 5, 30 and WDN systems that have 2, 3, 6 and 8 number of control variables.

Table 1 Comparison of various optimization methods for 5-bus system (load=185 MW)

	LP	FLP	GA	ACO
PG1	90.2	78.9	90.2	90.15
PG2	34.8	61.7	35.8	35.17
PG5	60	44.4	59	59.68
PF1	45	34.6	44.98	44.94
Cost. $/hr	**380.7**	**391.7**	**374.1**	**373.8**
Time. Sec	0.55	0.66	0.99	2.25

Table 2 Comparison of various optimization methods for 14-bus system (load=260 MW)

	LP	FLP	GA	ACO
PG1	208.1	196.8	208.1	208.01
PG2	51.86	63.2	51.9	51.99
PF1	150	140.4	149.96	149.92
Cost. $/hr	**958.1**	**961.4**	**767.5**	**763.4**
Time. Sec	0.5	0.72	1.1	2.1

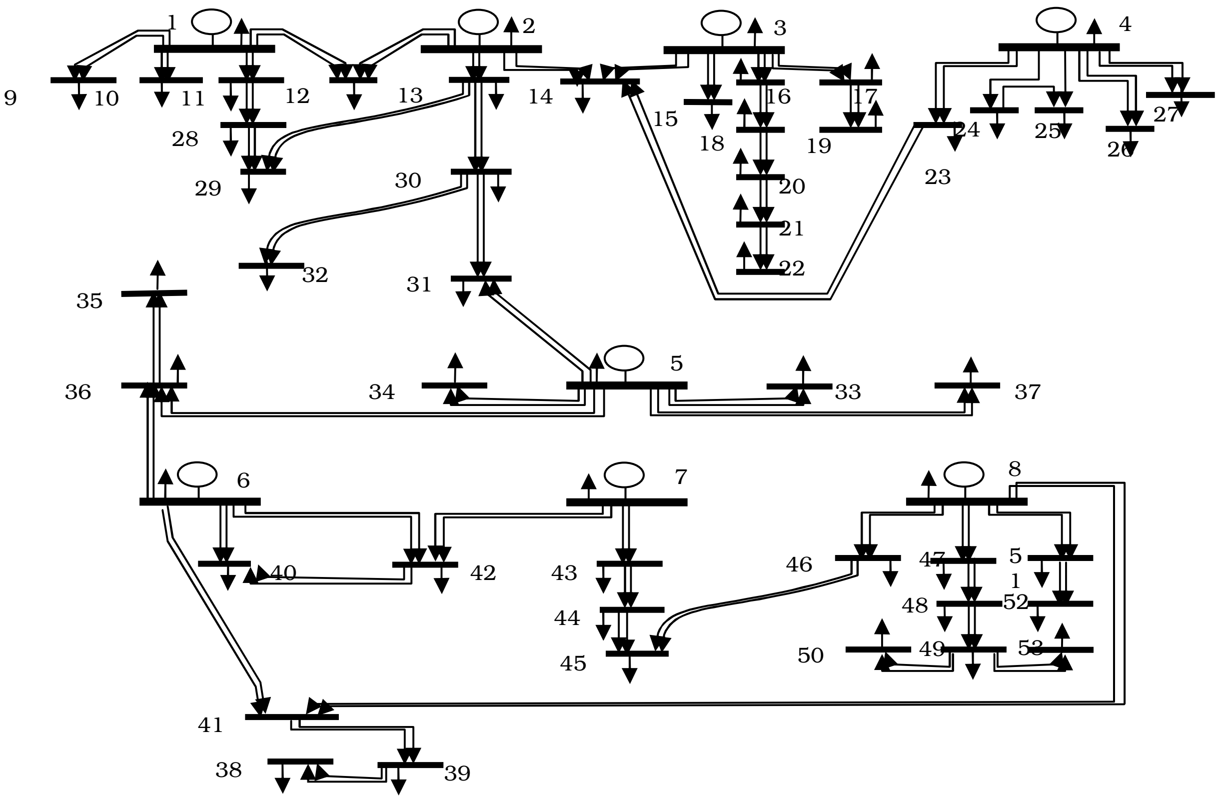


Fig. 2 Single line diagram of the WDN system

Table 3 Comparison of various optimization methods for 30-bus system (load=220 MW)

	LP	FLP	GA	ACO
PG1	10	52	49.1	59.73
PG2	80	62.3	65.6	55.89
PG3	39.4	28.9	21	40.81
PG4	10	16	23.7	17.5
PG5	30	25.5	16.5	27.12
PG6	50.6	35.3	44.1	18.95
PF1	-0.251	30.94	28.07	37.75
Cost. $/hr	**871.93**	**879.22**	**685.13**	**654.9**
Time. Sec	0.6	1.1	1.75	2.28

5. 2.2 Emergency Conditions

• ***Sudden increase in the load demand***

Tables 5 and 6 show the SCOPD using the ACO algorithm for different loading conditions for the 5-bus and 14- bus test systems.

