Journal of Engg. Research Vol. 7 No. (3) September 2019 pp. 244-257

Hybridization of Particle Swarm Optimization with Differential Evolution for Solving Combined Economic Emission Dispatch Model for Smart Grid

Naresh Kumar Yadav

Department of Electrical Engineering, Faculty of Engineering and Technology, Deenbandhu Chhotu Ram University of Science & Technology, Murthal (Sonepat) - Haryana, India
nareshyadhavdr@gmail.com

ABSTRACT

This paper introduces a CEED model for smart grid system and solves it by hybridizing the renowned optimization algorithms such as Particle Swarm Optimization (PSO) and Differential Evolution (DE). The hybridization of these two renowned algorithms is accomplished by using the solution updating process of both algorithms and combining them with random searching procedure. The CEED model is subjected to minimize its cost so that adequate trade-off between the economic and emission costs can be maintained in minimizing them. The proposed hybrid algorithm is experimented on three different bus systems, and its performance is compared against individual PSO and DE and a recently framed hybridization of PSO and DE. The comparison results show the superiority of the proposed hybrid heuristic search algorithm in terms of solution quality and the computational efficiency.

Keywords—CEED; PSO; DE; update; emission; economic; hybrid.

INTRODUCTION

The dynamic economic dispatch (DED) problem or simply the ED problem is one of the primary challenges to be addressed in the smart grid systems (Niknam, *et al.,* 2012). By solving the ED problem, an optimal schedule for the generating units, which are subjected to various operational as well as network constraints, can be accomplished with minimized fuel cost. Generally, there are two stages involved in an ED problem. They are (1) unit commitment (UC), which attempts to determine the generating units that can handle the hourly demand, and (2) ED that estimates the output power of the generating units to meet the demand prior to its implementation (Makarov *et al.,* 2009; Ruiz *et al.,* 2009) . The UC problem has been worked out by many researchers (Wang *et al*., 2008; Ruiz *et al.,* 2009; Bouffard & Galiana, 2008; Wang *et al.,* 2011; Jiang *et al.,* 2012) using the standard solvers such as CPLEX. Yet, the last couple of years has made its part more significant in the literature. For instance, Changhyeok Lee *et al.* (2014) have introduced the acceleration techniques for solving the two-stage UC problem, Niknam et al. (Niknam *et al.,* 2014) have introduced a self-adaptive bat algorithm, and Linfeng Yang *et al.* (2015) have worked on tight relaxation method. However, the UC problem has not considered the location-based marginal prices (LMPs) that are often taken care by solving the ED problem (Wang *et al.,* 2010) .

Significant constraints such as inter-temporal constraints have been considered in ED problem, and hence it has been successfully solved as a constrained optimization problem in the literature (Han *et al.,* 2001; Huang & Huang, 2003; Gaing, 2003). However, these methods face high computational overhead, slow convergence, and sticks with local best (Xia *et al.,* 2013). Lagrangian relaxation approaches using perturbation have also been reported in the literature of recent era to rectify the problem (Xia *et al.,* 2013). But the Langrage relaxation problems are not found suitable under realistic circumstances (Jadoun *et al.,* 2015). Though dynamic programming has been found as the suitable alternative, it suffers from the problem of "curse of dimensionality" (Liang & Glover, 1992). Moreover, the

ED problem has not considered the environmental criteria (Yang *et al.,* 1996; Selvakumar & Thanushkodi, 2007; Park *et al*., 2005) that have been strictly insisted on by the clear air amendments of 1990 (Le *et al.,* 1995). The ED problem becomes more complex, when the emission constraints are considered and solved in the name of DEED (dynamic economic and emission dispatch) or CEED (combined economic and emission dispatch) problems.

However, wide emission of hazardous pollutants such as oxides of carbon, nitrogen, and sulphur has necessitated the ED problem, which is subjected to the emission constraints, to be solved. This implies that it not only minimizes the fuel cost, but also minimizes the resultant emission from power generation (Wang *et al.,* 2008) . The economic and emission dispatch (EED) problem is addressed as a challenging research, since it considers both improvement in economy and the pollution reduction (Niknam, *et al.,* 2012; Gholami *et al.,* 2014). Yet, the practical constraints such as the prohibited operating zones, the ramp rate limits, and similar other constraints that are to be considered along with the generation as well as the emission constraints have increased the complexity of the EED problem (Jadoun *et al.,* 2015).

This paper introduces a CEED model for smart grid and a hybrid optimization algorithm to solve the CEED model. The CEED model has considered economic and emission constraints in such a way that adequate trade-off can be maintained between these two constraints. The model also includes security and network constraints of the smart grid for safe and reliable operation of the power system. The proposed optimization algorithm is a hybrid version of PSO and DE. It considers both the updating characteristics of the PSO and DE to determine the updated solution. The rest of the paper is organized as follows. Section II reviews the literature and Section III explains the proposed CEED model for smart grid. Section IV details the procedure of the proposed optimization algorithm to solve the CEED model. Section V discusses the performance results of various optimization algorithms and Section VI concludes the paper.

