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HYBRID DIFFERENTIAL EVOLUTION-ANT COLONY OPTIMIZATION FOR ECONOMIC LOAD DISPATCH PROBLEM

[1]N.A. RAHMAT, [2]I. MUSIRIN

[1]Faculty of Electrical Engineering, Universiti Teknologi MARA

[2]Assoc. Prof. Dr., Faculty of Electrical Engineering, Universiti Teknologi MARA

E-mail: [1]azamrahmat@gmail.com, [2]ismailbm@salam.uitm.edu.my

ABSTRACT

A distinctive optimization technique known as Ant Colony Optimization (ACO) has gained huge popularity in these recent years due to its flexibility and the ability to avoid reaching local optima. This optimization approach has become a candidate approach for many optimization problems. Unfortunately, this attractive algorithm suffers several downsides including stagnation and slow convergence toward optimal solution. Thus, a new algorithm, termed as Differential Evolution Ant Colony Optimization (DEACO) has been modelled to compensate the drawbacks. The algorithm was utilized to solve economic load dispatch problem in order to verify its performance. Economic Load Dispatch (ELD) problem concerns the planning of generators outputs that can meet load demand at minimum operating cost. Moreover, in this research, several ant parameters, including number of ants and nodes were manipulated to investigate the behaviour of DEACO algorithm. Comparative studies between DEACO and conventional ACO suggested that the new algorithm has successfully overcome the weaknesses of classical ACO.

Keywords: *Ant Colony Optimization (ACO), Differential Evolution (DE), Economic Load Dispatch (ELD)*

NOMENCLATURE

B_{ij}, B_{0i}, B_{00}	*B*-loss coefficient
C_r	Crossover factor
$Fi(P_i)$	Operating cost function
$J_{k(r)}$	set of unvisited nodes in order to make feasible solution
L_{gb}	Length of globally best tour from the beginning of the tour
N_D	Number of demand buses
N_g	Numbers of generating unit
P_D	Total load demand
P_{Dj}, Q_{Dj}	Real and reactive power demand at bus *j*
$P_{Gi}^{min}, P_{Gi}^{max}$	Lower and upper limit of real power generated at bus *i*
P_{Gj}, Q_{Gj}	Real and reactive power generated at bus *j*
P_L, Q_L	Real and reactive power losses
P_i	Real power of unit *i*
$P_{i\,min}, P_{i\,max}$	Minimum and maximum generation limit of unit *i*
$Q_{Gi}^{min}, Q_{Gi}^{max}$	Lower and upper limit of reactive power generated at bus *i*
$T_{(r,s)}$	Local pheromone update
T_0	Initial pheromone layer
$V_{Gi}^{min}, V_{Gi}^{max}$	Lower and upper limit of voltage at bus *i*
$X_{i+m,j}$	Pheromone mutation function
$X_{j\,min}, X_{j\,max}$	Smallest and largest visited node
a_i, b_i, c_i	Cost coefficient of unit *i*
d_i	Distance between two nodes
d_{max}	Maximum distances for every ant tour
f_i	distance travelled by ant
f_{max}	Longest distance travelled by ant
x_{max}	Maximum value of *x*
$\Delta\tau(r,s)$	The changes of pheromone intensity
H	Inverse of the distance travelled
S	Random variable selected by a probability distribution
T	Pheromone
m	Number of ants
n	Number of nodes
q	Randomly distributed numbers
r	Current node
u	Unvisited node
x	Fitness variable
α	Pheromone decay factor
β	Pheromone deposit factor

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1. INTRODUCTION

Among the greatest challenge in power system industry is to plan energy dispatch. Power flow analysis is a crucial attention during power system planning, analysis, scheduling and design. This area of studies is known as the Optimal Power Flow (OPF). Power flow analysis is the backbone of power system analysis. This non-linear and steady-state approach is essential for handling operation planning, economic scheduling, and energy exchange between energy providers. In essence, it is an optimization problem and whose objective is to narrow down the total operating cost of generators, without violating constrains [1]-[2]. The principle information obtained from this study for instance the voltage magnitude, shunt elements and phase angle are important for many research fields such as transient stability, load shedding, and contingency analysis. This analysis is not a simple one and consists of numerous variables. Power flow analysis is considered as nonlinear algebraic mathematical problems and researchers have developed several approaches to solve this problem. The first one is the Gauss-Seidel method. This method named after Carl Friedrich Gauss and Philipp Ludwig von Seidel. This approach apply iterative rule and known as the method of successive displacement. Convergence is achieved if the matrix is either diagonally dominant or positive definite [3]. The second one is known as the Newton-Raphson method. This method is widely used in power flow studies and was developed based on the Taylor's series expansion [4]-[5]. Even though this method is widely used, it suffers several drawbacks, especially the complexity in calculating derivative of a function, fail to achieve convergence, and overshooting that leads the solution to diverge away from the root [5].

