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Security constrained optimal dispatch using ant colony optimization algorithm

By

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Abstract:

This paper proposes a procedure for solving a security constrained optimal dispatch (SCOD) 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 settings the real power generation outputs under equality and inequality constraints. The proposed algorithm is applied to 5-bus system, IEEE 14-bus and IEEE 30-bus test systems. An application of the proposed algorithm to the west Delta network (WDN) as a part of the Unified Egyptian Network (UEN) considering the valve-points effects has been demonstrated. Numerical results are compared with those obtained using conventional optimization techniques as linear programming (LP), fuzzy linear programming (FLP) technique and genetic algorithm (GA). Simulation results show that the proposed ACO algorithm for the SCOD is more accurate and efficient, especially with increasing the system size.

Keywords:

Optimal dispatch, security, ant colony optimization algorithm, valve-points

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1. Introduction:

Security constrained optimal dispatch (SCOD) is one of the optimization problems in power systems that optimally allocate the power demand among the committed generators in 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. Different optimization methods were 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. Qing *et al*. [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.

Xihui 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. Rabih *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. Lin *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.

Dragan *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. Nima and Hadi [10] presented a real-coded genetic algorithm (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 ACO-based algorithm is proposed to solve the non-smooth ED problem. The minimization of the total fuel generation costs is considered as an objective function with equality and inequality constraints.

2.*Problem formulation:*

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

$$Min\ f\ (x)$$

subject to:

$$g(x) = 0$$

$$h(x) \leq 0 \qquad (1)$$

Where, *f(x)* is the objective function such as generators fuel costs, *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.

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:

$$Min\quad F_t = \sum_{i=1}^{NG} f_i \left(PG_i \right)$$

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

The objective function (2) 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:

$$\sum_{i=1}^{NG} PG_i = \sum_{j=1}^{NL} PD_j + P_{losses} \qquad (3)$$

The power loss is expressed using the B's coefficient as [11]:

$$P_{losses} = \sum_{i=1}^{NG}\sum_{j=1}^{NG} P_i B_{ij} P_j \qquad (4)$$

Where, P_i and P_j are the injected powers at buses i and j, respectively.

b) Inequality constraints
- The generator real power output must be within the feasible limits as:

$$PG_i^{min} \leq PG_i \leq PG_i^{max} \qquad (5)$$

- Power flow constraints

The power flow in each transmission line k must be less than the maximum permissible power flow in the line k as:

$$\left|PF_k\right| = \left|D_{k,i} PG_i\right| \leq PF_k^{max} \qquad (6)$$

3. ACO algorithm:

ACO algorithms were proposed by Dorigo [12-14]. A brief description of the ACO is presented as follows:

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).
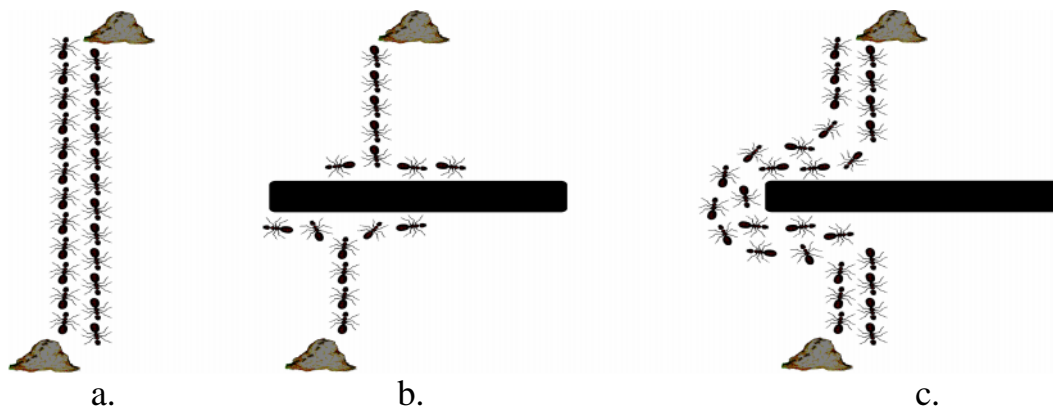

a. b. c.

