Integrated Evolutionary Path-Finder Optimization Technique for Dynamic Economic Dispatch

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Abstract

Dynamic economic dispatch (DED) is considered as the main element in the making plans of the energy system for achieving optimum operation and control of the power system. At certain duration of time, it measures or predicts the optimum operation of generating units at any planned load requirement. Any unpredictable events, such as unit failures and shifts in demand are faced by the real-life power grid. Some meta-heuristic optimization methods have been used successfully to solve complex economic dispatch problems using meta-heuristic without any need for some mathematical characteristics. Several optimization techniques are employed to solve the ED problems. However, some techniques are not reliable enough to achieve the optimal solution. Thus, this paper proposes a new meta-heuristic technique, termed the Integrated Evolutionary path-finder optimization (IEPFO) technique to solve DED problems. In this study, Evolutionary Programming (EP), Pathfinder Algorithm (PFA) and IEPFO optimization engines are developed. Validation process was performed on the IEEE 26-bus reliability test system (RTS) model. Comparative studies have been conducted to reveal the merit of the proposed IEPFO over the traditional EP and the PFA techniques, implying its merit over the others.

Keywords: -Dynamic economic dispatch; optimization techniques; evolutionary programming;pathfinder; meta-heuristic.

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Introduction

The major issue of allocating the load demand of clients among the available thermal generating units' low cost, reliably, and precisely attracted lot of attention during 1920s or even earlier. The approach was already reviewed to minimize the fuel cost on the requirement of load capacity including the constraints of different interest at some period. This has also been referred to as the dilemma of static economic dispatch (SED). SED can accommodate that just a specific degree of load at a given moment in time. Even so, according to the ramp - rate of the generators, SED can struggle to cope with the wide variations in load demand, and which does not have the look-ahead capability. The discovery of the optimal dynamic dispatch (ODD) issue was necessary due to the wide variance in customer load demand and the dynamic design of the power systems. ODD is an SED extension to assess the schedule of generation for the committed units in order to fulfil the planned load requirement throughout a duration of time during ramp-rate and other limitation such as reserve constraints [1] or emission constraints [2] at minimum operating costs. ODD can anticipate in future event that was considered as significant to prepare and manage schedule of the load beforehand so that unexpected shifts in demand can be expected by the device in the immediate future. The dynamic constraint of the ramp rate that is necessary for the existence of power generation to be maintained [3]. Some coupling limitations make the approach to the ODD issue very complicated than those of SED such as ramp rate constraints. The ODD process can be characterized under some constraints since about the 1980s as a constrained optimization problem of the capital amount over the dispatch duration and has been referred to as the dynamic economic dispatch (DED) problem. Usually, the DED issue is addressed by decentralizing the entire length of the shipping to the amount of short time periods when the requirement for load is expected to be constant and the device is considered to get into a balanced temporal condition. SED issues are resolved over each time interval under static constraints, as well as ramp rate limitations are implemented between those sequentially intervals. The optimization shall be evaluated in relation to the dispatch capability of the systems in the DED issue. By approaching the SED issue interval through interval and adding ramp rate restrictions to one interval to another, several researchers have discussed the ramp rate constraints. However, this approach could react to sub-optimal solutions, but it does not have the capacity to look forward. To solve the DED troubles with multi-objective problems [4] or limitations, many optimization processes and techniques have been used. A variety of traditional methods, such as those of the lambda iterative method [5], Lagrange relaxation [6], linear programming [7], dynamic programming [8] and the interior point method [9], are being applied to solve this issue. For function of cost which have non-smooth or nonconvex, most of these approaches are not valid. Most meta heuristic optimization techniques are being used to fixing the DED issues, including the optimization and algorithm of ant colony (ACO) [10], particle swarm (PSO) [11-12], artificial immune system (AIS) [13], bee swarm optimization [14] differential evolution (DE) [15] evolutionary programming (EP) and hybrid optimization [16]. Although the Evolutionary programming (EP) has a global and parallel search capability, and it can handle optimization problems with non-smooth or nonconvex objective. However, evolutionary programming (EP) requires long computation time and sometimes suffers from the convergence problem.

