Evolutionary Programming Approach for Solving Economic Dispatch in Power System

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ABSTRACT

The problem of economic dispatch has been forwarded and solved by numerous methods such as dynamic programming, tabu search, simulated annealing and genetic algorithm (GA). In this paper, Evolutionary Programming (EP) is used as the technique to solve the problem of economic dispatch in power system. Log-normal Gaussian mutation or commonly known as meta-EP, is used as the essential operator of generating the sufficient power in order to fulfil demand at a minimum cost. The proposed EP method provides a solution consisting suitable power generated of each generator and meeting the demand with minimum total cost. The study also investigates the differences of using standard EP against meta-EP to solve the same problem The study conducted for the comparison is based on the solution and performance of each algorithm in solving the problem.

1. INTRODUCTION

Optimization techniques such as dynamic programming, tabu search, simulated annealing and GA have successfully solved the problem of economic dispatch in power system. These techniques may have their own advantages and disadvantages. Some papers have also published the success of EP in solving economic dispatch problems.

Alternative technique of EP, known as meta-EP [1], is used to solve the economic dispatch problems. At the same time, the difference between the standard EP and meta-EP was reviewed as well as the performance of EP in general towards GA technique. The EP that was developed will provide a solution consisting of the suitable power generated for each generator that meets the demand with the minimum total costs.

2. ECONOMIC DISPATCH

The primary concern of an economic dispatch problem is the minimization of an objective function, usually the total cost of generation, while satisfying both the equality and inequality constraints. The objective function can be defined as:

$$F_T = \sum_{I=1}^{N} F_i P_i \qquad (1)$$

where

F_T = Total cost of generation (US Dollar per hour)
F_i = Cost function for unit i (US Dollar per hour)
P_i = Power generation for unit I (Megawatts)

The cost function is the form of

$$F_i (P_i) = a_i + b_i P_i + c_i P_i^2 \qquad (2)$$

where parameters a_i, b_i and c_i represent the unit cost coefficients.

The objective function is subjected to total power generated

$$P_T = P_D + P_L \qquad (3)$$

where

P_T = Total Power Generated (Megawatts)
P_D = Total load demand (Megawatts)
P_L = Total transmission loss (Megawatts)

Total transmission losses can be determined using Equation 4:

$$\sum_{i=1}^{N} B_i P_i^2 \qquad (4)$$

where

B_i = transmission loss coefficient

Power generated for each unit is subjected to certain limit:

$$P_i^{min} \le P_i \le P_i^{max} \qquad (5)$$

where

P_i^{min} = Lower limit of power generated by each unit (MW)
P_i^{max} = Upper limit of power generated by each unit (MW)

3. EVOLUTIONARY PROGRAMMING

EP has been used in the field of design search and optimization more thoroughly after the exposure from David B. Fogel [2]. At first, EP was primary studied in prediction of finite states machines by Lawrence Fogel in the 1960's. Since then, EP has undergone refinement process in which self-adaptation parameters and different mutation strategy has been implemented. As stated earlier, this paper will study both the standard EP and Meta EP [2],[3].

There are a quite number of papers that has shown the implementation of economic dispatch using classical EP [4]-[7]. Mainly, the interest of using classical EP as the method for economic dispatch problem is because of its simplicity to GA where EP does not involve any special coding. Real number valued is used in the process. Secondly, EP does not impose any alteration of the objective function or constraints restriction. Hence, the transfer of the problem into algorithm is fairly simplified.

The following implementation of EP [1], which is the revised version from the earlier EP is referred as Meta EP:

1. Generate the initial populations of α consisting of μ individuals and set generation $\kappa = 1$. Each individual is from a pair of real valued vector (x_i, η_i) $\forall_i$ ε{ 1,..., μ}, where η_i is a strategy parameter. Each α has η components α $(j), j = 1,...,n$

2. Evaluate the fitness score for each individual (x_i, η_i) $\forall_i$ ε{ 1,..., μ}, of the population according to the objective function, $f(x_i)$

3. For each parent (x_i, η_i,), i = {l,..., μ }, a single offspring is created (x_i', η_i') using:

   $$\eta_i'(j) = \eta_i(j)\exp(\tau' N(0,1) + \tau N_j(0,1)), \quad (6)$$
   $$x_i'(j) = X_i(j) + \eta_i'(j) N_j(0,1), \quad (7)$$