Among the related topic and widely discussed in OPF is the Economic Load Dispatch problem. Economic Load Dispatch (ELD) is the procedure of generating electrical energy at the lowest possible cost to feasibly feed the energy necessitated by its consumers. Economic load dispatch problem is among the fundamental topics in power system operation [6]-[7]. The entire energy demand must be dispersed accordingly among the generating units. Among the factors that influence load dispatch are the operating efficiencies of generating unit, fuel cost, and transmission losses. Note that even the most ideal generator could not guarantee a viable cost if the generator is positioned at a very remote location from the load distribution point or the fuel price is considerably expensive. While sustaining the demand, the energy provider must aware of the operational limits of the generating units and transmission facilities. Economic Load Dispatch requires the generation facilities to plan and forecast optimal energy dispatch. Several crucial considerations during energy scheduling are to determine the existing generating units, the distance between load centre and the generating unit, identifying the operating limits of each generating unit for example the ramp rate, maximum and minimum generation levels, and the maximum amount of the permissible running time for the generating unit, reliability, and efficiency. Formerly, ELD problems were solved by various mathematical analysis and optimization methods [8].

Currently, several numbers of techniques has been developed to help overcome ELD problems, such as Particle Swarm Optimization [9-10]. Artificial Bee Colony Algorithm [11], Genetic Algorithm [12], Pattern Search Algorithm [13], Neural Networks [14]-[15], Evolutionary Programming [16], and Harmony Search Algorithm [17]-[18]. Each of the implemented techniques has its own advantage and disadvantages. For example, Particle Swarm Optimization (PSO) is known for its ability to allow each particle to preserve a memory of the best solution and the best solution found by the in the particle's area. Simple idea, easy employment, and computationally efficient [19] are the main highlights of PSO technique. However, the inequality constraints in the next position of an individual produced by the PSO algorithm can disrupt the inequality constraints [9]. This method also displays inherent difficulties in performing local search for numerical applications [10].

Lately, Ant Colony Optimization (ACO) has become a candidate optimization technique for many applications [20]-[22] that stress on combinatorial optimization travelling salesman problem (TSP), quadratic assignment problem (QAP), and optimal design and scheduling problem of thermal units [23]. ACO is a probabilistic technique that was introduced by Marco Dorigo in 1992 in his PhD thesis. The algorithm resembles the behaviour of an ant colony, seeking a good path between food source and their nest. In their journey to search for food, ant will deposit a type of chemical trace called pheromone. If other ants found the pheromone trail, they will break random travelling and begin to follow the trail. In doing so, they will reconstruct the existing pheromone trail by spreading additional amount of the chemical essence on the track. However, less travelled path

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will have its pheromone layer evaporated, thus reducing its attractiveness.

Another highlighted approach in this research is the Differential Evolution (DE). DE was introduced by Storn and Price in 1995 [24], established to optimize real parameter and real valued functions. DE was used to solve the Chebychev Polynomial Fitting Problem, and iteratively improve the optimization agent with respect to a given parameter. In 1996, DE successfully won the third place during the First International Contest on Evolutionary Computer (1st ICEO) in Nagoya. DE optimizes an objective function by creating a new candidate solution, termed as "offspring" out of the original one. The algorithm then combines the offspring with the original one through a process called as crossover. Later on, a new fitness score will be calculated. Candidate with the best fitness score will be reserved, but the one with bad fitness will be discarded. Similar to Genetic Algorithm, DE is a typical Evolutionary Algorithm (EA), stochastic and population-based optimization algorithm [25]. DE is suitable to solve non-differentiable, non-continuous, non-linear, noisy, flat, and multi-dimensional objective function. In 1997, Storn and Price claimed that DE is much better and more efficient than Simulated Annealing and Genetic Algorithms [26]. DE has been applied broadly in optimization problems such as multiprocessor synthesis, Neural Network Learning, Radio Network design, optimization of non-linear chemical process, and gas transmission network design. DE also has been implemented into economic load dispatch problem [27].