Figure (1): Illustration of real ants behaviour

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) [14] as:

$$P_{ij}^{k}(t) = \frac{\left[\tau_{ij}(t)\right]^{\alpha}\left[\eta_{ij}(t)\right]^{\beta}}{\sum_{q}\left[\tau_{iq}(t)\right]^{\alpha}\left[\eta_{iq}(t)\right]^{\beta}} \; ; j, q \in N_{i}^{k} \tag{7}$$

If =0, the closest cities are more likely to be selected that corresponding to a classical greedy algorithm. On the contrary, if =0, the probability will be depend on the

pheromone trial only. These two parameters should be tuned with each other, Dorigo in [12] found experimentally the good values of   and   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).

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

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

the amount of pheromone for elite path can be calculated as:

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

4. ACO algorithm for SCOD problem:

ACO algorithm is applied to solve the SCOD 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. The SCOD aims at minimizing the total cost of generation real output power (2) with equality and inequality constraints (Equations (3) - (6)). So, a 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.

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 ant's 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 SCOD 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   and .

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 SCOD using an ACO algorithm. These standard systems are 5-bus [15], IEEE 14-bus and IEEE 30-bus test systems [16]. The 5-bus system has three generator units at buses 1, 2 and 5. The IEEE 14 bus system has two generators at buses 1 and 2. It is considered the first lines of the standard systems as most critical lines of these systems. The maximum permissible power flows of these critical lines are equal to 45, 150 and 65 MW for 5-bus, 14-bus and 30 bus test systems, respectively. However the power flows of other lines in the three systems are preserved within their security limits. An application to a real power system at the West Delta Network (WDN) is a part of the Unified Egyptian Network (UEN) [17] as shown in Fig. 2.

The results that obtained are compared with those obtained using conventional optimization techniques namely linear programming (LP), fuzzy linear programming (FLP) and genetic algorithm (GA) techniques [15]. The best values of ACO algorithm parameters are   =1,   =8,   =0.5 and   =5 .

Two different operation conditions are considered to obtain the SCOD, 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 shows 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 lowest generation cost compared with other optimization 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, respectively.

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

Variable	LP	FLP	GA	ACO
PG_1	90.2	78.9	90.2	90.15
PG_2	34.8	61.7	35.8	35.17
PG_5	60	44.4	59	59.68
PF_1	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)*

Variable	LP	FLP	GA	ACO
PG_1	208.1	196.8	208.1	208.01
PG_2	51.86	63.2	51.9	51.99
PF_1	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

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

Variable	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

Table (4): Comparison of various optimization methods for WDN system (load=890 MW)

Variable	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.				

5.2.2. Emergency conditions:

- **Sudden increase in the load demand:**

Tables 5 and 6 show the SCOD 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 (5): SCOD solution using ACO algorithm for different loading conditions for 5-bus system

Load (MW) Variable	150	170	185	200	220	230
PG_1	82.74	86.87	90.15	92.36	92.63	93.06
PG_2	14.51	27.93	35.17	49.76	69.83	79.67
PG_3	52.75	55.2	59.68	57.88	57.54	57.27
PF_1	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): SCOD solution using ACO algorithm for different loading conditions for 14-bus system

Load (MW)	220	240	260	270	280	285
PG_1	203.47	206.31	208.01	209.13	210.84	210.74
PG_2	16.53	33.69	51.99	60.87	69.16	74.26
PF_1	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 shows a comparison between the results obtained using ACO algorithm and GA for a WDN system for different loading conditions. In this table, the ACO algorithm has the minimum generation cost compared with GA.

Table (7): SCOD solution using ACO algorithm and GA for different loading conditions for the WDN system

Load(MW)	700		800		890		1000		1100	
Algorithm	GA	ACO	GA	ACO	GA	ACO	GA	ACO	GA	ACO
PG_1	70	55.56	70	59.73	70	62.22	75.6	72.17	83.1	84.6
PG_2	69.9	71.79	88.5	82.19	84.5	90.85	130	106.3	130	125.51
PG_3	73.3	72.68	70	76.37	81.2	83.74	113.8	94.80	114.9	114.71
PG_4	100	106.99	100	124.98	130.1	131.68	129.9	137.98	160.2	159.5
PG_5	101.2	101.6	161.7	146.11	192.5	170.08	186.6	189.77	197	198
PG_6	197.5	201.19	210.6	213.43	220.1	221.91	220	241.62	249.8	249.88
PG_7	40	39.13	40	51.70	56.2	66.42	69.3	77.46	82.8	83.15
PG_8	48.1	50.97	59.1	45.41	55.3	63.03	74.8	79.83	82.2	84.58
PF_{34}	9.44	9.53	15.22	13.74	18.19	15.98	17.45	17.81	18.41	18.52
PF_{40}	42.04	42.06	43.87	44.79	46.6	47.38	48.98	52.16	55.32	55.31
PF_{50}	2.87	5.08	6.26	5.73	9.15	7.15	8.85	8.52	9.58	9.66
PF_{76}	8.97	10.41	11.71	11.92	14.92	13.25	14.11	14.76	15.90	16.02
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