   $x_i(j)$, $x_i'(j)$, $\eta_i(j)$ and $\eta_i'(j)$ is the j^{th} component of the respective vector. $N(0,1)$ donates a normally distributed one-dimensional random number with mean 0 and 1. $N_j(0,1)$ indicates that the random number will be anew for each value of j.

   $$\tau = ((2(n)^{1l2})^{1l2})^{-1} \text{ and } t'' = ((2n)^{1/2})^{-1} \quad (8)$$

4. Calculate the fitness of each offspring (x_i', η_i') for i = {l,... ,μ}.

5. Pair wise comparison is conducted over the union of both parent and offspring. For each individual, q opponents are chosen randomly from the union with equal probability. For each comparison, an individual receives a "win" if its fitness number is not smaller than the opponents.

6. The μ individuals out of the union that have the most wins will be selected as parents of next generation.

7. Stop if the halting creation is satisfied, otherwise go the next generation, $\kappa = \kappa + 1$ and continue at step 3.

Meanwhile, Standard EP is differed in the way the mutation is conducted and doesn't use self-adaptation method as Meta EP. That will remove the need to use strategy parameter initialization and updating from the algorithm. For standard EP, step 3 above will be computed as follows:

$$x'(j) = x_i(j) + N_j(0, \sigma_j^2) \quad (9)$$

$$\sigma_j = \beta \times f_{pi} / f_{min}(P_{i,min} - P_{i,max}) \quad (10)$$

where σ_j is the standard deviation, β is the scaling factor, f_{min} is the minimum cost among the trial solutions, and f_{pi} is the objective function.

The standard EP that will be used in this paper also use the adaptive scheme to adjust the value of β which is the scaling factor where as the value will become smaller and smaller as the fitness reaches optimum point.

3.1. TYPES OF EP

For the purposes of this study, types of EP to be used are the General EP, Fast EP and Selective EP.

General EP consists of Standard EP (SEP), Meta-EP (MEP), Meta-EP2 (MEP2) and R-Meta EP (RMEP). The inclusion of Adaptive Meta EP2 (AMEP2) and Adaptive R-meta EP (ARMEP) into the group was because of the similarities of using Normal or Gaussian distribution in the mutation.

Fast EP consists of SEP, MEP, MEP2 and AMEP2 with a different mutation strategy and it uses Cauchy distribution. The use of Cauchy distribution is also said to spend less time in exploiting the local neighbourhood and results more samples to be taken at the farther away of the center f the distribution.

The same type of EP from Fast EP will be in the Selective EP group. The Selective EP uses both types of distribution in its mutation.

4. RESULTS AND DISCUSSIONS

In this study, only three generating units are involved and the operating range of the units is given in Table 1 [9].

Table 1: Operating range of the generating units

	Unit 1	Unit 2	Unit 3
P^{max}	600 MW	400 MW	200 MW
P^{min}	150 MW	100 MW	50 MW

In order to study the robustness of EP in finding the optimal solutions, different demand load error allowances (search space) are used as shown in Table 2. This gives the range of demand that the system is allowed to generate. Load demand (P_D) is assigned to 850.0000 MW.

Table 2: Load demand range for the system

P_D max	Max Limit
P_{D1} max	850.9999
P_{D2} max	850.0999
P_{D3} max	850.0099
P_{D4} max	850.0009

The input-output equations for the three generating units are:

H_1 (Mbtu/h) = $510.0 + 7.2P_1 + 0.001142P_1^2$
H_2 (Mbtu/h) = $310.0 + 7.85P_2 + 0.001942P_2^2$
H_3 (Mbtu/h) = $78.0 + 7.97P_3 + 0.00482P_3^2$

The fuel costs for each of the units are given as:

Unit 1: 1.1 \$/Mbtu
Unit 2: 1.0 \$/Mbtu
Unit 3: 1.0 \$/Mbtu

For the purpose of this study, total transmission losses can be assumed as [9]:

$P_L = 0.00003P_1^2 + 0.00009P_2^2 + 0.00012P_3^2$

4.1. RESULTS WITHOUT TRANSMISSION LOSSES

Table 3, Table 4 and Table 5 show the results for the economic dispatch without losses using General EP, Fast EP and Selective EP, respectively.