This paper presents Differential Evolution Ant Colony Optimization (DEACO) technique in solving Economic Load Dispatch problem. The study stress on the development of new algorithm called as DEACO which integrates DE and ACO together to improve the performance of both algorithms. To verify its performance, DEACO is used to optimizing the ELD on a reliable test system namely the IEEE 26-Bus Reliable Test System and IEEE 57-Bus Reliable Test System. The results from this study indicates that the proposed technique outperformed the traditional ACO in terms of cost minimization and computation time.

2. ECONOMIC LOAD DISPATCH

For interconnected systems, the goal of economic load dispatch is to find the real and reactive power scheduling in order to cut-down the cost function of different generating units in the system. Operating efficiency of prime mover, fuel cost and transmission losses are among the issues that might impact the operating cost. The generator costs are typically characterized by several types of quadratic curves. Energy output can be measured by using a wattmeter over a period of time. The generator's input can be identified by measuring the fuel tonnage used to fire the generator in MBTU/ton unit. The fuel input can be plot in MBTU/hour as a function of the output power in MW. Such plot is known as input-output curve as indicated in Figure I

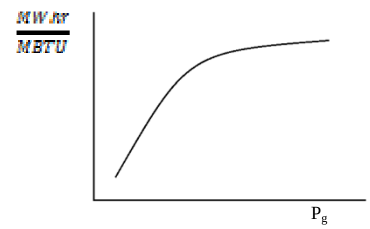

Figure I. Input-Output Curve

The second representation is the fuel-cost curve as depicted in Figure II. The plot begins by extracting the ratio of fuel rate to the power for every point from the input-output curve. The plot of these ratios versus the generation level will produce the fuel-cost curve.

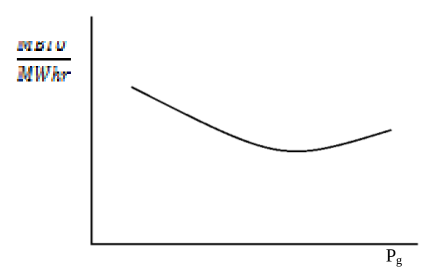

Figure II. Fuel-Cost Curve

Figure III depicts the heat rate curve. This curve is not to be confused with Figure I since it is almost identical to the input-output curve. The difference is that heat rate curve represents the ratio of values of fuel rate to values of generation. This curve expresses how the cost per MWhr varies with the output generation.

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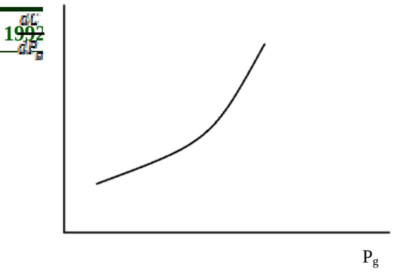

Figure III. Heat Rate Curve

Another illustration of generator cost is the incremental cost curve, as reflected by Figure IV, which represent the desired $/MWhr characteristic of the operating cost. The data on its y-axis can be obtained by differentiating operating cost ($/hr) with respect to the generation output. Another approach to acquire the incremental cost rate is by multiplying fuel price by the incremental heat rate.

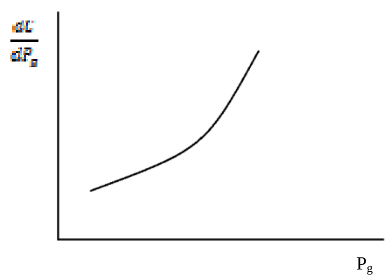

Figure IV. Incremental Cost

The total operating cost is modeled by summing up the individual cost function of each generator. Thus, an optimal generated output can be acquired from the solution. Figure V below is a graphical representation of a simple, single line diagram which encompasses the basic elements of a power system.