- **Unexpected outage of transmission line:**

Tables 8 and 9 show the SCOD 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 (8): *SCOD solution for different line outage for 5-bus system (load=185 MW)*

Variables	Outage					
	Line 1		Line 2		Line 6	
	LF	ACO	LF	ACO	LF	ACO
PG_1	90.15	59.98	90.15	59.89	90.15	85.61
PG_2	35.17	69.10	35.17	69.24	35.17	40.12
PG_3	59.68	55.92	59.68	55.87	59.68	59.27
PF_1	Outage		77.15*	44.78	49.46*	44.23
PF_2	73.557*	44.735	Outage		31.65	26.35
* Denotes an overflow in transmission line, Where, the PF_2^{max} is 45 MW						

Table (9): *SCOD solution for different line outage for 14-bus system (load=260 MW)*

Line Outage	7		6		10	
Algorithm	LF	ACO	LF	ACO	LF	ACO
PG_1	208.01	185.63	208.01	203.45	208.01	204.28
PG_2	51.99	74.37	51.99	56.55	51.99	55.72
PF_1	166.49*	149.38	151.99*	148.46	151.45*	149.41
PF_7	Outage		47.016	28.204	98.379	94.251
* Denotes an overflow in transmission line Where, Where, the PF_7^{max} is 100 MW						
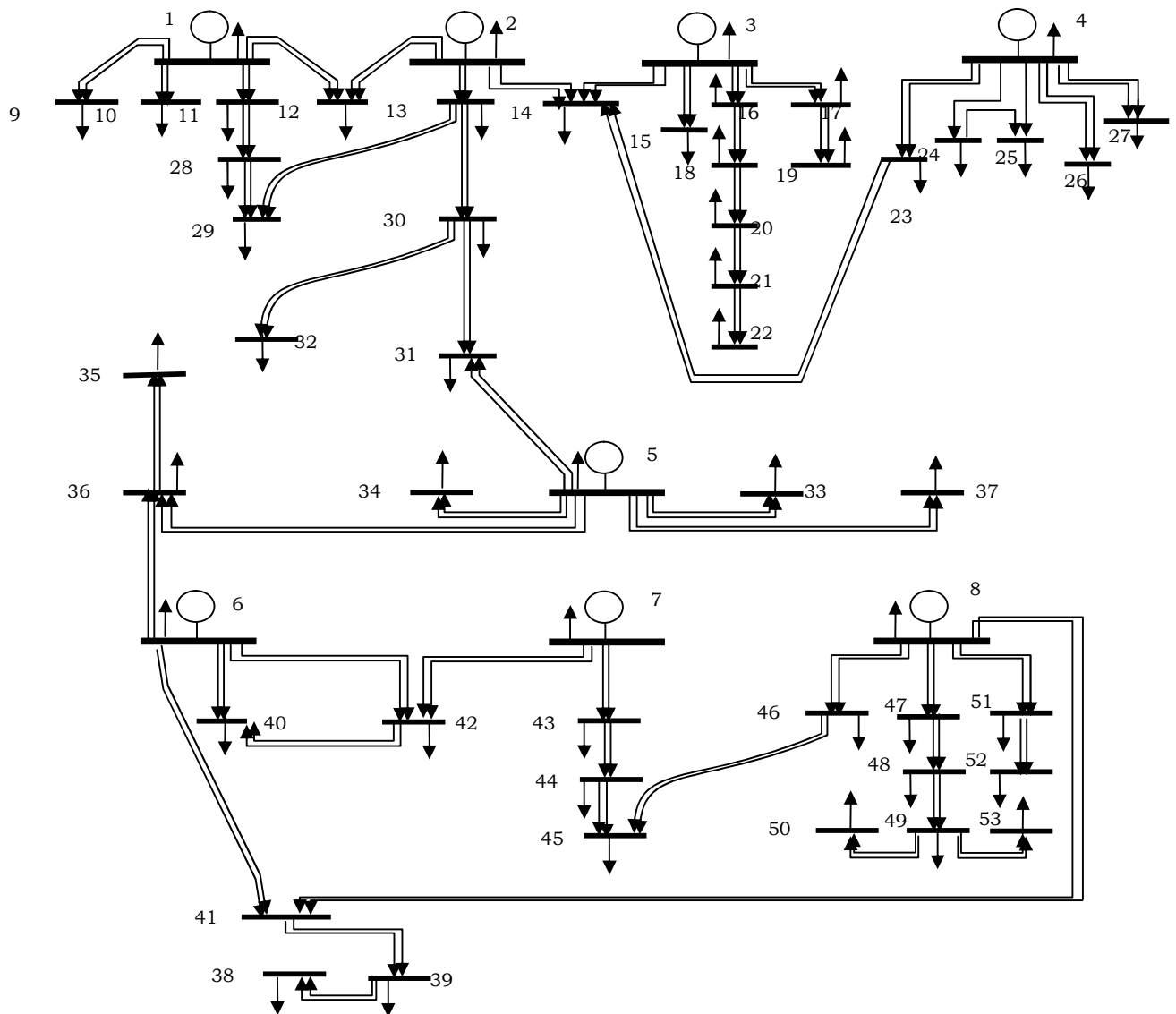
Figure (2): *Single line diagram of the WDN system*