The pathfinder algorithm (PFA) has been used for network reconfiguration issues [17] and for tilt-integral-derivative (TID) with proportional-integral-derivative (PID) automatic generation control [18]. However, PFA has a key drawback in that its ability to scan decreases in extremely large dimensions. Several variants have been implemented in an attempt to boost the performance of the PFA such as updated PFA with Differential Evolutionary (DE) in view of convergence speed and local optima prevention [19], and enhanced PFA using a quasi-oppositional learning mechanism to enhance the principle of convergence speed and chaos to enhance the exploration portion [20]. The PFA has been applied to several research areas in terms of its ability to make the transition between exploration and exploitation, avoiding local optima and achieving a better convergence rate. This paper proposed a new optimization technique which integrates the traditional EP and PFA, termed Integrated Evolutionary path-finder optimization (IEPFO). The proposed IEPFOoptimization engine is employed to solve DED problems in the attempt to achieve near global solution, validated on the IEEE 26-Bus reliability test system (RTS). Through the comparative studies with respect to the traditional EP and PFA, IEPFA exhibited outstanding results. The results would be beneficial to power system operators and planners in the relevant power utilities.

Problem Formulation

The aim of the DED formulation is to assess the amount of generation for the committed units that reduce the overall cost of fuel from over duration of dispatch [0, T]. T is the maximum time duration. The objective function can be described by:-

$$Min\ \ C_T = \sum_{t=1}^{T} \sum_{i=1}^{N} C_i\ (P_i^t) \tag{1}$$

Where:

C	=	Cumulative cost of service over entire periods of dispatch
T	=	Length of time within the horizon of time
$C_i(P_i$(t))	=	Production cost of the particular generation in terms of actual power output of $P_i$at t-time.

The parameter to the terms of constraints:

a. The power balance equation can be presented as in (2):

$$\sum_{i=1}^{N} P_i^t\ = D^t\ + Loss^t, t = 1,\dots,T, \tag{2}$$

b. Formula of generation limits:

$$P_i^{min}\ \le P_i^t \le P_i^{max}\ , i = 1, \dots, N,\quad t = 1, \dots, T, \tag{3}$$

c. Formula of generating unit ramp rate limits:

$$-DR_i \le P_i^t - P_i^{t-1} \le UR_i, i = 1,\dots, N, t=2, \dots, T, \tag{4}$$

N represents the number for the committed units from equation (4); P_i^t is the generation of unit i at the t-th time interval [t-1, t); T is the range for the time horizon intervals; D^t is the demand at time t (i.e., the t-th time interval); UR_i and DR_i are the higher and lower ramp levels for unit I P_i^minand P_i^max are respectively the highest and lowest unit i capacity. The fuel cost of the unit can be expressed as:

$$C_i(P_i^t) = a_i + b_i(P_i^t) + c_i(P_i^t)^2 \quad (5)$$

Where the parameters *a*, *b*, and *c* are the cost coefficient of the units and *P* is power generator of each unit.

Optimization Techniques

Although the EP has a global and parallel search capability, it can handle complex optimization problems. However, EP requires long computational time and sometimes suffers from the convergence problem. The PFA has been applied to several research areas in terms of its ability to make the transition between exploration and exploitation, avoiding local optima and achieving a better convergence rate. Improving the optimization technique for DED problems is a major importance when a large amount of cost could be saved by the optimal scheduling of electricity generation from various energy plants to meet the needs and requirement of the consumer.

In order to produce a global and optimal solution, this paper proposed two methodsof optimization. For the first part, EP engine will be used to solve DED problems to obtain near global solution. PFA has a robust capability to solve optimization problems and can find better solutions. The PFA is introduced as a simple method, easily adapting to optimization problems as it has several parameters that can be adjusted andit is more effective in converging to the global optimum.

A. Evolutionary Programming

EP evolving a population of candidate solutions over a series of generations or iterations to find the optimum solution. Via the use of a mutation operator, a second new population from the original population is created at each iteration. By disrupting each part of an existing solution by a random number, this operator creates a new solution. The degree of optimality of each of the candidate solutions or persons is calculated by their fitness, which can be characterized as a function of the problem's objective function. In order to seek an ideal (minimum) solution, it is necessary to pay a great price in terms of emission and time. The mathematical formulation of these alternatives is continuously changing and improving. For the EP, the flowchart is shown in Fig. 1. EP usually requires initialization, mutation, fitness computation, combination, and selection.

i. Initialization

Random number parameters will initially be created to represent the control parameters that maximize the function of the main objective. To distribute the actual power produced in the method, these random variables will be used. Defined five variables x1, x2, x3, x4 and x5 for generating random number which represent the real power generator.

ii. Offspring Mutation / Development

Mutation is a mechanism by which original populations (parents) are converted into offspring (children). These descendants are developed based on the Gaussian mutation approach provided by the following equation:

$$X_{i+m,j} = X_{i,j} + N(0, \beta(X_{j\ max} - X_{j\ min})(\frac{f_i}{f_{max}})) \quad (6)$$