Table 3: Results for economic dispatch without losses using General EP

	Maximum load			
	P_{D1} max		P_{D2} max	
	Iteration	F_T	Iteration	F_T
SEP	125	8141.8726	64	8141.7918
MEP	1000	8141.8932	1000	8141.7920
MEP2	261	8141.8282	424	8141.7920
AMEP2	397	8141.8034	406	8141.7908
RMEP	358	8141.8971	287	8141.8077
ARMEP	197	8141.7953	597	8141.7967
	P_{D3} max		P_{D4} max	
	Iteration	F_T	Iteration	F_T
SEP	62	8141.7910	68	8141.7905
MEP	1000	8141.7908	1000	8141.7905
MEP2	905	8141.7905	-	-
AMEP2	346	8141.7907	1560	8141.7905
RMEP	674	8141.7905	-	-
ARMEP	473	8141.7906	-	-

Table 4: Results for economic dispatch without losses using Fast EP

	Maximum load			
	P_{D1} max		P_{D2} max	
	Iteration	F_T	Iteration	F_T
SEP	150	8141.8459	201	8141.7933
MEP	1000	8141.7932	1000	8141.7928
MEP2	247	8141.8015	145	8141.7908
AMEP2	480	8141.9408	296	8141.7907
	P_{D3} max		P_{D4} max	
	Iteration	F_T	Iteration	F_T
SEP	124	8141.7905	-	-
MEP	1000	8141.7906	-	-
MEP2	464	8141.7905	-	-
AMEP2	386	8141.7906	-	-

Table 5: Results for economic dispatch without losses using Selective EP

	Maximum load			
	P_{D1} max		P_{D2} max	
	Iteration	F_T	Iteration	F_T
SEP	61	8141.7984	95	8141.7915
MEP	1000	8141.7978	1000	8141.7911
MEP2	274	8141.9042	167	8141.7906
AMEP2	1219	8142.2741	250	8141.7905
	P_{D3} max		P_{D4} max	
	Iteration	F_T	Iteration	F_T
SEP	165	8141.7905	-	-
MEP	1000	8141.7908	-	-
MEP2	541	8141.7905	-	-
AMEP2	-	-	-	-

It can be seen from Table 3 that each type of EP solved the problem with the total cost equals USD 8141.7905 with some manage to reach the solution in a bigger demand range. Meta EP manages to converge in a bigger search landscape compared to Standard EP making it a more robust of the two. On the other hand, Standard EP shows a lesser number of generations in converging to its solutions.

As shown in Table 4, the solutions obtained using Fast EP also reach the minimum total cost of USD 8141.7905. All types of EP found the solutions in a bigger maximum load limit.

In Selective EP, individuals are mutated using both Gaussian and normal mutation with Cauchy distribution. The best out of two is selected. Again, as shown in Table 5, the optimum solution is obtained in the bigger load limit.

4.2. RESULTS WITH TRANSMISSION LOSSES

Table 6, Table 7 and Table 8 show the results for the economic dispatch with losses using General EP, Fast EP and Selective EP, respectively.

Table 6: Results for economic dispatch with losses using General EP

	Maximum load			
	P_{D1} max		P_{D2} max	
	Iteration	F_T	Iteration	F_T
SEP	238	8281.7960	79	8281.7919
MEP	1000	8281.7915	1000	8281.7882
MEP2	139	8281.8157	219	8281.7897
AMEP2	135	8281.7929	189	8281.7939
RMEP	318	8281.8280	143	8281.7883
ARMEP	127	8281.8565	785	8281.7908
	P_{D3} max		P_{D4} max	
	Iteration	F_T	Iteration	F_T
SEP	192	8281.7881	110	8281.7879
MEP	1000	8281.7879	-	-
MEP2	1209	8281.7879	-	-
AMEP2	810	8281.7879	-	-
RMEP	154	8281.7879	-	-
ARMEP	763	8281.7879	-	-

When the transmission losses are considered, General EP gives optimal solution of USD 8281.7879 as shown in Table 6. Excluding SEP, all other types of EP find solution at the third search space (maximum load limit is between 850.0000 – 850.0099). Despite being robust, MEP, MEP2 and AMEP2 require large iteration number merely bigger than 700. Only RMEP solves the problem in 154 iterations.

SEP, despite being less robust then the other types of EP, reached the optimum solution in a much smaller number of iteration. Computational time wise, it faired much better compared to MEP, MEP2 and AMEP2, which require large number of iteration to reach optimum solution.