RELATED WORKS

Researchers have found that the meta-heuristic search algorithms can be assumed as the potential solution for such constrained optimization problem. The last five years has gained considerable attention towards the application of the meta-heuristic search algorithms for solving EED. Basu M has attempted to solve the EED problem as a multi-objective optimization problem using the multi-objective differential evolution approach (Basu, 2011). Meantime, a Nondominated Sorting Genetic Algorithm II (NSGA - II) has also been introduced by King RTFA *et al.* (2011) and it has solved the economic and emission dispatch problem with prohibited operating zones. Hooshmand *et al.* (2012) have introduced a hybrid bacterial foraging – Nelder – Mead algorithm for solving the ED problem with both the emission as well as the reserve constraints. On the other hand, Hamedi (2013) has solved the CEED problem using a parallelized particle swarm optimization algorithm (PSPSO). Shayeghi H and Ghasemi A have modified the traditional artificial bee colony (ABC) algorithm by considering the chaos theory in it to solve the EED problem (Shayeghi & Ghasemi, 2014). In Jadoun *et al.* (2015), Vinay Kumar Jadoun et al. have introduced a modulated PSO (MPSO) for solving the EED problem, wherein the wide operational constraints have been considered. Few other meta-heuristic search algorithms that are contrast to the natural inspiration have also been reported in the literature for solving the EED problem. For instance, Bhattacharjee K et al. have used the chemical reaction algorithm (Bhattacharjee *et al.,* 2014), whereas Benasla L et al. have used the spiral optimization algorithm (Benasla et al., 2014) and Jeddi *et al.* (2014) have modified the harmony search algorithm in the year of 2014.

The literature has highly contributed towards exploiting the meta-heuristic searching concepts for solving the CEED or DEED problems. However, very few research works have been reported for strengthening the EED problems and thereby, the emission mitigation can be focused well in the future. For instance, Siyu Lu *et al.* (2013) have worked on carbon capture and storage (CCS) technology to reformulate the traditional EED model by incorporating the operational characteristics of carbon capture plants. The resultant function has been solved to mitigate the carbon emission at the higher economical generation strategy. Similarly, Nnamdi *et al.* (Nwulu & Xia, 2015) have worked to introduce the incentive based demand response program in DEED and hence, they have proposed GTDR (Game Theory Based Demand Response) – DEED model. Few other such contributions have also been reported (Liu & Li, 2015; Lamadrid *et al.,* 2015) .

Though the EED models in Lu *et al.* (2013) and Nwulu & Xia (2015) have reconstructed the traditional models, they conflict with each other. The reason is that the erstwhile model deals with the emission constraint, while the later model considers the economic constraints. Moreover, there is no robust optimization algorithm that has been considered to solve such models. The current problem in the literature is to introduce an EED model, wherein the economic as well as the emission constraints are to be considered in a more effective way. Subsequently, a robust meta-heuristic search algorithm is required to solve the problem because the problem can be a large scale and it may sometimes lead to the problem of 'curse of dimensionality'.

SMART GRID CEED MODEL

Cost Model

The cost model is the traditional economic load dispatch model in which diverse generator types are introduced to determine the economic way of meeting the power demand. Given such N_g generating units, the cost model $f_1(\bullet)$ can be defined as

$$f_1(P_g)=\sum_{g=1}^{N_g}\sum_{h=0}^{N_c-1} a_{h+1}(P_g)^h \tag{1}$$

where a is a set of cost coefficients, N_c is the number of cost coefficients, and P_g refers to generating limits of the g^{th} generating unit. Hence, P_g is subjected to meet the generation capacity constraint given in Eq. (2), where $P_g^{\min}$ and $P_g^{\max}$ are minimum and maximum generation capacities, respectively. Since the cost model is considered as the quadratic coefficient, N_c has become 3.

$$P_g^{\min} \le P_g \le P_g^{\max} \tag{2}$$

In addition to the generation capacity constraints, P_g should also meet the real power balance constraint,

$$\sum_{g=1}^{N_g} P_g - (P_D + P_L) = 0 \tag{3}$$

where P_D and P_L refer to the power demand and transmission losses, respectively. The P_L can be determined using Eq. (4), in which B, B' and B'' are loss coefficients.

$$P_L = \sum_{g_1=1}^{N_g}\sum_{g_2=1}^{N_g} P_{g_1} B_{g_1 g_2} P_{g_2} + \sum_{g=1}^{N_g} B'_g P_g + B'' \tag{4}$$

Emission Model

The emission model refers to the quantity of greenhouse gas emissions occurring in certain period, when the generating units are under operation. Here, the emission model $f_2(\bullet)$ can be represented as

$$f_2(P_g)=\sum_{g=1}^{N_g}\sum_{h=0}^{N_E-1} \alpha_{h+1}(P_g)^h \tag{5}$$

where α is a set of emission coefficients and N_E is the number of emission coefficients. Similar to the cost model, the emission model is a quadratic equation and hence N_E has become 3.

CEED Model

The general CEED model attempts to minimize the sum of the cost and emission models that are subjected to meet the constraints given in Eq. (2-4). Hence, it can be solved as a constrained minimization problem. This paper transforms it as an unconstrained minimization problem $F_u(\bullet)$ in which the constraints are included in the minimization model with respective penalty factors as given in Eq. (6).

$$F_u\left(P_g\right)=F\left(P_g\right)+\sigma_1\left|P_b\right|+\sigma_2\left|P_L\right| \quad (6)$$

where P_b is the real power balance constraint used in the LHS of the Eq. (3). The first two terms of the CEED model refer to the cost model and the emission model, respectively, whereas the third and fourth terms refer to the network and security constraints, respectively. Based on the CEED model, the objective function can be formulated as

$$P_g^* = \arg\min_{P_g} F_u\left(P_g\right) \quad (7)$$

where P_g^* is the optimal power to be generated by the generating units under minimized cost, emission, and transmission losses.

BHYBRID PSO – DE FOR CEED MODEL

Background

A general Meta–heuristic search algorithm uses the following basic steps to solve a minimization or maximization function.