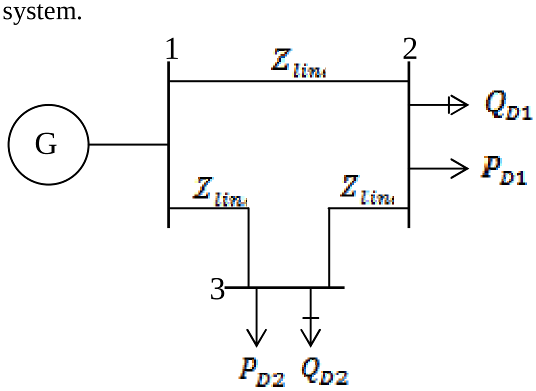

Figure V. Single Line Diagram Of A Power

Where G is the generating unit, Z_{line1}, Z_{line2}, and Z_{line3} are the line impedances, P_{D1} and P_{D2} are the real power demand, and Q_{D1} and Q_{D2} are the reactive power demand. Some of the equations in this research were referred from [24]. Equation (1) represents the cost of generating units in a power system.

$$C_{Tot} = \sum_{i}^{Ng} C_i(P_i) \tag{1}$$

Where C_{Tot} is the summation of operating cost, $C_i(P_i)$ of generator G_i. The cost function is used to calculate the cost of operating each generator in the bus system. The operating cost can be written as a quadratic equation with respect to the generated power, P_i as shown below:

$$C_i(P_i) = a_i P_i^2 + b_i P_i + c_i \tag{2}$$

Where a_i, b_i, and c_i are the cost coefficients of unit i. The cost function for each generating units are required to calculate the total operating cost. The followings are the generators' operating costs for IEEE 26-Bus System.

C_i	a	b	c
C_1	200	7.0	0.0070
C_2	200	10.0	0.0095
C_3	220	8.5	0.0090
C_4	200	11.0	0.0090
C_5	220	10.5	0.0080
C_{26}	190	12.0	0.0075

The operating costs for IEEE 57-Bus System also use equation (12) and are shown as follows:

C_i	a	b	c
C_1	400	7.0	0.0070
C_2	200	10.0	0.0095
C_3	220	8.5	0.0090
C_6	200	11.0	0.0090
C_8	240	10.5	0.0080
C_9	200	12.0	0.0075
G_{12}	180	10.0	0.0068

Moreover, the power loss P_L is another important consideration during dispatch planning. The power loss must be kept as minimal as possible.

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The equation to calculate P_L is shown below:

$$P_L = \sum_{i}^{N}\sum_{j}^{N} P_i B_{ij} P_j + \sum_{i}^{N} B_{0i} P_i + B_{00} \quad (3)$$

Where B_{ij}, B_{0i}, and B_{00} are the *B-loss* coefficient.

3. DIFFERENTIAL EVOLUTION ANT COLONY OPTIMIZATION FORMULATION

ACO algorithm can easily couple with other optimization method. It requires small number of search agents, and can avoid falling into local optima problem. Because of these attractive features, this optimization approach quickly acquires a good reputation among researchers. However, this algorithm converges to an optimal solution slowly due to its positive feedback design and random selection process, and may experience stagnation problem which may limit its wide application in various optimization problems [28]. Moreover, recent employment of ACO shows that the technique is not effective enough to solve complex problems. On the contrary, DE is more robust, and able to quickly reach convergence. Therefore, the benefits reflected by DE were taken into account to compensate for the disadvantages of ACO algorithm.

The pheromone layer in ACO will be modified by DE mutation, crossover, and selection process. In this paper, DEACO algorithm is devised into ELD problem. The following steps explain briefly about the algorithm.

Step 1: Initialization
The algorithm starts with heuristically initialize all the parameters. The parameters are assigned within a certain limits in order to overcome large computation time [28]. The followings are the necessary parameters during initialization:

r	: no. of nodes
s	: no. of ant
ρ_β	: relative importance of pheromone versus distance ($\rho_\beta > 0$)
ρ_e	: pheromone evaporation coefficient ($0 < \rho_e < 1$)
ρ_α	: pheromone decay coefficient ($0 < \rho_\alpha < 1$)
ρ_0	: initial pheromone level

Each ant will tour and select the next unvisited node and the ants are not permitted to make the random tour more than once. Therefore, the random travelling distance for each ant is different. The longest distance, l_{max} is determined by calculating the longest distance that the ant would travel.