Table 10 shows the SCOD computed using the ACO algorithm for different lines outage compared with the load flow (LF) using the Newton-Raphson method for WDN system.

The power flows in all lines are kept within their permissible limits.

Table (10): SCOD solution for different line outage for WDN system (load=890 MW)

| Line Outage	34		40		50	
Technique	LF	ACO	LF	ACO	LF	ACO
PG_1	62.22	64.56	62.22	63.32	62.22	64.97
PG_2	90.85	91.08	90.85	90.98	90.85	91.18
PG_3	83.74	84.21	83.74	85.081	83.74	85.82
PG_4	131.68	131.5	131.68	131.8	131.68	132.1
PG_5	170.08	174.28	170.08	175.99	170.08	174.28
PG_6	221.91	224.71	221.91	223.77	221.91	221.88
PG_7	66.42	63.92	66.42	65.23	66.42	64.92
PG_8	63.03	55.67	63.03	53.764	63.03	54.78
PF_{34}	Outage		79.49	16.23	82.23	16.41
PF_{40}	40.74	47.21	Outage		38.9	47.44
PF_{50}	22.83	6.66	19.692	3.83	Outage	
PF_{76}	5.384	13.015	5.387	13.02	5.38	13.01
Where, PF_{34}^{max}, PF_{40}^{max}, PF_{50}^{max} and PF_{76}^{max} are 200, 150, 200 and 200 MW, respectively						

- **Unexpected outage of some units inside the generation plant:**

Figures 3 and 4 show the SCOD 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 (PG_2) is increased largely according to an increase in the percentage outage of power generations 1 and 3. While, the power generations at buses 3 (PG_3) and 1 (PG_1) 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).