1) *Initialization:* Randomly the solutions are generated and subjected to constraints, if any.
2) *Evaluation:* The solutions are evaluated using the objective function to understand the quality of the solutions.
3) *Solution Update:* Each heuristic search algorithm has its own operators to update the existing solutions, improving the quality.
4) *Termination:* When the termination criteria are met by the process, the highest quality solution is returned as the optimum solution. Otherwise, the process is iterated from Step 2 using the updated solutions. The termination criteria can be either maximum number of iterations or evaluations or saturation of solution quality or accomplishment of expected solution quality or combination of any of the above criteria.

In the hybrid PSO – DE, the solution updates took place using either PSO update or DE update or random update based on the progress in the quality of the solutions that are accomplished till the current iteration.

Solving CEED Model using Hybrid PSO - DE

Consider a pool of solutions, which are the power to be generated by each generation unit, S in which a p^{th} solution can be referred to as $S_p=\left\{P_1,P_2,P_3,\ldots,P_{N_g}\right\}_p : p=1,2,\ldots,N_s$, where N_s is the number of solutions in the solution pool. The initial solution set S is arbitrarily generated in such a way that $S_p(g)\in\left[P_g^{\min},P_g^{\max}\right]$ to meet the constraints given in Eq. (2-4). An operator selection mask O_p^{mask} with randomly generated binary elements is generated. Each p^{th} binary element refers to the operator to be applied on the p^{th} solution and so $\left|O^{mask}\right|=N_s$, where $|x|$ refers to the cardinality of a set x. Though the initial O^{mask} is a binary set, it gets integer values over the increasing number of iterations. The initial solution pool is evaluated using Eq. (6) and so each solution gets its evaluation score, which can be represented as $F_u\left(S_p\right)$. A set of local best solutions, termed as S_{local}, is set as S_p at the initial iteration, whereas S_{global} is set as the $S_q : q\in\left[1,N_s\right]$, which has good evaluation score, i.e., $F_u\left(S_q\right)<F_u\left(S_p\right): p\neq q$. The current iteration I is set as 1 and it is incremented by one after every solution updates. The number of solution evaluations is also memorized for

terminating the process. Every p^{th} solution is updated using the proposed hybrid operator given in Eq. (8) to obtain a new solution $\hat{S}_p$.

$$\hat{S}_p = \begin{cases} \psi_{PSO}\left(O_p^{mask}\right)U_{PSO}\left(S_p\right) \\ +\psi_{DE}\left(O_p^{mask}\right)U_{DE}\left(S_p\right) \\ +\psi_{RAND}\left(O_p^{mask}\right)U_{RAND}\left(S_p\right) \end{cases} \quad (8)$$

where ψ_{PSO}, ψ_{DE} and ψ_{RAND} are the selection operators for PSO, DE, and random updating process, respectively. Similarly, U_{PSO}, U_{DE} and U_{RAND} are the updating models of PSO, DE, and randomization, respectively. These three models can be commonly referred to as

$$U\left(S_p\right) = \begin{Bmatrix} \overline{U}\left(S_p\right); if\ f\left(U\left(S_p\right)\right) < f\left(S_p\right) \\ S_p; otherwise \end{Bmatrix} \quad (9)$$

This common updating model $U(\bullet)$ takes the actual updating process of either PSO or DE or randomization as given in Eq. (9), respectively. The selection operators $\psi(\bullet)$ in Eq. (8) enable any of the updating process to determine the updated solution. It is a step function operated within specific limits for every updating process as given in Eq. (10-12).

$$\psi_{PSO}(x) = \begin{Bmatrix} 1; if\ 0 \le x < L^{PSO} \\ 0; otherwise \end{Bmatrix} \quad (10)$$

$$\psi_{DE}(x) = \begin{Bmatrix} 1; if\ L^{PSO} \le x < L^{DE} \\ 0; otherwise \end{Bmatrix} \quad (11)$$

$$\psi_{RAND}(x) = \begin{Bmatrix} 1; if\ x > L^{DE} \\ 0; otherwise \end{Bmatrix} \quad (12)$$

The step limits L^{PSO} and L^{DE} lie in a common plane and exhibit the relationship $L^{PSO} < L^{DE}$.

The traditional PSO update process is exploited here as given in Eq. (13). However, the acceleration constant c_1 of the traditional PSO is set here as an acceleration variable that varies with respect to the current iteration status as given in Eq. (15).

$$\overline{U}_{PSO}\left(S_p\right) = S_p + \hat{V}_p \quad (13)$$

$$\hat{V}_p = w_I \times V_p + c_1 r_1\left(S_{local} - S_p\right) + c_2 r_2\left(S_{global} - S_p\right) \quad (14)$$

$$c_1 = W_c c_2 \frac{I}{I_{\max}} \quad (15)$$

where W_c is the weight of the constant, set here as 0.1, c_2 is the second acceleration constant and $I_{\max}$ is the maximum number of iterations, which can be $I_{\max} = \frac{E_{\max}}{N_s}$. Here, $E_{\max}$ is the maximum number of evaluations to be done. it shows that, in an iteration, N_s number of solutions are to be evaluated and hence $I_{\max}$ iterations lead to N_s times $I_{\max}$ number of evaluations.