Step 2: Generate the First Node
The ant will randomly select the first node to visit. The possibilities are based on a uniform distribution ranged between 1 to *n*.

Step 3: State Transition Rule
The ant that is initially situated at node (m) will move to the next node (n). The selection of the consecutive node is based on equation (19):

$$\rho_k(m,n) = \begin{cases} \dfrac{[\rho(m,n)]\cdot[\eta(m.n)^{\rho_\beta}]}{\sum \mu\varepsilon\rho_{k(m)}[\rho(m,u)]\cdot[\eta(m.u)^{\rho_\beta}]}, if\ s \in \rho_{k(m)} \\ 0, otherwise \end{cases} \quad (19)$$

Where:

ρ	: pheromone trace
$\rho_{k(r)}$	: set of unvisited nodes
η	: $1/l$ is the inverse of the distance $l(m,n)$
m	: current node
n	: next node
u	: unvisited node

During the random tour, each ant can only visit the same node once. Once an ant has stopped a definite node, the ant is prohibited to visit the same node again. The length for each travel is different. The longest distance, l_{max} is determined by calculating the longest ant tour.

Step 4: Local Updating Rule
After reaching the new node, the pheromone level will be updated. The pheromone level of the travelled path will be varied to alter its attractiveness. The updating process is according to the following equation:

$$\rho(m.,n.) \leftarrow (1-\rho_e)\tau(m,n) + \rho(m,n) \quad (20)$$

Where:

$\rho(m,n)$	: current pheromone trace
$\rho(m.,n.)$	: new pheromone trace

In this research, the pheromone evaporation rate, ρ_e is set to 0.45. This process allows the ant to discover the visited node once again during their next exploration.

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Step 5: Pheromone Mutation

DE Mutation process was integrated into ACO, where the level of pheromone is the candidate of mutation. This research is focusing on Gaussian Distribution Equation. The pheromone mutation rate shown in (23) is derived from Gaussian Distribution function.

$$M_{i+m,j} = M_{i,j} + N\left(0, \beta \cdot \left(M_{j\,max} - M_{j\,min}\right) \cdot \frac{l_i}{l_{max}}\right) \quad (23)$$

Where:

$M_{i+m,j}$: mutator function
M_{jmax} : maximum node value
M_{jmin} : minimum node value
l_{max} : longest ant tour
l_i : length of current ant tour

Mutation process will improve the diversification of pheromone trail by creating the mutated pheromone trail, $\rho_x(m,n)$.

Step 6: Crossover

DE crossover process is very similar to that of GA [21]. The mutated and the original pheromone trail will merge together into the trial matrix, M_{trial}. M_{trial} will sort the pheromone level in descending order.

Step 7: Selection

Comparison between the trial and the original pheromone trail are made during the selection process. Firstly, the trial and original pheromone trail will be normalized, and compared with a predetermined selection variable, A_{sel}. A_{sel} is set between 0 to 1. The selection process will choose pheromone layer that scored 1 or near to 1.

Step 8: Fitness Evaluation

Fitness evaluation is performed after all ants have completed their tour. The control variable F_x, is calculated by means of equation (27):

$$F_x = \frac{l}{l_{max}} \cdot F_{x\,max} \quad (27)$$

Where:

l : distance for every ants tour
l_{max} : maximum distance for every ants tour
F_{xmax} : maximum of F_x

The values of variable F_x will be assigned and multiplied with fitness of this research.

Step 9: Global Updating Rule

After all ants have completed their travels, the best ant is allowed to update the amount of pheromone level to determine the best global fitness. The following equation is applied to update the pheromone level globally:

$$\rho(m,n) \leftarrow (1-\rho_\alpha)\rho(m,n) + \rho_\alpha . \Delta\rho(m,n) \quad (28)$$

The best route will have its pheromone level amplified.

Step 10: End Condition

Once the maximum number of iteration (Q_{max}) has been reached and all ants have completed their tour, DEACO will stop its processes.