Where the parameter are:

$X_{i+m,j}$	:	parents of mutations (offspring)
X_{ij}	:	the parents
N	:	Random Gaussian parameter with mean μ and variance, γ^2
β	:	scale of mutations, $O<\beta<I$
X_{jmax}	:	for each vector the highest random number
X_{jmin}	:	the minimum random number of each vector

f_i : fitness the random number ith,
f_{max} : fitness of maximum random number

iii. Selection/Tournament
The Gauss equation for populations (parents) are converted into offspring (children) as mutation process is completed, the value of offspring is used for new real power of generator at part of fitness two. The objective function which represents the fitness equation minimization of the generation cost have two fitness part which are fitness one and fitness two being combined. The lowest value will be arranged at the top and the higher value will be at the bottom as the objective function is to minimize the cost. 40 individuals for each parameter are displayed which represent the output of fitness one and fitness two in cascode form. The combination of fitness one and fitness two will display 40 rows and 10 columns. It will choose the best 20 individuals for each parameter for the derivation of the fittest individuals based on the fitness value. The importance of this part is to minimize the generation cost in the system. The matric structure of the combination has become [2n x m]. The variable, n represents the number of population size in the system were become two times at this process, while m representsnumber of the control variables.

iv. Check for convergence
In order to obtain the optimum solution, the stopping criterion determines the convergence of the optimization process. It will converge when the difference value is the smallest. The criterion for convergence is defined in (7). If the convergence criterion is not reached, it would repeat the entire operation:

$$Fitness_{max} - Fitness_{min} \leq 0.001 \tag{7}$$

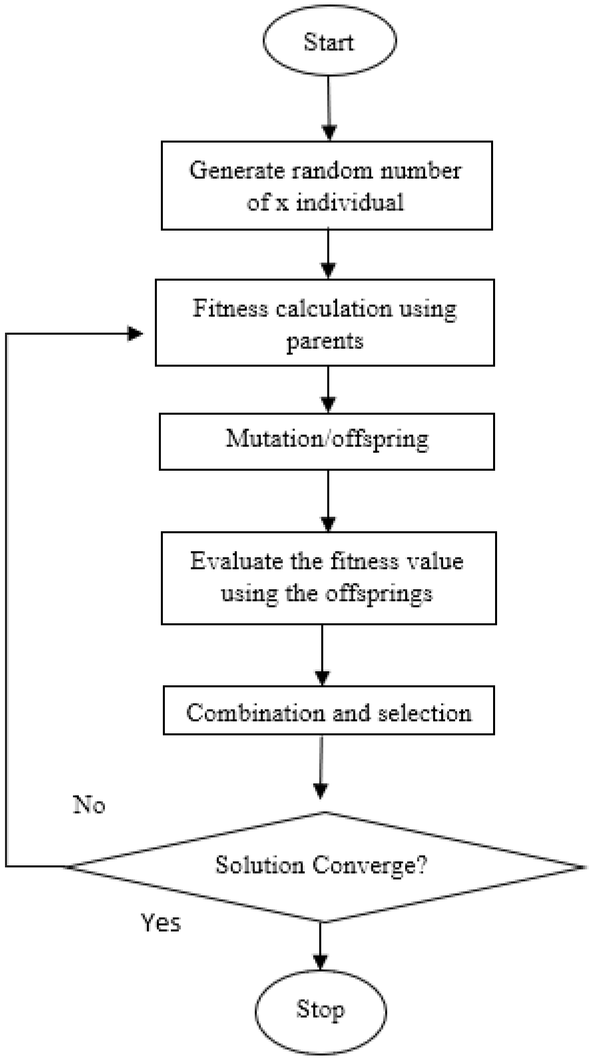

Figure 1: General Flowchart for Evolutionary Programming

B. *Pathfinder Algorithm*

The PFA is an SI-based method inspired by the collective movement of swarms with a leader member. This method allows all members of swarm to explore the search space randomly, while they decide to move towards any location by following the leader. When a member locates in the most promising area, then this individual is chosen as the leader. In particular, it is worth stating that the movements of the leader and the members are completely different mathematically. The leader member is called the pathfinder. It saves the best solution in each iteration. The other members use Equation (8), whereas the pathfinder moves towards the next location using equation (9).