In these tables, the power flows in the critical lines are kept within their limits, and the generation costs are increased according to the increasing of the load demand.

Table 7 shows a comparison between the results obtained using ACO algorithm and GA for a real power system for different loading conditions. In this table, the ACO algorithm has the minimum generation cost compared with GA.

• ***Unexpected outage of transmission line***

Tables 8 and 9 show the SCOPD computed using the ACO algorithm for different lines outage compared with the load flow (LF) using the Newton-Raphson method for 5-bus and 14-bus test systems. In these tables, overflows in the critical lines are removed using the ACO algorithm.

Table 10 shows the SCOPD computed using the ACO algorithm for different lines outage compared with the load flow (LF) using the Newton-Raphson method for real power system. The power flows in all lines are kept within their permissible limits.

Table 4 Comparison of various optimization methods for the west delta network system (load=890 MW)

	LP	FLP	GA	ACO
PG1	10	107.6704	70	62.218
PG2	10	123.2776	84.5	90.853
PG3	10	116.9019	81.2	83.74
PG4	250	104.6504	130.1	131.68
PG5	339.75	140.9867	192.5	170.08
PG6	250	74.3218	220.1	221.91
PG7	10	104.6519	56.2	66.42
PG8	10	117.2894	55.3	63.026
PF34	32.417	12.88	18.192	4.325
PF40	46.248	26.636	46.603	12.522
PF50	4.5307	12.535	9.1532	16.665
PF76	15.734	12.298	14.918	16.745
Cost. $/hr	**3149.3**	**3890.4**	**2909.8**	**2903.9**
Time. Sec	0.375	0.594	2.937	2.344

Where, the maximum power flow in lines 34, 40, 50 and 76 are 200, 150, 200 and 200 MW, respectively.

Table 5 SCOPD solution using ACO algorithm for different loading conditions for 5-bus system

Load (MW)	**150**	**170**	**185**	**200**	**220**	**230**
PG1	82.74	86.87	90.15	92.36	92.63	93.06
PG2	14.51	27.93	35.17	49.76	69.83	79.67
PG3	52.75	55.2	59.68	57.88	57.54	57.27
PF1	44.83	44.86	44.94	43.92	40.397	38.88
Cost ($/hr)	**295.12**	**340.01**	**373.8**	**409.626**	**460.24**	**485.92**

Table 6 SCOPD solution using ACO algorithm for different loading conditions for 14-bus system

Load (MW)	**220**	**240**	**260**	**270**	**280**	**285**
PG1	203.47	206.31	208.01	209.13	210.84	210.74
PG2	16.53	33.69	51.99	60.87	69.16	74.26
PF1	149.1	149.52	149.92	149.94	149.97	149.98
Cost ($/hr)	**615.75**	**689.06**	**763.4**	**807.98**	**850.3**	**872.53**

Table 7 SCOPD solution using ACO algorithm and GA for different loading conditions for the west delta system

Load(MW)	**700**		**800**		**890**		**1000**		**1100**	
Algorithm	GA	ACO	GA	ACO	GA	ACO	GA	ACO	GA	ACO
PG1	70	55.588	70	59.732	70	62.218	75.6	72.165	83.1	84.598
PG2	69.9	71.789	88.5	82.189	84.5	90.853	130	106.3	130	125.51
PG3	73.3	72.679	70	76.366	81.2	83.74	113.8	94.801	114.9	114.71
PG4	100	106.99	100	124.98	130.1	131.68	129.9	137.98	160.2	159.5
PG5	101.2	101.6	161.7	146.11	192.5	170.08	186.6	189.77	197	198
PG6	197.5	201.19	210.6	213.43	220.1	221.91	220	241.62	249.8	249.88
PG7	40	39.13	40	51.702	56.2	66.42	69.3	77.459	82.8	83.146
PG8	48.1	50.967	59.1	45.413	55.3	63.026	74.8	79.832	82.2	84.583
PF34	9.4366	9.5258	15.2154	13.7417	18.192	15.9839	17.4488	17.8139	18.4086	18.5239
PF40	42.0418	42.0556	43.8706	44.787	46.603	47.3803	48.9796	52.1595	55.3235	55.3071
PF50	2.8701	5.0786	6.2583	5.7262	9.1532	7.148	8.8535	8.5202	9.5783	9.6635
PF76	8.974	10.4068	11.7094	11.9146	14.918	13.2523	14.1096	14.7584	15.9008	16.0192
Cost. $/hr	**2173**	**2169.3**	**2549.1**	**2544.6**	**2909.8**	**2903.9**	**3367.9**	**3365**	**3799.4**	**3798.9**
Time. Sec.	3.063	2.219	2.891	2.266	2.937	2.344	2.922	2.343	3.031	3.462