4. RESULTS AND DISCUSSION

The modelling and program development of DEACO was accomplished by using MATLAB R2010a software. To test the engine's capability and effectiveness, two case studies, involving IEEE 26-Bus system and IEEE 57-Bus System were applied. The effect of ant parameters to DEACO algorithm is also investigated for both cases. Since DEACO shares several similar parameters of ACO, therefore, DEACO requires the same parameters setting as the original ACO algorithm.

Case study 1: IEEE 26-Bus System

This case study considers IEEE 26-Bus System which contains 6 generating units. The objective is to reduce the total operating cost, while conserving the system constraints under the allowable limits. While cutting down the operating cost, it was initially projected that the power loss might be reduced to minimal. Power loss is the marginal value between the demanded power and the total generated power by the generating units.

Table I. Generating Limits For 6 Generators

Generating Unit	Minimum (MW)	Maximum (MW)
1	100	500
2	50	200
3	80	300
4	50	150
5	50	200
26	50	120

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To prove the effectiveness of the DEACO engine, comparisons are made between DEACO and the conventional Ant Colony Optimization technique. Table I tabulates the operation limit for each generating unit in the bus-system.

Table II depicts the results of comparative studies between DEACO and ACO. Both algorithms were implemented into economic load dispatch problem. The table clearly shows that DEACO generates smaller outputs than ACO. It is also observed that the computation time for DEACO is much superior to that in ACO as highlighted in the table.

Table II. Results Comparison Between ACO And DEACO

Engine	**ACO**	**DEACO**
G_1 (MW)	447.1142	447.0700
G_2 (MW)	172.7343	172.7460
G_3 (MW)	261.6889	261.4793
G_4 (MW)	138.4072	138.3812
G_5 (MW)	168.6463	168.9707
G_{26} (MW)	87.1335	87.0760
Total Generated Power (MW)	1275.7244	1275.7000
Total Loss (MW)	12.7244	12.7232
Total Cost ($/Hour)	15446.4091	15446.2634
Computation Time (s)	25.554026	0.414134

The results indicate that DEACO has successfully minimized each of the generators' output to an optimal point. After the economic power scheduling for each generating units has been calculated, Equation (27) was used to compute the total operating cost for this case study. DEACO slightly cuts down the total operating cost by 0.00009%. In this case study, the discount percentage is insignificant due to the fact that the considered system is a small system. Next, DEACO has successfully minimized the total power loss, from 12.7244MW to 12.7232MW by 0.01%. Note that power loss is the difference between total power demand and total generated power. In this small bus system, DEACO might not reveal substantial differences from its ACO counterpart. However, DEACO has already outperformed ACO through its rapid computation capability. While ACO requires 25.554026 seconds to run its task, DEACO only needs 0.414134 second to finish its job. This noteworthy capability is the new improvement DEACO introduced to the conventional ACO.

Case study 2: IEEE 57-Bus System

The IEEE 57-Bus System which contains 7 generating units has been chosen as the second test system. Similar to the previous case study, the total operating cost is the summation of the generators' operating cost equations. Table III tabulates the generating limits for each generating units. Table IV indicates that DEACO has effectively minimized the generation output of each generating unit. The total operating cost was reduced by 0.5%, from $17,347.57 per hour to $17245.85 per hour. It is found that DEACO demonstrated to be beneficial in reducing the total power loss. In this case study, DEACO outperformed ACO by significantly reducing the total power loss. Furthermore, DEACO optimizes ELD problem at a faster computation rate that the conventional ACO as highlighted in the table.

Table III. Generating Limits For 7

Generating Unit	**Minimum (MW)**	**Maximum (MW)**
1	100	575
2	50	100
3	50	140
6	50	100
8	100	550
9	50	100
12	100	410

Table IV. Results Comparison Between ACO And DEACO

Engine	**ACO**	**DEACO**
G_1 (MW)	136.2812	133.3403
G_2 (MW)	98.2218	95.8749
G_3 (MW)	45.3719	45.1676
G_6 (MW)	73.5391	73.1239
G_8 (MW)	457.9186	457.4348
G_9(MW)	98.8826	98.4765
G_{12}(MW)	364.0922	362.3069
Total Generated Power (MW)	1274.3074	1265.7249
Total Loss (MW)	11.3074	2.7249
Total Cost ($/hour)	17347.5731	17245.8531
Computation Time (s)	23.367137	2.721103

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Case study 3: The Effect of Ant Parameters to DEACO

The effect of ant parameters to DEACO has also been investigated. The involved parameters were the number of ants and number of nodes. Ant is the search agent for ACO algorithm, while node is the term that defines the visiting point of ants during their tour.