The DE updating process can be defined as

$$\overline{U}_{DE}\left(S_p(g)\right)=\begin{Bmatrix} D_p(g); if\ r_3 < R_{DE} \\ S_p(g); otherwise \end{Bmatrix} \tag{16}$$

$$D_p = S_x + w_D\left(S_y - S_z\right): p \neq x \neq y \neq z \tag{17}$$

$$w_D = w_{\max} - I\,\frac{w_{\max} - w_{\min}}{I_{\max}} \tag{18}$$

where $(w_{\max}, w_{\min})$ refers to the differential weight, and S_x, S_y and S_z are three different solutions randomly selected from the population pool, i.e., $p, x, y, z \in [1, N_s]$. In Eq. (16), R_{DE} refers to the rate of DE recombination and r_3 is arbitrary integer generated within the interval [0,1].

In addition to the PSO and DE updating strategies, we use a random searching strategy, which can be defined as

$$\overline{U}_{RAND}\left(S_p(g)\right)=\begin{Bmatrix} R_p(g); if\ r_4 < R_{RAND} \\ S_p(g); otherwise \end{Bmatrix} \tag{19}$$

$$R_p(g) = P_g^{\min} + r_5\left(P_g^{\max} - P_g^{\min}\right) \tag{20}$$

In Eq. (19), R_{RAND} is the rate of random recombination and r_4 and r_5 are arbitrary integers generated within the interval [0,1].

Once the p^{th} solution gets updated, the O_p^{mask} is incremented by tolerance step δ (here, it is set as 0.1) if the updated solution does not show any improvement. The O_p^{mask} can be reset to zero, when either of the conditions given in Eq. (21, 22) is met.

$$F_u\left(\widehat{S}_p\right) < F_u\left(S_p\right) \tag{21}$$

$$O_p^{mask} > L^{RAND} \tag{22}$$

This iterative process is terminated when a maximum number of evaluations have been reached and the qualified solution is returned as the optimal generation strategy to minimize the CEED cost.

RESULTS AND DISCUSSION

Experimental Setup

The proposed CEED model and the hybrid PSO – DE have been developed in MATLAB and the experimental investigations have been carried out on three test systems. The first and second test systems have three and six different types of generators, respectively.

Table I. Technical Specifications of the generators used in the three-generator-bus system.

Generation units	Generation Capacity		Cost Coefficients			Emission Coefficients		
	P^{min}	P^{max}	a_0	a_1	a_2	α_0	α_1	α_2
1	10	85	0.008	7	200	0.01531	1.3751	18.60
2	10	80	0.009	6.3	180	0.01381	0.7511	23.82
3	10	70	0.007	6.8	140	0.1020	1.2021	20.62

Table II. Technical Specifications of the generators used in the six-generator-bus system.

Generating units	Generation Capacity		Cost Coefficients			Emission Coefficients		
	P^{min}	P^{max}	a_0	a_1	a_2	α_0	α_1	α_2
1	100	500	0.007	7	240	0.01531	1.3751	18.60
2	50	200	0.0095	10	200	0.01381	0.7511	23.82
3	80	300	0.009	8.5	220	0.1020	1.2021	20.62
4	50	150	0.009	11	200	0.1066	0.7053	11.90
5	50	200	0.008	10.5	220	0.01543	1.7657	24.35
6	50	120	0.0075	12	120	0.1810	1.4682	27.59

Table III. Technical Specifications of the generators used in the benchmark ieee 30-bus system.

Generation units	Generation Capacity		Cost Coefficients			Emission Coefficients		
	P^{min}	P^{max}	a_0	a_1	a_2	α_0	α_1	α_2
1	50	200	0.00375	2.00	0	0.0126	-1.1000	22.983
2	20	80	0.01750	1.75	0	0.0200	-0.1000	25.313
3	15	50	0.06250	1.00	0	0.0270	-0.0100	25.505
4	10	35	0.00834	3.25	0	0.0291	-0.0050	24.900
5	10	30	0.02500	3.00	0	0.0290	-0.0040	24.700
6	12	40	0.02500	3.00	0	0.0271	-0.0055	25.300

The third system is the benchmark IEEE 30 bus system with six generating units. Each generating unit has varying generation capacities and incurs varying cost to generated one MW of power and different emission characteristics. Tables I, II, and III detail the specifications of the generators of three-bus system, six-bus system, and IEEE 30 -us system, respectively. In order to demonstrate the performance of the hybrid PSO – DE, we have also simulated the individual PSO and DE for comparative study. Moreover, we have developed an existing hybrid PSO – DE to demonstrate the superiority of our hybridization process. The existing hybrid PSO – DE method has been reported in

Sahu1 *et al.* (2014), where the interconnected power system has been controlled. The user-defined parameters in PSO and hybrid PSO – DE such as $w_{\max}$, $w_{\max}$, c_1 and c_2 have been set as 0.9, 0.4, 2.05, and 2.05, respectively. Similarly, the user-defined parameters in DE such as R_{DE} and w_D have been set as 0.4 and 0.6, respectively. In addition, the proposed hybrid PSO – DE takes few constants such as L^{PSO}, $L^{DE}$and L^{RAND}, which are always 1, 2, and 3, respectively, and R_{RAND} is equal to R_{DE}. The maximum number of evaluations has been set to 10000 for all the algorithms. To ensure fair results, the CEED model for every test system is attempted to optimize 100 times by every optimization algorithm. The best, worst, mean, median, and standard deviation of the accomplished CEED function values are observed and investigated. Based on these values, the optimization algorithms are ranked and the final rank is determined based on the average of all the ranks.