Table 8 SCOPD solution for different line outage for 5-bus test system (load=185 MW)

Line Outage	1		2		6	
Algorithm	LF	ACO	LF	ACO	LF	ACO
PG1	90.15	59.98	90.15	59.89	90.15	85.61
PG2	35.17	69.10	35.17	69.24	35.17	40.12
PG3	59.68	55.92	59.68	55.87	59.68	59.27
PF1	----	----	77.15*	44.78	49.46*	44.23
PF2	73.557*	44.735	----	----	31.65	26.35

* Denotes an overflow in transmission line

Where, the maximum power flow in line 2 is 45 MW

Table 9 SCOPD solution for different line outage for 14-bus test system (load=260 MW)

Line Outage	7		6		10	
Algorithm	LF	ACO	LF	ACO	LF	ACO
PG1	208.01	185.63	208.01	203.45	208.01	204.28
PG2	51.99	74.37	51.99	56.55	51.99	55.72
PF1	166.49*	149.38	151.99*	148.46	151.45*	149.41
PF7	----	----	47.016	28.204	98.379	94.251

* Denotes an overflow in transmission line

Where, the maximum power flow in line 7 is 100 MW

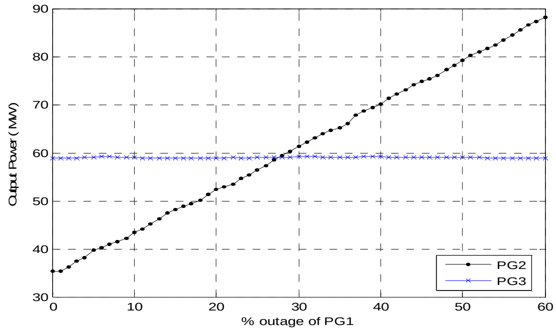
Table 10 SCOPD solution for different line outage for the west delta network system (load=890 MW)

Line Outage	34		40		50	
Technique	LF	ACO	LF	ACO	LF	ACO
PG1	62.218	64.559	62.218	63.315	62.218	64.973
PG2	90.853	91.079	90.853	90.981	90.853	91.177
PG3	83.74	84.212	83.74	85.081	83.74	85.818
PG4	131.68	131.5	131.68	131.8	131.68	132.1
PG5	170.08	174.28	170.08	175.99	170.08	174.28
PG6	221.91	224.71	221.91	223.77	221.91	221.88
PG7	66.42	63.92	66.42	65.227	66.42	64.92
PG8	63.026	55.668	63.026	53.764	63.026	54.775
PF34	----	----	79.492	16.234	82.231	16.408
PF40	40.739	47.209	----	----	38.897	47.443
PF50	22.833	6.6624	19.692	3.8329	----	----
PF76	5.384	13.015	5.387	13.015	5.384	13.009

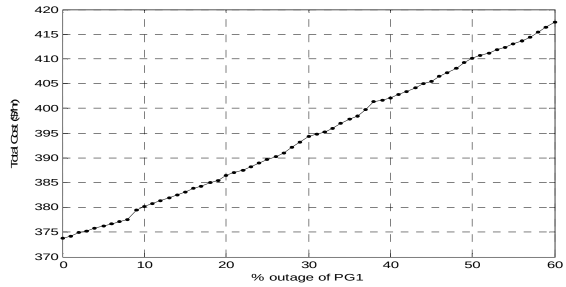
Where, the maximum power flow in lines 34, 40, 50 and 76 are 200, 150, 200 and 200 MW, respectively.