Figure 5 shows the SCOD 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.
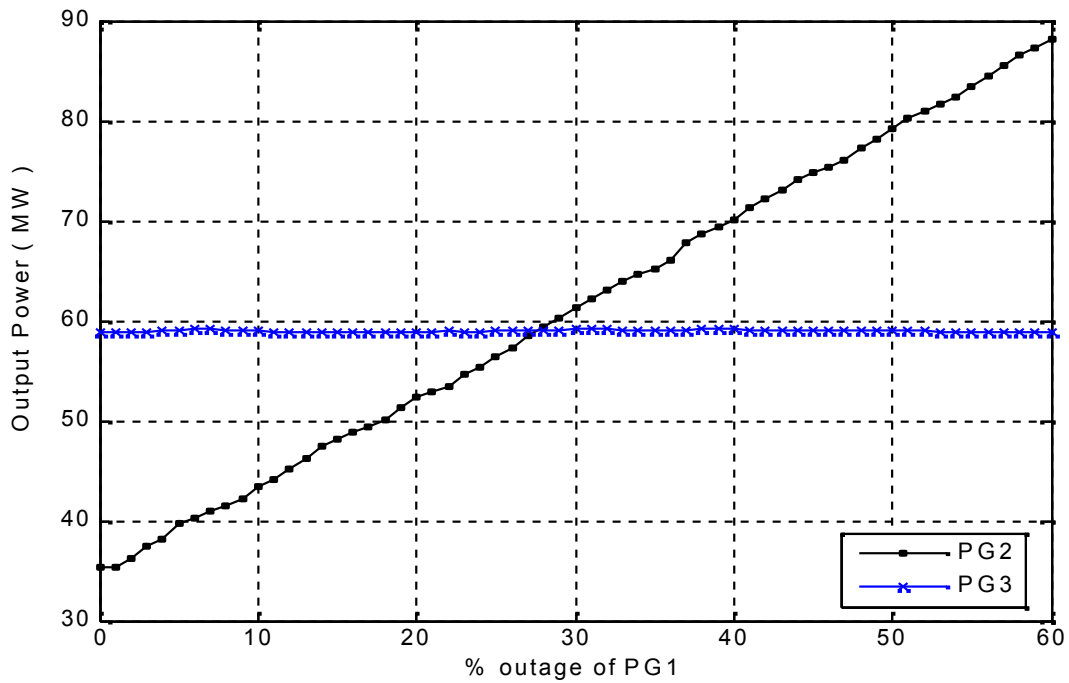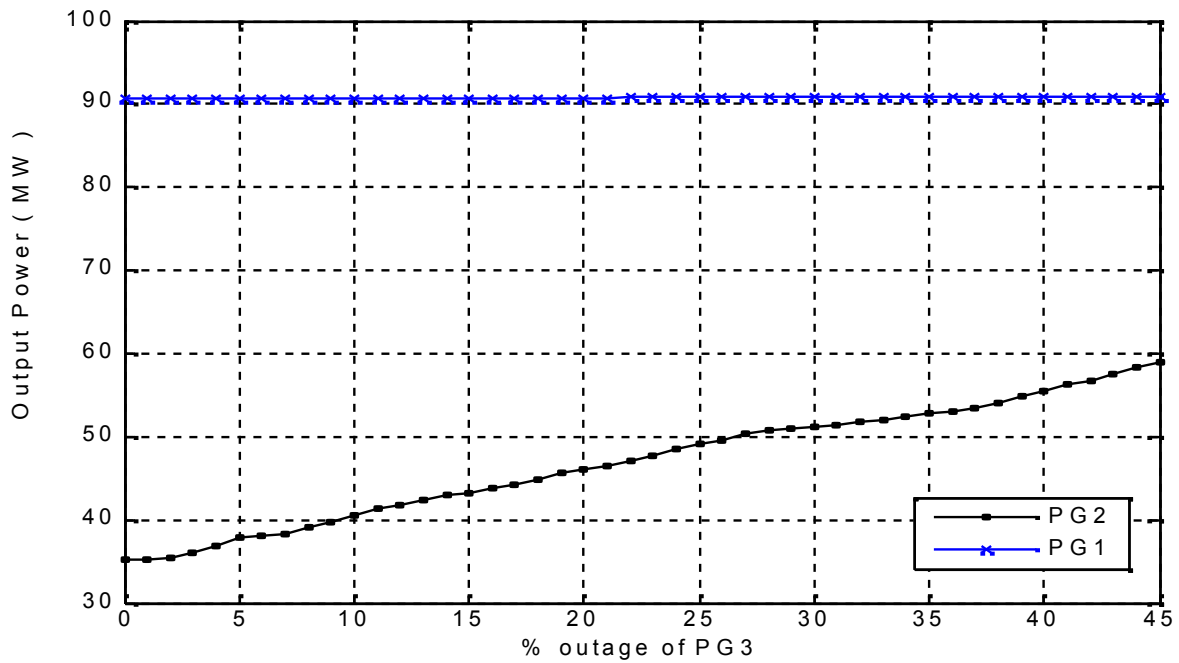