CEED Minimization

The performance of the optimization algorithms on minimizing the CEED cost can be observed from Tables IV, V, and VI, where the algorithms are ranked based on the accomplished costs for their generation strategy. For the three-generator bus system (test case 1), the proposed hybrid algorithm has gained first rank as it has produced the least cost through its generation schedule, whereas the conventional hybrid algorithm, DE, and PSO have secured second, third, and fourth ranks, respectively. A similar kind of performance has been achieved under the investigation of median and worst cost accomplishment. However, the proposed algorithm could gain only third rank in achieving the best cost throughout the 100 iterations. Yet, the average rank has led the algorithm to hold the first position among all the optimization algorithms. The progress of accomplishing such minimum CEED cost by every optimization algorithm can be visualized with the help of the convergence graph presented in Fig. 1. The graph illustrates the improvement of the algorithm over the solution updates, i.e., number of evaluations, which is incremented in the algorithm when an updated solution is evaluated. According to Fig. 1 (a), PSO has shown saturated performance for around 8000 numbers of evaluations followed by a rapid performance improvement at the final end. Despite the improvement is appreciable, it remains unreliable. In contrast, the rest of the algorithms have shown gradual improvement and have reached saturation at the final set of evaluations. More specifically, the proposed hybrid optimization algorithm has initiated the progress among the other algorithms. A similar kind of characteristics can be found in Fig. 1 (b) and (c). Although few saturation instants have been reached in the performance of the proposed algorithm, further improvement has also been achieved even after the saturation level.

Table IV. Statistical results on the Minimized CEED Cost used in the three-generator-bus system.

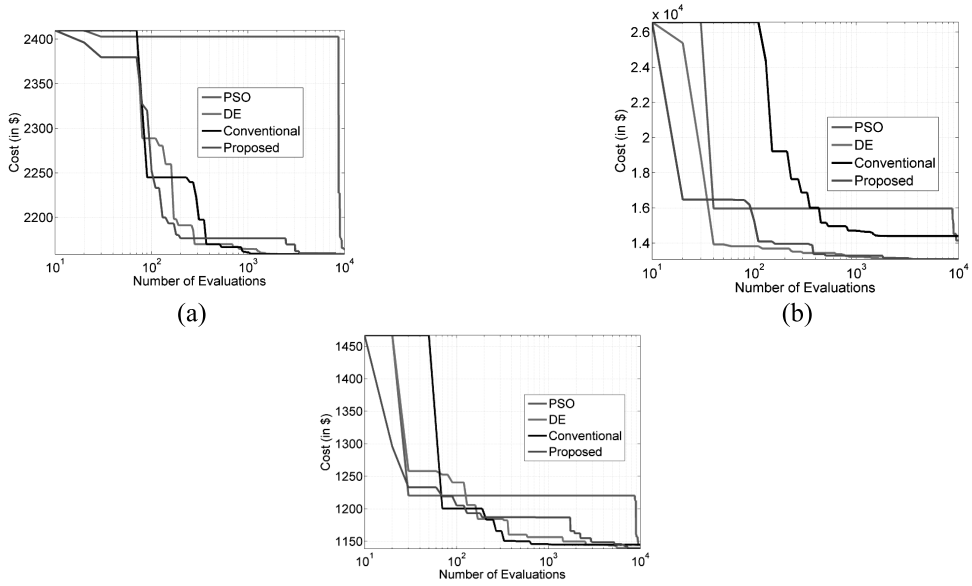
Statistical metrics	**PSO**	**DE**	**Hybrid PSO – DE (Sahu1 et al., 2014)**	**Proposed Hybrid PSO - DE**
Best Cost (in $)	2178.2482 (4)	2158.7172 (1)	2158.7172 (1)	2158.9799 (3)
Worst Cost (in $)	2286.1008 (4)	2169.3665 (3)	2159.4645 (2)	2159.3732 (1)
Mean Cost (in $)	2246.4587 (4)	2162.7484 (3)	2158.4785 (2)	2158.2144 (1)
Median Cost (in $)	2223.9555 (4)	2161.752 (3)	2158.8892 (2)	2158.7402 (1)
Cost Deviation (in $)	50.8364 (4)	7.3914 (3)	0.3468 (2)	0.2465 (1)
Average Rank	4	2.6	1.8	1.4
Final Rank	4	3	2	1

Table V. Statistical results onthe Minimized CEED Cost used in the Six-generator-bus system.

Statistical metrics	**PSO**	**DE**	**Existing Hybrid PSO – DE (Sahu1 et al., 2014)**	**Proposed Hybrid PSO - DE**
Best Cost (in $)	13471.6852 (4)	13083.6545 (3)	13077.8774 (2)	13080.3136 (1)
Worst Cost (in $)	13596.4705 (4)	13325.4328 (3)	13084.7348 (2)	13081.9735 (1)
Mean Cost (in $)	13495.6488 (4)	13250.4785 (3)	13081.6512 (2)	13080.6789 (1)
Median Cost (in $)	13491.9906 (4)	13270.469 (3)	13082.2348 (2)	13080.6669 (1)
Cost Deviation (in $)	102.5647 (3)	121.4547 (4)	3.4577 (2)	1.2214 (1)
Average Rank	3.8	2.6	2	1
Final Rank	4	3	2	1

Table VI. Statistical results on the Minimized CEED Cost used in the IEEE 30-Bus System.

Statistical metrics	**PSO**	**DE**	**Existing Hybrid PSO – DE (Sahu1 et al., 2014)**	**Proposed Hybrid PSO - DE**
Best Cost (in $)	1144.67 (3)	1144.76 (4)	1138.00 (2)	1136.12 (1)
Worst Cost (in $)	1197.23 (4)	1147.33 (3)	1139.86 (2)	1137.59 (1)
Mean Cost (in $)	1158.41 (4)	1145.51 (3)	1138.57 (2)	1136.85 (1)
Median Cost (in $)	1167.59 (4)	1145.41 (3)	1138.5435 (2)	1136.99 (1)
Cost Deviation	17.15 (4)	2.14 (3)	0.78 (2)	0.72 (1)
Average Rank	3.8	2.6	2	1
Final Rank	4	3	2	1



(a) (b) (c)

Fig. 1. Convergence graphs of various optimization algorithms on minimizing CEED cost of (a) three-generator-bus system, (b) six-generator-bus system and (c) IEEE 30-bus system.