$$x_i^{k+1} = x_i^k + r_1(x_j^k - x_i^k) + r_2(x_p^k - x_i^k) + \varepsilon, i\epsilon[2, N_{pop}] \quad (8)$$
$$x_p^{k+1} = x_p^k + 2r_3(x_p^k - x_p^{k-1}) + A \quad (9)$$

Where $k$is the current iteration, $x_i$is the position vector of member i, $x_j$is the position vector of member j, R_1 and R_2 are random variables which are equal to αr_1andβr_2, and $N_{pop}$is the population size. Here,r_1, $r_2$and r_3 are random variables generated uniformly in the range of [0, 1], $x_p$is the position vector of the pathfinder, and $\varepsilon$and $A$are the vibration and fluctuation coefficients.ε and A are generated over the course of iterations via Equations (10) and (11) respectively. Also,$\alpha$and $\beta$are selected randomly in the range of [1, 2] in each iteration.

$$\varepsilon = (1 - \frac{k}{k_{max}})u_1 D_{ij}, D_{ij} = |x_i - x_i| \quad (10)$$

$$A = u2e^{\frac{-2k}{k_{max}}} \quad (11)$$

Where u_1 and $u_2$are random variables in the range $[-1, 1]$, and D_{ij} is the distance between two members andK_{max} is the maximum number of iterations. The pathfinder is trying to find the best food/hunting region in the PFA. The global optimum can be the best food/hunt region. The position of the pathfinder in each iteration is allocated to the current iteration as the current optimum, so the other members step towards it.

i. Initialization

In this process, the random number are generated on the system which represent the power generator to feed the desired power to the load demand and transmission losses. The value of random number is based on the data of the generator limits. The inequality constraint and equality constraint is put in this part for satisfying the generator limits and real power balance. The value of total generation must depend on the load demand and transmission losses in the system. The five variables $P_{g2}, P_{g3}, P_{g4}, P_{g5}$ and P_{g26}were created for represent the bus unit in the system. The total generated power must equal to the total demand and transmission losses. The fitness function is the equation to minimize the generation cost.

$$x(k) = [x_1, x_2, x_3 ... x_{Upper}, x_{lower} \ ... x_{dim}] \quad (12)$$

$$x_d = x_{lower} + (x_{Upper} - x_{lower}) * rand(pop\ size, 1) \quad (13)$$

Where $k=1, 2, 3, 4..., N$ is respectively the population size and $d=1, 2, 3, 4...,$ dim is respectively the problem size in the system.

ii. Create a new pathfinder

In this process, the latest location refersto the present location and before the present location. Thelatest pathfinder is built for renewing by own self. The parameters of pathfinder *A*(9) must define in the system before creatingthe latest pathfinder. After that, the fitness value is calculated and obtained from the latest pathfinder and the pathfinder will renew when the latest one is better than the present pathfinder.

iii. Create new members in the population

In this process, every individual in the population and the parameter *A*are renewed. Before calculating the fitness values, the parameter ε in equation (10) is evaluated before creating the new members. After that, the fitness equation will be used in the objective function; use the latest candidate for calculating the function and the location of the individual is renewed if the latest individuals are much better than the corresponding individuals in the population. The last step is thatthe best individual in the population is evaluated referringto the objective function. At that time, it will be related with the pathfinder and when it is better than the value of pathfinder, it will come to be the pathfinder.

iv. Stopping criterion

If the maximum iteration is reached, the searching of the fitness function of global solution of the pathfinder is stopped and when the maximum iteration is not reached it will continue searching the fitness function of global solution until it reaches the maximum iteration that have been set up.

$$K < iter_{max} \quad (14)$$

C. Proposed Integrated Evolutionary Path-Finder Optimization (IEPFO) technique

Evolutionary programming is indeed approach form of meta-heuristic optimization originating from manystages which demonstrating the behavioural relation between parenting and their offspring rather than trying to mimic particular genetic operators to find a solution as found in nature. Even so, EP takes a long computation time to measure to get the solution and often EP suffers from the problem of convergence. On the other hand, the Pathfinder algorithm is capable of making the transition between discovery and exploitation, avoiding local optimism and achieving a better convergence rate. A two-part approach has been suggested in this paper in order to achieve a high-quality solution. The first step of the proposed method is to simulate the EP part until the combination and selection process is completed. At that part, the ranking process is taken place for choose the best 20 of the individuals.

After that, the minimum value of the fitness function will be set as the pathfinder. Last step, the PFA operators will be applied to the system by searching through the transition between exploration and exploitation in order to obtain the best solution.