- ***<u>Unexpected outage of some units inside the generation plant</u>***

Figures 3 and 4 show the SCOPD using ACO algorithm for different percentage outage of generation plants 1 and 3 for the 5-bus test system. From these figures, the power generation at bus 2 (PG2) is increased largely according to an increase in the percentage outage of power generations 1 and 3. While, the power generations at buses 3 (PG3) and 1 (PG1) are increased smallly according to an increase in the percentage outage of power generations 1 and 3, respectively shown in figures 3(a) and 4(a), as well as the generation costs are increased shown in figures 3(b) and 4(b).

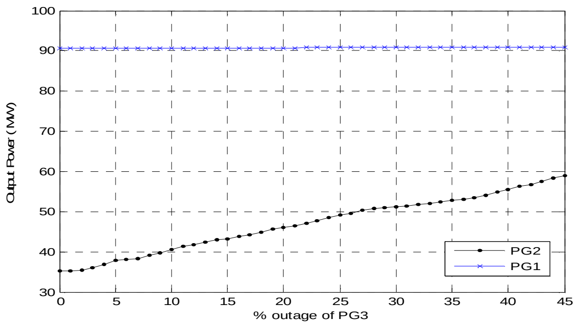


3. a) Variation of generation setting

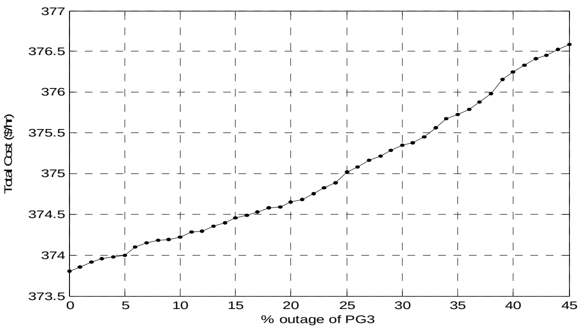


3. b) Variation of generation cost

Fig. 3 The SCOPD using ACO algorithm for different percentages outage of power generation 1



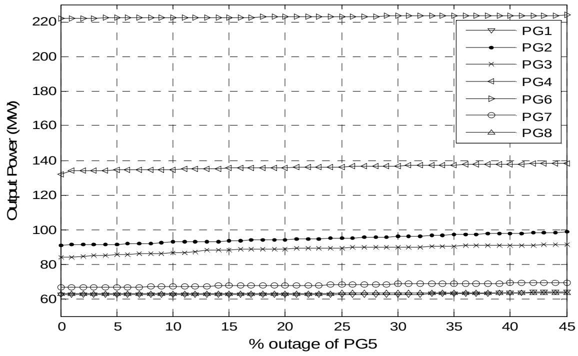
4. a) Variation of generation setting



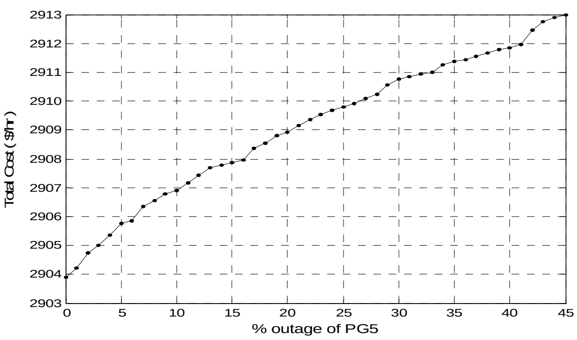
4. b) Variation of generation cost

Fig. 4 The SCOPD using ACO algorithm for different percentages outage of power generation 3

Figure 5 shows the SCOPD using ACO algorithm for different percentage outage of generation plant 5 for the WDN system. From this figure, the power generation at other generation buses is increased according to an increase in the percentage outage of power generations 5, as well as the generation costs are increased.



5. a) Variation of generation setting



5. b) Variation of generation cost

Fig. 5 The SCOPD using ACO algorithm for different percentages outage of power generation 5

6. CONCLUSION

This paper presents an approach based on ACO algorithm to solve the problem of SCOPD with equality and inequality constraints under normal and emergency conditions. The proposed algorithm has been tested on a three test systems and real actual system is the WDN system as a part of the Unified Egyptian Network (UEN), the results obtained are compared with other conventional LP, FLP and GA. The results show that, ACO algorithm leads to minimum generation costs for normal condition, while all the power flows in the critical lines are kept within their permissible limits. So, the proposed ACO algorithm gives more accurate and efficiently solution to remove the insecure operation at different emergency conditions. Moreover, it needs a low memory in a PC because it is running in a decimal code unlike GA that running using a binary code. Therefore, the proposed algorithm represents a potential tool to aid the power system operators in the on-line environment.

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