The experiment is conducted on IEEE 57-Bus System. All the constraint and system limitation were similar to case study 2. The number of ants and number of nodes will be manipulated to see the effect of ant parameters to the performance of DEACO algorithm.

Table V. Effects Of Ant Parameters To ACO Algorithm

Ant	Node	P_{g1} (MW)	P_{g2} (MW)	P_{g3} (MW)	P_{g6} (MW)	P_{g8} (MW)	P_{g9} (MW)	P_{g12} (MW)	P_{total} (MW)	P_{loss} (MW)	Time (s)	Total Cost ($/MWhr)
5	5	136.6417	90.0463	45.145	76.1207	463.3798	100	358.7636	1270.0971	20.0971	4.423952	17317.36
	10	136.2812	95.8749	45.3719	73.5391	457.4348	98.8826	362.3069	1269.6914	19.6914	3.367137	17284.48
	15	138.2162	96.6722	45.4058	75.0607	458.231	95.9256	360.7044	1270.2159	20.2159	9.785236	17280.75
	20	136.2812	95.957	45.3719	73.5391	457.4348	99.7539	362.9261	1271.264	21.264	15.785419	17306.45
	25	136.2812	95.957	45.3719	73.5391	457.4348	99.7539	362.9261	1271.264	21.264	32.16484	17306.45
10	5	137.1195	91.1863	44.975	74.5774	463.2704	100	358.6723	1269.8009	19.8009	8.780039	17317.36
	10	136.2812	95.957	45.3719	73.5391	457.4348	99.7539	362.9261	1271.264	21.264	5.739441	17306.45
	15	136.2812	95.957	45.3719	73.5391	457.4348	99.7539	362.9261	1271.264	21.264	11.52213	17306.45
	20	136.2812	95.957	45.3719	73.5391	457.4348	99.7539	362.9261	1271.264	21.264	18.22156	17306.45
	25	136.2812	95.957	45.3719	73.5391	457.4348	99.7539	362.9261	1271.264	21.264	30.158742	17306.45
15	5	136.2812	95.957	45.3719	73.5391	457.4348	99.7539	362.9261	1271.264	21.264	5.65861	17306.45
	10	136.2812	95.957	45.3719	73.5391	457.4348	99.7539	362.9261	1271.264	21.264	8.55872	17306.45
	15	136.2812	95.957	45.3719	73.5391	457.4348	99.7539	362.9261	1271.264	21.264	16.445782	17306.45
	20	136.2812	95.957	45.3719	73.5391	457.4348	99.7539	362.9261	1271.264	21.264	25.366521	17306.45
	25	136.2812	95.957	45.3719	73.5391	457.4348	99.7539	362.9261	1271.264	21.264	38.11695	17306.45

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Table VI. Effects Of Ant Parameters To DEACO Algorithm