Step 1) Set up the input data

The input of maximum iteration is set up to 100 iterations. When the system reached the maximum iteration automatically it will stop the final process of finding the best solution.The size of thepopulation is set to 20 individuals. The load demand are inserted manually in the system using data on Table 2. Run the IEEE 26-Bus Reliability Test System (RTS) data into the system which have the power demand, real power generator and line data.

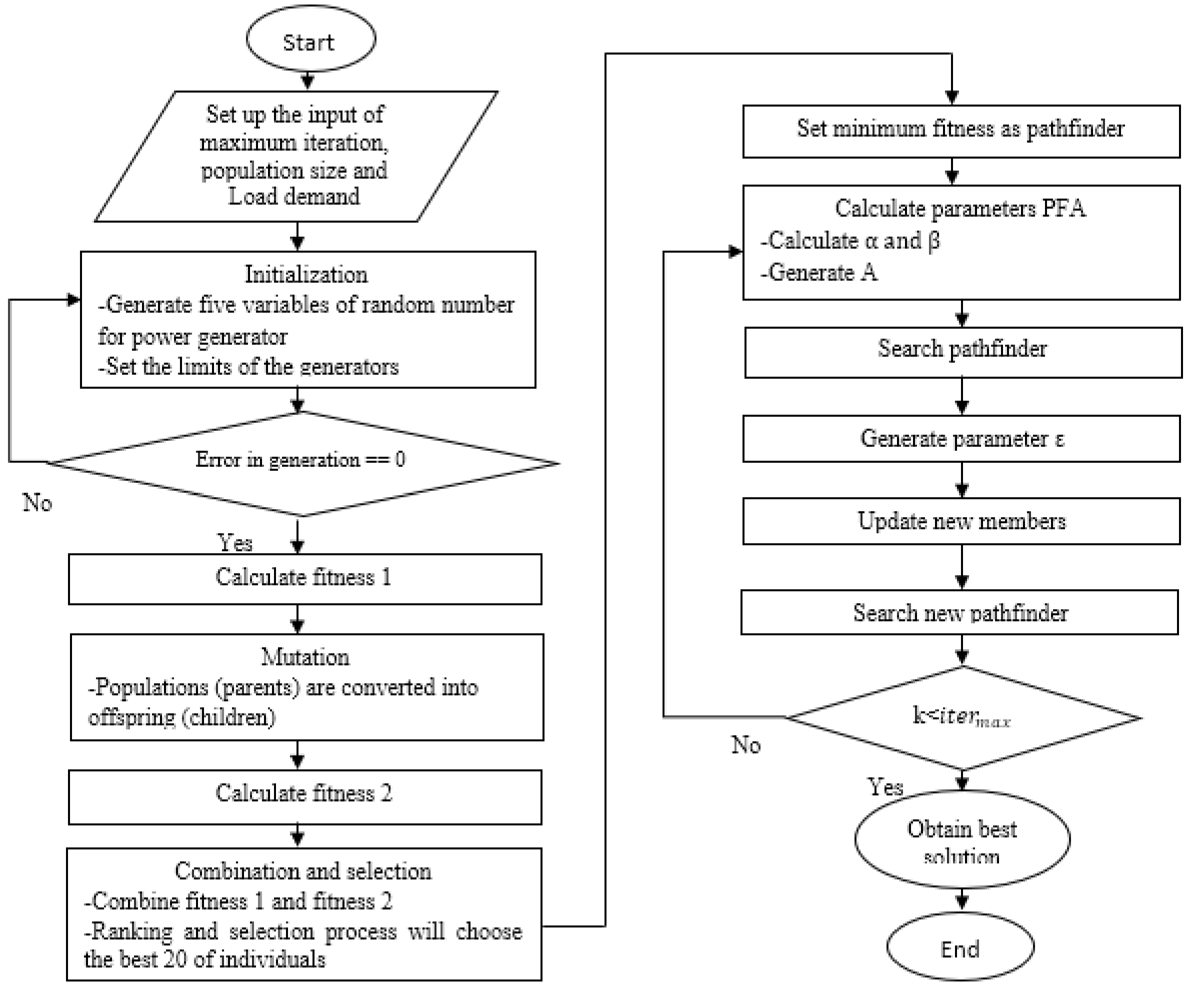

Figure 2: The flowchart of IEPFO to solve DED problem

Step 2) Initialization

In this phase, the five variables of random numbers are generated in the system which represent the real power of each generator unit. The inequality constraint is applied to the random number for satisfying the real power limits of generators. The error in generation is used for satisfying the equality constraint of real power balance. The total generation must be equal with the summation of load demand and transmission losses.