Table VII. Statistical results on the Minimized CEED Cost used in the IEEE 30-Bus System.

Test Cases	PSO	DE	Existing Hybrid PSO – DE (Sahu1 et al., 2014)	Proposed Hybrid PSO - DE
1	.5744	1.8591	1.9706	0.8054
2	1.3702	1.5347	1.6527	0.77015
3	1.2658	1.6181	1.5915	0.81639

This nature of the algorithm has revealed the reliability in minimizing the CEED cost; even it had a probability to stick with local minima. The cost deviation in Tables IV, V, and VI has also shown that the proposed algorithm has exhibited minimum deviation from its average minimized cost. Hence, the performance of the proposed algorithm can be ascertained for performance consistency.

Generation Strategy

The proposed algorithm has strategized well to minimize the CEED model, as per the statistical metrics. In order to substantiate further and to understanding the strategizing behavior of the proposed optimization algorithm, the recommended generation quantities of each generating unit by all the optimization algorithms are given in fig. 2. In fig. 2 (a), the generating units 1 and 3 are recommended to utilize moderately, whereas maximum utilization has to be done on the generating unit 2. As a result, the CEED cost has become \$2158, which is lesser than PSO and DE and closer to the conventional hybrid model. According to fig. 2 (b), generating unit 1 has been recommended to exploit relatively higher than the recommendations of the other algorithms. The other generating units are recommended to use moderately or closer to the recommendations of the other algorithms. Such generation strategy has significantly reduced the CEED cost to \$13080, whereas the conventional hybrid optimization, PSO, and DE have accomplished only \$13216, \$13083, and \$13596, respectively. Such contrasting generation strategy has been applied by the proposed optimization algorithm for IEEE 30-bus system to attain relatively lesser CEED cost than the other algorithms.

Computational Efficiency

The computational efficiency of all the optimization algorithms on handling the CEED model has been observed using the computing time required to reach its minimum CEED cost. The details are given in Table VII, where the average computational time has been given.

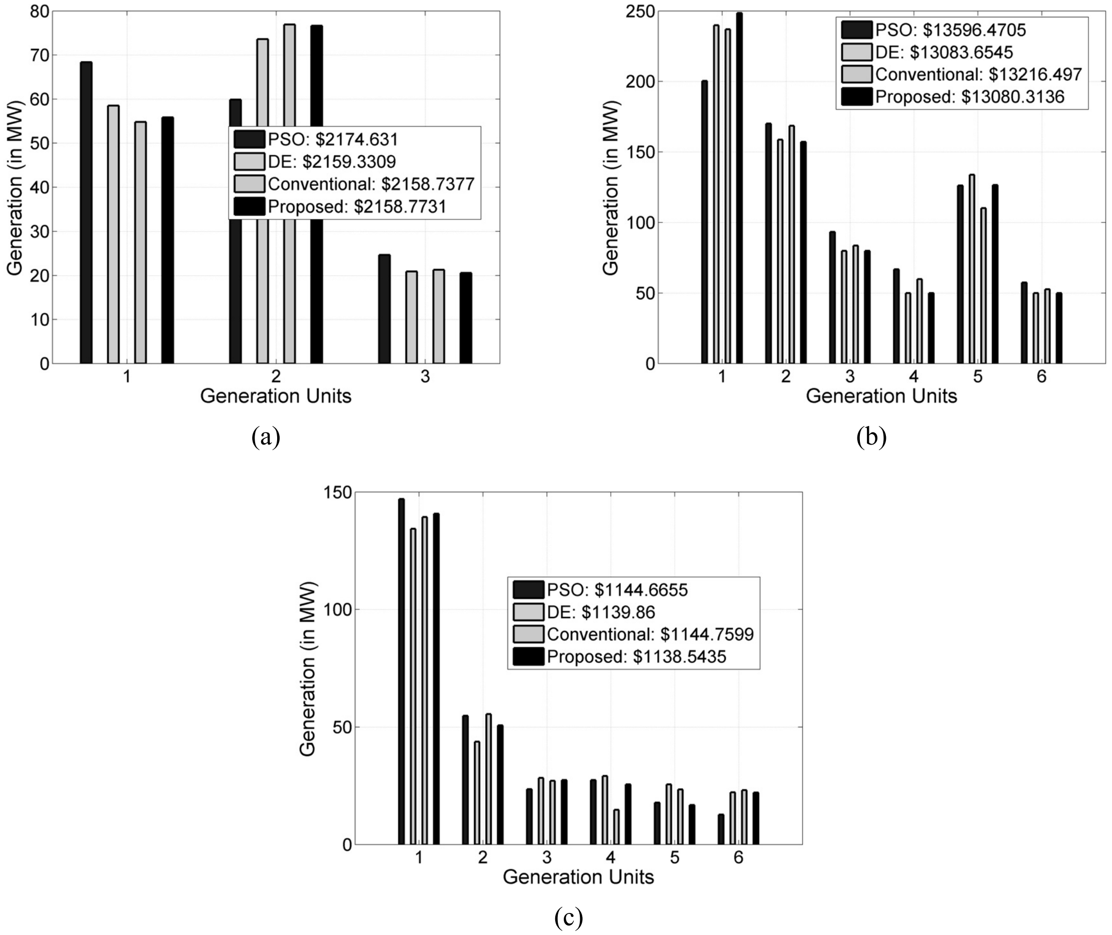


Fig. 2. Generation strategies recommended by various optimization algorithms (a) three-generator-bus system, (b) six-generator-bus system, and (c) IEEE 30-bus system.