Table 7: Results for economic dispatch with losses using Fast EP

	Maximum load			
	P_{D1} max		**P_{D2} max**	
	Iteration	F_T	Iteration	F_T
SEP	170	8281.8164	130	8281.7889
MEP	1000	8281.7943	1000	8281.7898
MEP2	118	8281.8924	678	8281.7891
AMEP2	235	8281.7852	279	8281.7897
	P_{D3} max		**P_{D4} max**	
	Iteration	**F_T**	**Iteration**	**F_T**
SEP	172	8281.7879	-	-
MEP	1000	8281.7880	-	-
MEP2	851	8281.7879	-	-
AMEP2	802	8281.7882	262	8281.7879

As shown in Table 7, all types of EP reach optimum solution in the third search space except for AMEP2. SEP reached the optimum solution in 172 iteration in a bigger load limit compared to the General EP.

Table 8: Results for economic dispatch with losses using Selective EP

	Maximum load			
	P_{D1} max		**P_{D2} max**	
	Iteration	**F_T**	**Iteration**	**F_T**
SEP	89	8281.8098	90	8281.7889
MEP	1000	8281.7905	1000	8281.7881
MEP2	418	8281.8533	424	8281.7912
AMEP2	323	8281.8343	231	8281.7899
	P_{D3} max		**P_{D4} max**	
	Iteration	**F_T**	**Iteration**	**F_T**
SEP	72	8281.7881	53	8281.7879
MEP	1000	8281.7880	-	-
MEP2	328	8281.7885	273	8281.7879
AMEP2	633	8281.7879	-	-

From the results obtained in Table 8, it can be proved that Selective EP is less effective for solving economic dispatch problem when losses are considered. The visible difference is probably in SEP where the number of iteration is reduced to less than 100. Robustness in Selective EP also works for AMEP2, where it manages to reach optimum solution within a reduced number of iteration compared to General EP and Fast EP methods.

Computation times for the solutions in Table 3 through 8 to reach the optimal value are depending on the types of EP and number of iterations.

For the solutions without considering the transmission losses, the computation times are 6.5 seconds, 6 seconds and 12 seconds for General EP, Fast EP and Selective EP, respectively.

For the solutions with the transmission losses, the computation times are 14 second, 10.5 seconds and 24 seconds for General EP, Fast EP and Selective EP, respectively.

4.3. COMPARISON OF SOLUTION USING EP AND GA TECHNIQUES

The solutions obtained in this study are compared to the solutions obtained using GA, which is based on the paper by T.K. Abdul Rahman, L.Y Khuan and W.N. Wan Abdullah [10]. Table 9 gives the solutions using GA for the problem without losses whilst Table 10 gives the solutions if the losses are considered.

Table 9: Solution obtained using GA without losses

P_1	**P_2**	**P_3**	**P_T**	**Fitness**
395.3069	331.9648	122.7761	850.0488	8194.83

Table 10: Solution obtained using GA with losses

P_1	**P_2**	**P_3**	**P_T**	**P_L**	**P_T - P_L**	**Fitness**
436.363	297.165	131.378	864.898	15.731	849.167	8336.77

From the comparison made between EP and GA, it can be seen that EP has managed to find an improved solution than the solution obtained using GA.

5. CONCLUSIONS

EP has proven to be an efficient tool for economic dispatch problem. This type of optimization technique has been used in this study to solve the problem of economic dispatch. The study also included the solutions obtained for different types of EP in three groups, General EP, Fast EP and Selective EP. The comparison was made according to the solutions, robustness and computational time.

For Economic Dispatch without losses, Meta EP performed better than Standard EP but generate more iteration or generation than the latter. It did solve the problem of economic dispatch with losses in bigger problem solving environment but Standard EP perform fairly well in term of computational time and iterations. But as computational time becomes one of the determining factors, Standard EP did perform well with a close to optimum solution generated.

For economic dispatch excluding losses, Fast EP outperformed the Gaussian or Normal mutation used in General EP. Fast EP provides more robustness and a lesser iteration and computational time compared to General EP. Selective EP with combines the uses of both mutations managed to solve the problem just as Fast EP.

For economic dispatch including losses, RMEP performs better than other types of EP. The effect of Cauchy mutation in Fast EP and the implementation of both mutations in Selective EP produced mixed results.

EP was also found to outperform GA in both cases. The optimal solutions and power generation demand that can be met has been improved.

In term of robustness, Meta EP again manages to converge to an optimum solution in a bigger search space compared to Standard EP. Again, Standard EP converge with a lesser generation number than Meta EP.

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