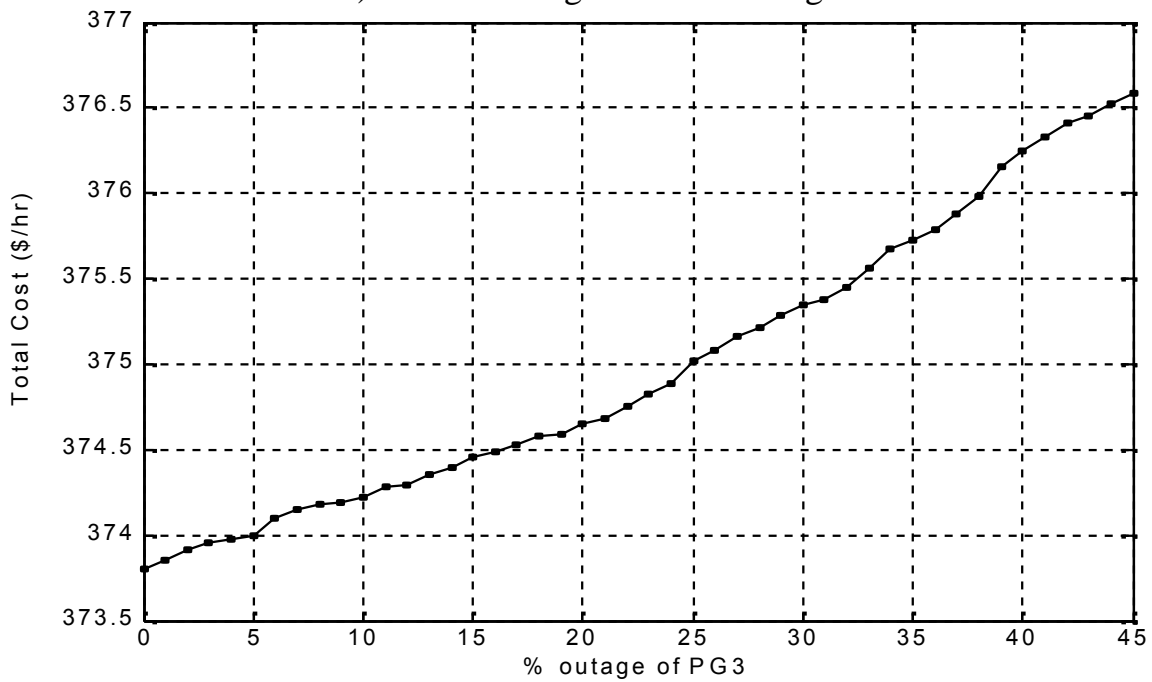
3. a) Variation of generation setting
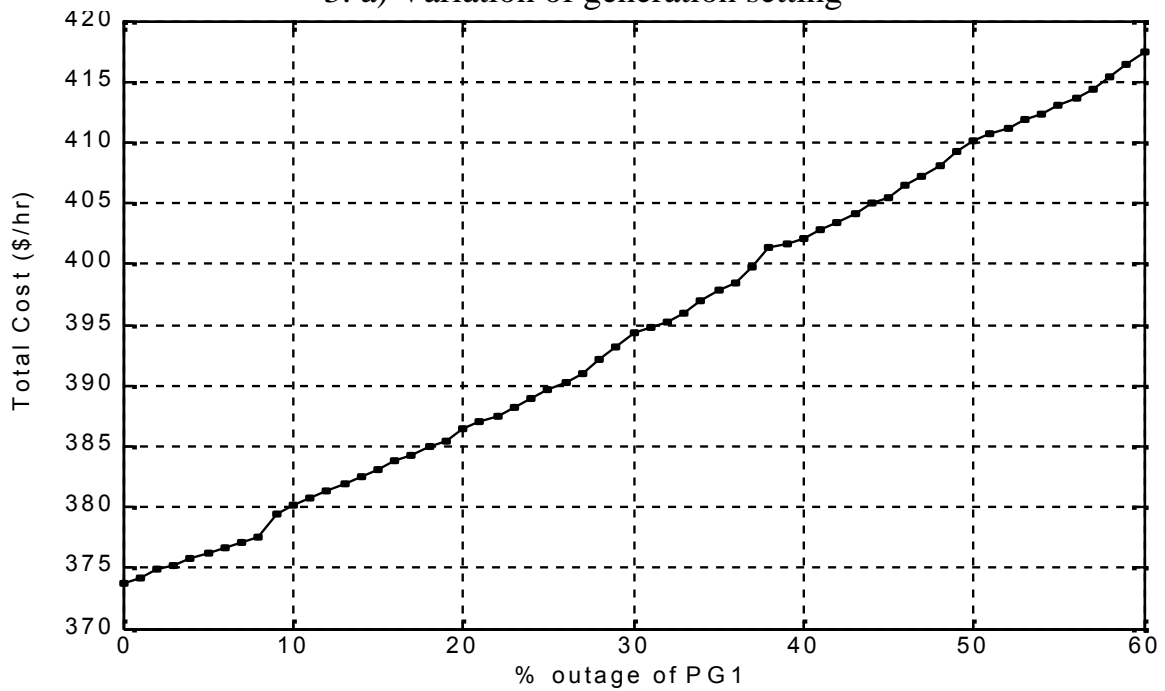
3. b) Variation of generation cost