While the proposed optimization algorithm has achieved significant performance in minimizing the CEED model through its unique generation model, it has also exhibited its computational efficiency. According to Table VII, the proposed optimization algorithm has consumed just 50% of the computational time of the conventional hybrid optimization algorithm, PSO, and DE. This shows that the proposed optimization algorithm is able to handle even complex generation strategies for smart grid environment.

CONCLUSION

This paper hybridized the optimization process of PSO and DE to solve the CEED model for smart grid system. The hybridization has been done by combining the update process of DE, PSO, and random searching process. The CEED model has considered economic and emission constraints along with security and transmission constraints. The experimentation was carried out on a three-generator-bus system and two six-generator-bus systems. One of the six-generator-bus systems was the benchmark IEEE 30-bus system. The results have revealed that the proposed heuristic search algorithm is better than the conventional algorithms. The conclusion about the superiority of the proposed hybrid optimization algorithm has been ensured by the statistical analysis on the minimized CEED cost. The computational efficiency of the proposed hybrid algorithm has also proved better than the conventional algorithms.

REFERENCES

Wang, J., Shahidehpour, M. & Li, Z. 2008. Security-constrained unit commitment with volatile wind power generation, *IEEE Trans. Power Syst.,* 23(3):1319-1327.

Makarov, Y., Loutan, C., Ma, J. & Mello, P.D. 2009. Operational impacts of wind generation on California power systems, *IEEE Trans. Power Syst.,* 24(2): 1039-1050.

Ruiz, P., Philbrick, C., Zak, E., Cheung, K. & Sauer, P. 2009. Uncertainty management in the unit commitment problem, *IEEE Trans. Power Syst.,* 24(2): 642-651.

Bouffard, F. & Galiana, F. 2008. Stochastic security for operations planning with significant wind power generation, *IEEE Trans. Power Syst.,* 23(2): 306-316.

Wang, J., Botterud, A., Bessa, R., Keko, H., Carvalho, L., Issicaba, D., Sumaili, J. & Miranda, V. 2011. Wind power forecasting uncertainty and unit commitment, *Applied Energy*, 88(11):4014-4023.

Jiang, R., Wang, J. & Guan, Y. 2012. Robust unit commitment with wind power and pumped storage hydro, *IEEE Trans. Power Syst.,* 27(2): 800-810.

Wang, C., Luh, P.B., Gribik, P., Zhang, L. & Peng, T. 2010. The subgradient-simplex based cutting plane method for convex hull pricing, *in Proc. IEEE Power Energy Soc. Gen. Meet.,* 1-8.

Lee, C., Liu, C., Mehrotra, S. & Shahidehpour, M. 2014. Modeling Transmission Line Constraints in Two-Stage Robust Unit Commitment Problem, *IEEE Trans. on Power Systems*, 29(3): 1221-1231.

Niknam, T., Bavafa, F. & Abarghooee, R.A. 2014. New self-adaptive bat-inspired algorithm for unit commitment problem, *Science, Measurement & Technology, IET,* 8(6): 505-517.

Yang, L., Jian, J., Zhu, Y. & Dong, Z. 2015. Tight Relaxation Method for Unit Commitment Problem Using Reformulation and Lift-and-Project, *IEEE Trans. on Power Systems,* 30(1): 13-23.

Han, X., Gooi, H. & Kirschen, D. 2001. Dynamic economic dispatch: Feasible and optimal solutions, *IEEE Trans. Power Syst.,* 16(1): 22-28.

Huang, C.M & Huang, Y.C. 2003. A novel approach to real-time economic emission power dispatch, *IEEE Trans. Power Syst.,* 18(1): 288-294.

Gaing, Z.L. 2003. Particle swarm optimization to solving the economic dispatch considering the generator constraints, *IEEE Trans. Power Syst.,* 18(3): 1187-1195.

Xia, Y., Ghiocel, S.G., Dotta, D., Shawhan, D., Kindle, A. & Chow, J.H. 2013. A Simultaneous Perturbation Approach for Solving Economic Dispatch Problems With Emission, Storage, and Network Constraints, *IEEE Transactions on Smart Grid,* 4(4): 2356-2363.

Lamadrid, A.J., Shawhan, D.L., Sanchez, C.E.M., Zimmerman, R.D., Zhu,Y., Tylavsky, D.J., Kindle, A.G. & Dar, Z. 2015. Stochastically Optimized, Carbon-Reducing Dispatch of Storage, Generation, and Loads, *IEEE Trans. on Power Systems,* 30(2): 1064 -1075.

Jadoun, V.K., Gupta, N., Niazi, K.R. & Swarnkar, A. 2015. Modulated particle swarm optimization for economic emission dispatch, *Int. J. of Electrical Power & Energy Systems,* 73: 80-88.

Liang, Z.X. & Glover, J.D. 1992. A zoom feature for a dynamic programming solution to economic dispatch including transmission losses, *IEEE Trans Power Syst.,* 7 (2):544-550.

Basu, M. 2011. Economic environmental dispatch using multi-objective differential evolution, *Applied Soft Computing,* 11(2): 2845-2853.