Ant	Node	P_{g1} (MW)	P_{g2} (MW)	P_{g3} (MW)	P_{g6} (MW)	P_{g8} (MW)	P_{g9} (MW)	P_{g12} (MW)	P_{total} (MW)	P_{loss} (MW)	Time (s)	Total Cost ($/MWhr)
5	5	129.4661	90.9768	45.5035	77.388	464.3614	100	363.4766	1271.1724	20.8724	2.861099	17371.57
	10	133.3403	98.2218	45.1676	73.1239	457.9186	98.4765	364.0922	1270.3409	20.0409	2.721103	17308.94
	15	135.2651	95.8749	45.3371	73.095	457.3123	98.8826	362.3069	1268.0739	17.7739	3.696133	17267.46
	20	135.2651	95.8749	45.3371	73.095	457.3123	98.8826	362.3069	1268.0739	17.7739	4.447404	17267.46
	25	135.2651	95.8749	45.3371	73.095	457.3123	98.8826	362.3069	1268.0739	17.7739	5.428638	17267.46
10	5	129.4661	90.9768	45.5035	77.388	464.3614	100	363.4766	1271.1724	20.8724	6.231112	17371.57
	10	135.2651	95.8749	45.3371	73.095	457.3123	98.8826	362.3069	1268.0739	17.7739	7.076732	17267.46
	15	135.2651	95.8749	45.3371	73.095	457.3123	98.8826	362.3069	1268.0739	17.7739	7.308825	17267.46
	20	135.2651	95.8749	45.3371	73.095	457.3123	98.8826	362.3069	1268.0739	17.7739	5.194667	17267.46
	25	135.2651	95.8749	45.3371	73.095	457.3123	98.8826	362.3069	1268.0739	17.7739	7.044118	17267.46
15	5	135.2651	95.8749	45.3371	73.095	457.3123	98.8826	362.3069	1268.0739	17.7739	9.183012	17267.46
	10	135.2651	95.8749	45.3371	73.095	457.3123	98.8826	362.3069	1268.0739	17.7739	6.054304	17267.46
	15	135.2651	95.8749	45.3371	73.095	457.3123	98.8826	362.3069	1268.0739	17.7739	7.420403	17267.46
	20	135.2651	95.8749	45.3371	73.095	457.3123	98.8826	362.3069	1268.0739	17.7739	7.697243	17267.46
	25	135.2651	95.8749	45.3371	73.095	457.3123	98.8826	362.3069	1268.0739	17.7739	8.850506	17267.46

Table V tabulates the calculated generation output of each generating unit. The total power is the summation of all generating units in the system. P_{loss} is the loss that was introduced by the transmission line. It is the difference between the demanded power and the total generated power. Table V depicts that ACO is greatly dependent of ant parameters. To generate consistent and promising total operating cost, ACO requires high number of ants and nodes. For example, at 10 nodes and 5 ants, the algorithm computes a total operating cost of 17317.36 $/MWhr, and calculated 1270.0971MW of power loss. ACO continues to generate fluctuating and irregular total operating cost while having small number of ants.

However, by setting the number of nodes and number of ants to a greater value, the algorithm starts to generate consistent and more promising solution. Starting from 10 numbers of ants with 10 numbers of nodes, ACO computed the total operating cost of 17306.45 $/MWhr. The solution remains constant afterwards. Table VI tabulates the effect of ant parameters towards the performance of DEACO algorithm.

The first properties that need to be noted is that DEACO has effectively reduced the total operating cost lower than ACO. At small number of ants, for example 5 ants; the algorithm seems to be depending on the number of nodes to properly generate a desired solution. DEACO performance increased correspondingly to the increased number of nodes. For example, initially the algorithm produced fluctuating operating cost that varies between 17371.57$/MWhr and 17267.46$/MWhr.

However, these undesired outcomes have been overcome by increasing the number of ant, from 5, 10 and 15 ants. At large number of ants, DEACO appears to be very independent of the number of nodes in order to work appropriately.

Taking the example of DEACO having 10 numbers of ants; starting from 10 nodes to 25 nodes, the algorithm consistently generated the total operating cost of 17267.46$/MWhr. It implies that DEACO can perform ideally with less impact from ant parameters. Based on the results tabulated in Table V and Table VI, it was found that DEACO has outperformed the original ACO in terms of the requirement of search agent. DEACO proved to be

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requiring only small numbers of search agent to achieve optimal solutions. However, ACO starts to produce constant solution after the number of nodes has been increased.

The result also implies that DEACO can rapidly hit convergence and more dependable than ACO algorithm. This attractive characteristic reveals that DEACO can work faster, yet can still provide effective solutions for suitable optimization problem

5. CONCLUSION

In this research, the development and implementation of Differential Evolution Ant Colony Optimization algorithm has been demonstrated. DEACO engine is achieved by symbiotically combines several elements of Differential Evolution into Ant Colony Optimization engine, in a way to compensate any disadvantages that were suffered by both algorithms. It is revealed that DEACO algorithm has successfully solved economic load dispatch optimization problem. By comparing DEACO results with its conventional counterpart, it is revealed that DEACO does better jobs than ACO. DEACO optimizes ELD problem by cutting down the operational cost of generating units. DEACO has minimized the power loss with better performance as those in ACO. Future works will be performed by implying several modifications to the mutation operation in order to enhance and control the evolution rate of pheromone.

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