When the value of desired power and real power are not same, the system will not work in ideal condition and not satisfying the constraints of real power balance. The penalty constant is used for detecting the error in the generation.

Step 3) EP part

In the first step, EP technique is applied for solving the DED problems. In this process, fitness 1 is calculated using the value of random number from the initialization process. The fitness function is to be used in the objective function for minimizing the generation cost. It consists of the formula of the DED problems in order to minimize the fitness value. Once the values of fitness 1 arecomputed, mutation process will be subsequently conducted. In the mutation process, the gauss equation is used for breeding the populations (parents) into offspring (children). The values of the children will be used for calculating the fitness 2. Both fitness 1 and fitness 2 will be combined for ranking and the selection process for identifying the best of 20 individuals from the 40 individuals in the combined population.

Step 4) PFA operators

The positioning of the pathfinder is ideal at the moment. It decides α and β in an iterative process and updates the location of the pathfinder. If the new position is better than the previous position, changes should be made. Then the positions of the followers are changed with the boundaries being considered. The PFA measures the new fitness for every member, and it is allocated as a new pathfinder when any member has a better position than the pathfinder. PFA upgrades the final population using the "if then" rules and then updating the A and ε vectors. Finally, to avoid the iterative process from being performed, the PFA tests the end criterion.

In the first step, the minimum value of the fitness population will be set as the pathfinder. The position of the minimum fitness population will be defined as the global population. The parameters of PFA ofα and β are calculated for generating A. After generating A, create a pathfinder in the population. Use the latest pathfinder for calculating the fitness value. Renew the pathfinder if the latest one is better that the old pathfinder. Subsequently, generate parameters ε for creating the new members in the population. Use the population of members for calculating the fitness value. Renew the population fitness if the latest candidates is better than the corresponding candidates in the population. Finally, renew the pathfinder if the best candidates is better than pathfinder.

Step 5) Stopping criterion

The parameters of the maximum number of iterations is 100. When the maximum iteration is reached, the system will stop searching for the best candidates of the fitness function.

Result and Discussion

This section presents the results and discussion of the study. The five-unit generator in the IEEE 26-bus RTS model was used in this study to validate the performance of the proposed techniques. The daily load demand divided into 24 hours was applied in the system. The proposed methods were simulated on Intel® CORE(TM) i7-7700HQ CPU 2.80 GHz processor.Table 1 tabulates the data for the generator limits in the IEEE 26-Bus RTS. These values are utilized in the simulations.

Table 1: Data Unit of Generator Limits and Fuel Cost Coefficient

Bus no.	Bus 2	Bus 3	Bus 4	Bus 5	Bus 26
P_{max} (MW)	200	300	150	200	120
P_{min} (MW)	50	80	50	50	50
a ($/h)	200	220	200	220	190
b($/MWh)	10.0	8.5	11.0	10.5	12.0
c($/M$W^2h$)	0.0095	0.009	0.009	0.008	0.0075

On the other hand, Table 2 tabulates the daily load demand of the system which makes it performing the dynamic element of the economic dispatch (ED) process. In the traditional ED, this condition was not addressed.

Table 2: Daily Load Demand for 24 Hours

Hour	Load (MW)	Hour	Load (MW)	Hour	Load (MW)
1	630	9	683	17	719
2	633	10	695	18	667
3	635	11	725	19	668
4	641	12	730	20	665
5	642	13	729	21	655
6	655	14	728	22	645
7	660	15	720	23	634
8	675	16	723	24	636

In this study, four cases have been performed on the IEEE 26-bus RTS model usingdifferent load demand within 24 hours. The main objective for this study is to obtain the cheapest generation cost using the proposed techniques for solving the DED problems. The three methods EP, PFA and IEPFO have been simulated for comparing the total generation cost. The constant parameters consist of population size, maximum iteration and penalty constant.Tables 3 tabulates the results for the comparison of total cost, total generation and transmission losses using the three methods with load demand from hour 1 to hour 6. Based on the results in Table 3, the total load demand is 3836 MW which is consumed from 1 hour to 6 hours. It is also noticed that the proposed IEPFO managed to achieve the lowest total cost worth $/h 50524.50. On other hand, PFA achieves $/h 50614.5, while EP achieves $/h 51178.2. Apparently the proposed IEPFO outperformed the traditional PFA and EP. This result is promising and reveals the merit of the proposed IEPFO.