King, R.T.F.A., Rughooputh, H.C.S. & Deb, K. 2011. Solving the multi-objective environmental/ economic dispatch problem with prohibited operating zones using NSGA-II, *in Proc. of 2011 IEEE Pacific Rim Conf. on Communications, Computers and Signal Processing (PacRim),* 298-303.

Hooshmand, R.A., Parastegari, M. & Morshed, M.J. 2012. Emission, reserve and economic load dispatch problem with non-smooth and non-convex cost functions using the hybrid bacterial foraging-Nelder–Mead algorithm, *Applied Energy,* 89 (1):443–453.

Hamedi, H. 2013. Solving the combined economic load and emission dispatch problems using new heuristic algorithm, *Int. J. of Electrical Power & Energy Systems,* 46: 10-16.

Shayeghi, H. & Ghasemi, A. 2014. A modified artificial bee colony based on chaos theory for solving non-convex emission/ economic dispatch, *Energy Conversion and Management,* 79: 344-354.

Bhattacharjee, K., Bhattacharya, A. & Dey, S.H.N. 2014. Solution of economic emission load dispatch problems of power systems by real coded chemical reaction algorithm, *Int. J. of Electrical Power & Energy Systems,* (59):176-187.

Benasla, L., Belmadani, A. & Rahli, M. 2014. Spiral optimization algorithm for solving combined economic and emission dispatch, *Int. J. of Electrical Power & Energy Systems,* 62: 163-174.

Jeddi, B. & Vahidinasab, V. 2014. A modified harmony search method for environmental/ economic load dispatch of real-world power systems, *Energy Conversion and Management, 78*: 661-675.

Nwulu, N.I. & Xia, X. 2015. Implementing a model predictive control strategy on the dynamic economic emission dispatch problem with game theory based demand response programs, *Energy,* 91: 404-419.

Niknam, T., Golestaneh, F. & Sadeghi, M.S. 2012. Multiobjective Teaching–Learning-Based Optimization for Dynamic Economic Emission Dispatch, *IEEE Systems Journal,* 6(2): 341-352.

Le, K.D., Golden, J.L., Stansberry, C.J., Vice, R.L., Wood, J.T., Ballance, J., Brown, G., Kamya, J.Y., Nielsen, E.K., Nakajima, H., Ookubo, M., Iyoda, I. & Cauley, G.W. 1995. Potential impacts of clean air regulations on system operations, *IEEE Trans. Power Syst.,* 10 (2): 647-656.

Gholami, A., Ansari, J., Jamei, M. & Kazemi, A. 2014. Environmental/economic dispatch incorporating renewable energy sources and plug-in vehicles, *Generation, Transmission & Distribution*, IET, 8(12): 2183 – 2198.

Yang, H.T., Yang, P.C. & Huang, C.L. 1996. Evolutionary programming based economic dispatch for units with non-smooth fuel cost functions, *IEEE Trans. Power Syst.*, 11(1): 112-118.

Selvakumar, A.I. & Thanushkodi, K. 2007. A new particle swarm optimization solution to nonconvex economic dispatch problem, *IEEE Trans. Power Syst.,* 22(2): 42-51.

Park, J.B., Lee, K.S., Shin, J.R. & Lee, K.Y. 2005. A particle swarm optimization for economic dispatch with non smooth cost functions, *IEEE Trans. Power Syst,* 20(1): 34-42.

Lu, S., Lou, S., Wu, Y. & Yin, X. 2013. Power system economic dispatch under low-carbon economy with carbon capture plants considered, *Generation, Transmission & Distribution, IET, 7*(9): 991-1001.

Liu, J. & Li, J. 2015. A Bi-Level Energy-Saving Dispatch in Smart Grid Considering Interaction Between Generation and Load, *IEEE Trans. on Smart Grid,* 6(3): 1443-1452.

Sahu1, B.K., Pati, S. & Panda, S. 2014. Hybrid differential evolution particle swarm optimisation optimised fuzzy proportional–integral derivative controller for automatic generation control of interconnected power system, *IET Generation, Transmission & Distribution*,(8)11:1789–1800.

Submitted: 07/12/2016
Revised: 22/02/2018
Accepted: 13/03/2018

تهجين استمثال عناصر السرب مع خوارزمية التطور التفاضلي لحل نموذج CEED لنظام الشبكة الذكية

ناريش كومار ياداف
قسم الهندسة الكهربائية، كلية الهندسة والتكنولوجيا، جامعة دينباندو شوتو رام للعلوم والتكنولوجيا،
مورثال (سونيبات) – هاريانا، الهند

الخلاصة

يقدم هذا البحث نموذج CEED لنظام الشبكة الذكية وتقديم الحلول له عن طريق تهجين خوارزميات الأمثلية المعروفة مثل خوارزمية استمثال عناصر السرب (PSO) وخوارزمية التطور التفاضلي (DE). تم تهجين الخوارزميتين عن طريق تحديث الحلول لهما والجمع بينهما بواسطة عملية البحث العشوائي. يخضع نموذج CEED لتقليل تكلفته إلى الحد الأدنى بحيث يمكن الحفاظ على المفاضلة الكافية بين التكاليف الاقتصادية وتكاليف الانبعاثات. تم تجربة الخوارزمية الهجينة المُقترحة على ثلاثة أنظمة نقل مختلفة، وتم مقارنة أدائها مع خوارزميات PSO و DE كلاً على انفراد. وأوضحت نتائج المقارنة تفوق خوارزمية البحث الهجينة المقترحة من حيث جودة الحل والكفاءة الحسابية.