***Figure (3):** The SCOD using ACO algorithm for different percentages outage of power generation 1 for 5-bus system*
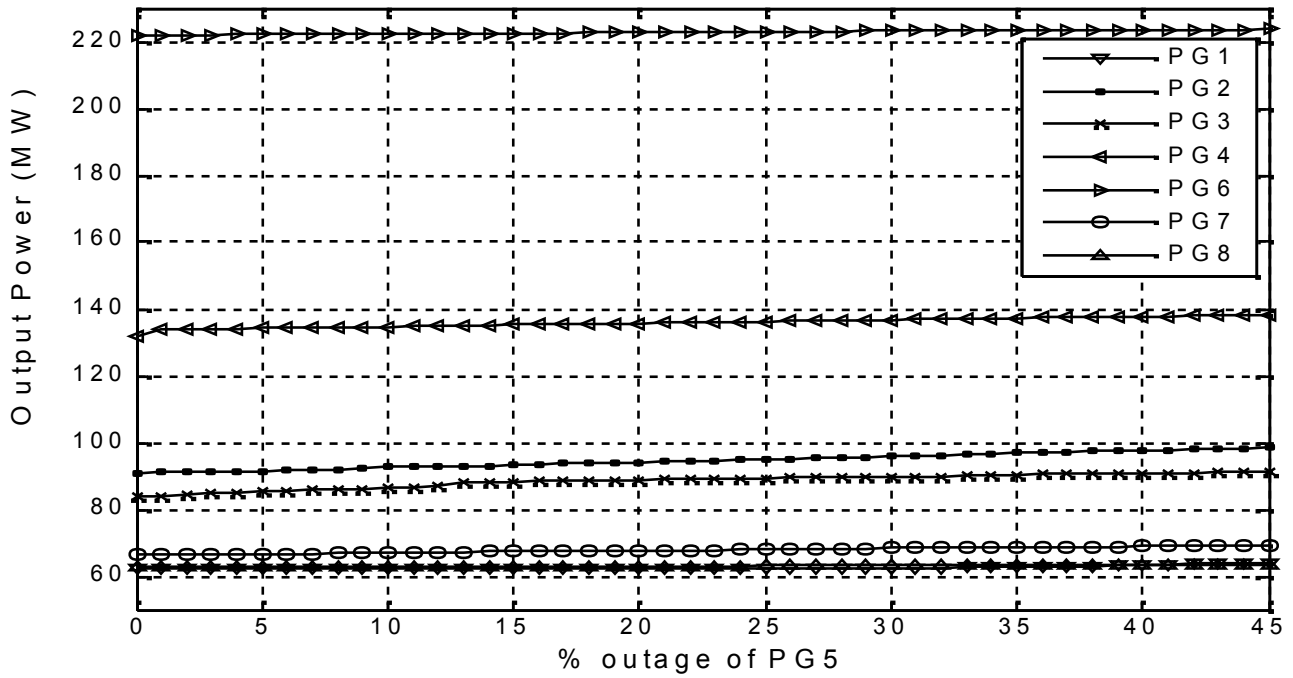
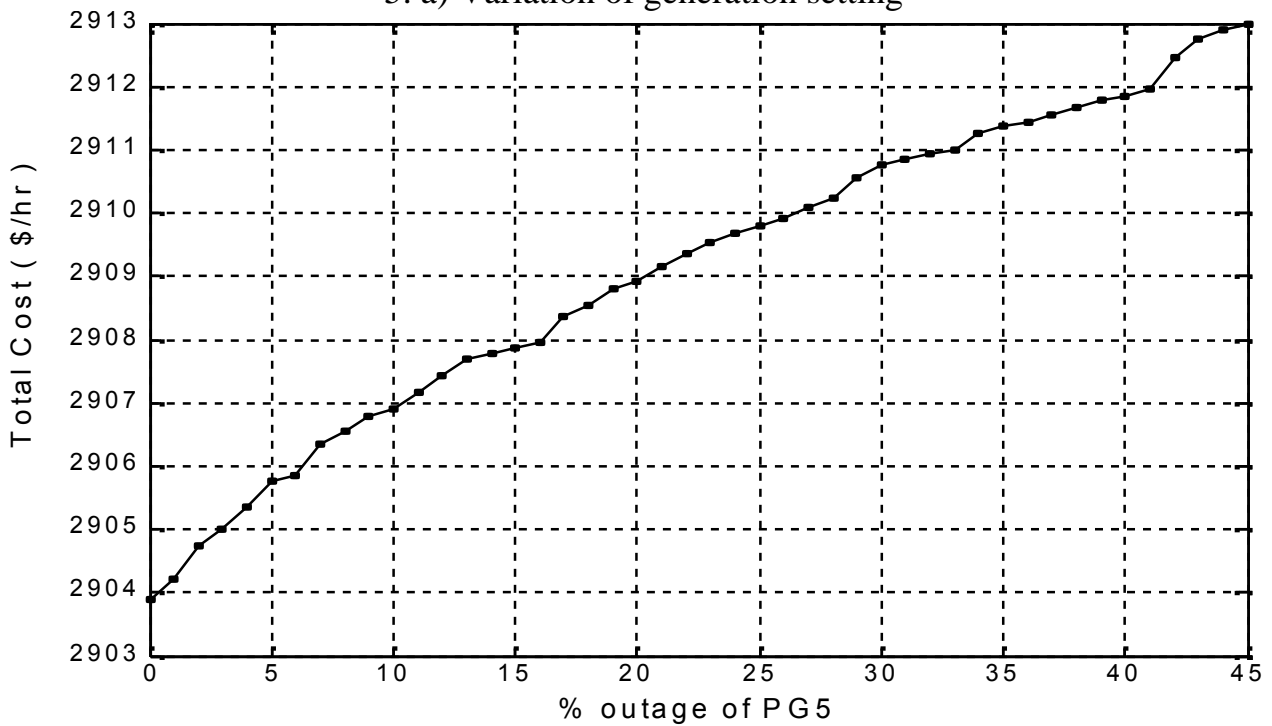4. a) Variation of generation setting