Table 3: Case 1: Comparison of Total Cost, Total Generation and Transmission Losses

Method	IEPFO	PFA	EP
Total generation (MW)	3919.7189	3922.0794	3915.3280
Load Demand (MW)	3836	3836	3836
Transmission Losses (MW)	83.8974	86.1325	80.2188
Total Cost ($/h)	50524.5	50614.5	51178.2

Table 4 tabulates the results for the comparison of total cost using IEPFO, PFA and EP.Based on the results in Table 4, the total load demand is 4168 MW are consumed from hour 7 to hour 12. In this table, the proposed IEPFO has significantly achieved the lowest total cost worth $/h 54701.3 indicating its superiority over PFA and EP. Nevertheless, the lowest transmission losses were experienced by EP. This is acceptable as the objective function is not minimizing the loss. This phenomenon can be avoided if the transmission loss is chosen as the fitness value to be minimized.

Table 4: Case 2: Comparison of Total Cost using IEPFO, PFA and EP

Method	IEPFO	PFA	EP
Total generation (MW)	4251.4442	4255.0231	4245.39
Load Demand (MW)	4168	4168	4168
Transmission Losses (MW)	83.5805	87.1222	78.9661
Total Cost ($/h)	54701.3	54820.9	55300.3

Table 5 tabulates the results for case 3: comparison of total cost, total generation and transmission losses using IEPFO, PFA and EP.From Table 5, the total load demand is 4286 MW which are consumed from hour 13 to hour 18. The lowest value of total generation and power transmission losses are achieved by EP. While the highest value of total generation and power transmission losses produced are achieved using PFA. The cheapest generation cost is achieved by the proposed IEPFO worth $/h 56235, while PFA gives $/h 56282.9 and EP gives $/h 56670.9. The highest generation cost is produced by EP method as can be seen in the table. Apparently the proposed IEPFO outperformed EP and PFA implying its superiority. The lowest total cost is experienced by the implementation of IEPFO as desired due to the objective function is minimization of the total cost. It indicates that the proposed IEPFO outperformed the others.

Table 5: Case 3: Comparison of Total Cost, Total Generation and Transmission Losses Using IEPFO, PFA and EP

Method	IEPFO	PFA	EP
Total generation (MW)	4368.8256	4371.0447	4363.127
Load Demand (MW)	4286	4286	4286
Transmission Losses (MW)	82.4646	84.9708	78.6934
Total Cost ($/h)	56235	56282.9	56670.9

Tables 6 tabulates the results for the comparison of total cost, total generation and transmission losses using the three methods with load demand from 19 hour to 24 hour. From Table 6, the total load demand is 3903 MW which are consumed from hour 19 to hour 24. The lowest value of total generation and power transmission losses are given by EP method. The lowest total cost is experienced by the implementation of IEPFO as desired due to the objective function is minimization of the total cost. It indicates that the proposed IEPFO outperformed the others.

Table 6: Case 4: Comparison of Total Cost, Total Generation and Transmission Losses Using the Three Method with Load Demand from 19 Hour to 24 Hour

Method	IEPFO	PFA	EP
Total generation (MW)	3984.9956	3988.7105	3981.23
Load Demand (MW)	3903	3903	3903
Transmission Losses (MW)	81.3419	85.722	79.8934
Total Cost ($/h)	51322.4	51458.7	52018.6

The highest value of total generation and power transmission losses was given by PFA method. On the other hand, the cheapest generation cost is achieved by the proposed IEPFO

worth $/h 51322.4 as compared with PFA which produces $/h 51458.7 and EP which produces $/h 52018.6. This phenomenon conforms that the proposed IEPFO outperforms the others. The highest generation cost is given by EP method. Figure 3 illustrates the cost versus load demand using EP, PFA and IEPFO. Based on Figure 3, on the overall;the proposed IEPFO technique produces the cheapest total generation cost in 24 hours which is $/h212783.2; while PFA gives $/h 213177 and EP achieves$/h 215168.1. The PFA method can save more generation cost than EP with difference of $/h 1991.1 (=$/h 215168.1-$/h 213177). In one year (365 days), the PFA method can save up to $/h 726751.5 as compared to EP. The proposed IEPFO method can save more generation cost than PFA and EP methods with difference $/h 393.8 (=$/h 213177-$/h 212783.2) and $2384.8 (=$215168.1-$212783.2). In one year (365 days), the proposed IEPFO technique may save up about $/h 143737 and $/h 870452. This indicates the superiority of the proposed IEPFO in terms of cost saving.
The different load demands are applied for producing different generation cost. When the system consumes high load demand, it will produce high generation cost. The generation limits are applied in the system for controlling the limits of the generator in each unit. The total generation Pg depends on the load demand consumed in that area and the transmission losses in the power system. The penalty parameter is used for detecting the error in the generation. When the error in the generation is high, the system will not work in good condition and may produce power of generation inaccurately.