4. b) Variation of generation cost

Figure (4): *The SCOD using ACO algorithm for different percentages outage of power generation 3 for 5-bus system*

5. a) Variation of generation setting

5. b) Variation of generation cost

Figure (5): *The SCOD using ACO algorithm for different percentages outage of power generation 5 for WDN system*

6. Conclusions:

This paper presents an approach based on ACO algorithm to solve the problem of SCOD 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. Therefore, the proposed algorithm represents a potential tool to aid the power system operators in the on-line environment.

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Nomenclatures:

F_t	The non-linear objective function of power generation cost Rotor speed
a_i, b_i and c_i	The coefficients of power generation cost function Conductance
e_i and f_i	The fuel cost coefficients of the *i*th unit with valve-points effects
NG	The number of generation buses
PG_i	The power generation at bus *i*
PD_j	The load demand at load bus *j*
NL	The number of load buses
P_{losses}	The total power losses in the system
PG_i^{max}	The maximum limit of power generation at bus *i*
PG_i^{min}	The minimum limit of power generation at bus *i*
PF_k	The power flow in line *k*
PF_k^{max}	The maximum power flow in line *k*

$D_{k,i}$ The distribution parameters of the power flows related to the power generations

τ_{ij} The pheromone trail deposited between city i and j

η_{ij} 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 Two parameters that influence the relative weight of pheromone trail and heuristic guide function, respectively

N_r^k A tabu list in memory of ant that recodes the cities are visited to avoid stagnations

ρ The pheromone evaporation constant

σ The elite path weighting constant

d_{bes} The shortest tour distance found as in TSP