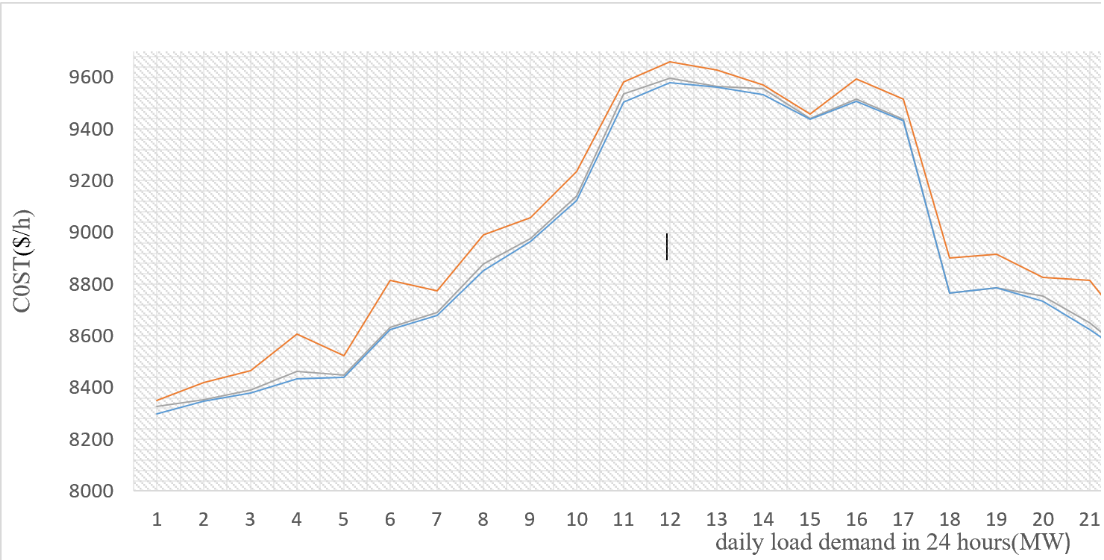

Figure 3: Cost versus load demand using EP, PFA and IEPFO

The proposed IEPFO technique is considered as the best technique compared to PFA and EP. This is due to the fact that the IEPFO technique used the ranking process for searching the best fitness value and searching the best pathfinder until the maximum iteration is reached. By using the EP selection process and searching of new pathfinder, it gives the best fitness to minimize the generation cost. Based on the results in case 1, case 2, case 3 and case 4; it is discovered that the proposed IEPFO technique achieved the cheapest generation cost in all cases, followed by PFA method. It shows that the combination technique is the best technique as compared to the traditional PFA and EP methods. It also shows that the PFA method is much better the EP method in terms of searching the best candidate in the fitness function and also improve the computation time in the EP methods and convergence rate.

Conclusion

This paper has presented integrated evolutionary path-finder optimization (IEPFO) technique for dynamic economic dispatch. In this study the PFA and EP have been integrated to form the proposed IEPFO. Results from the study implemented in IEEE 26-Bus RTS indicated that the proposed IEPFO technique have produced the cheapest generation cost compared to EP and PFA. The EP optimization is finding the population of the candidate solution and the solution in parallel by using the process of evaluation. EP can produce near global optimal solution but sometimes suffer from convergence rate and long computational time. The particles of the PFA are led by a leader member, which is completely different from the follower members in terms of its mathematical model. This difference facilitates the transition between exploration and exploitation. The followers move towards the next position in a non-regular order and thus, they can explore the search space effectively. Therefore, the PFA has a robust capability to solve optimization problems and can find better solutions. As a results, PFA have produce the lowest generation cost compared to EP method. The IEPFO techniques for the optimization have been able to reduce the limitation for the individual technique. Furthermore, IEPFO technique can improve the convergence rate and the exploration of the neighbourhood area for searching the best local optima. The proposed IEPFO technique is better than EP and PFA as the integration has overcome the problem of convergence to local optima. In conclusion, the integrated technique termed IEPFO is good attempt in solving DED problems. The proposed method can be further explored by implementing it in solving other optimization problems in power system, with minimal iteration in the algorithm and the developed optimization engine.

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