AEFA Based Optimal Dynamic Economic Load Dispatch Problem Considering Penetration of Renewable Energy Systems

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Received 09 October 2021; Accepted 28 December 2021;
Publication 22 April 2022

Abstract

In power system, maintaining the load generation balance is critical. This paper proposes an artificial electric field algorithm (AEFA) for dynamic economic load dispatch (DELD) in a power system with security constraints, taking into account renewable energy sources (RES).. The RES penetration and total savings are examined considering variation of underestimation and overestimation costs associated with RES. Further, the impact of increased RES penetration on thermal fuel and overall costs has been studied. The AEFA algorithm performs better than PSO and DE, in terms of performance. The result reveals that when RES penetration rises savings as well as net cost of RES rises. Numerically, at 65% penetration of RES, a savings of

Distributed Generation & Alternative Energy Journal, Vol. 37_4, 979–998.
doi: 10.13052/dgaej2156-3306.3745

28.19% is achieved in the generator fuel cost and the RES penetration leads to a reduction in the thermal unit's fuel cost.

Keywords: Dynamic economic load dispatch, artificial electric field algorithm, renewable energy sources, optimization.

Nomenclature

P_r	Rated wind power
$P_{w,t}$	Wind power at any time *t*
v_r	Rated wind speed
v_t	Wind speed at any time *t*
v_{cf}	Cut-off wind speed
v_{in}	Cut-inwind speed
σ_t	Standard deviation
θ_t	Angle of inclination of sun
S_t	Solar power at time *t*
$S_{max,t}$	Maximum solar power at time *t*
$(\cdot)$	gamma function
$P_{Gi,t}$	Thermal power from unit *j* at time *t*
$P_{wj,t}$	Wind power from unit *j* at time *t*
$P_{PVK,t}$	Solar power from unit *j* at time *t*
N_G	Number of thermal generators
N_W	Number of wind generators
N_{PV}	Number of solar power generator
H	Total number of hours under consideration
P_{load}	Power demand by load
C	Total cost
$C(P_{Gi,t})$	Fuel cost of thermal generators
$C(P_{wj,t})$	Operating cost of wind generators
$C(P_{PVK,t})$	Operating cost of solar generators

1 Introduction

Complexity is rising with the increasing integration of renewable energy sources (RESs) in the existing power. The operation and planning of this system have become a challenging issue for the utilities [1]. The scheduling of the generators is one of such operational issues, which is essential for secure power system operation to fulfill the load demand [2]. The issue of generator scheduling has been addressed using several methodologies [3], such as Static economic load dispatch (SELD) [4]. The SELD fails to include the time-varying load and generator ramp rates. Also, the look ahead capability is missing [5]. The dynamic economic load dispatch (DELD) is an extension of SELD, allowing the power system's load variations and dynamic nature, i.e., generator ramp rates [6]. It is equipped with the look-ahead capability for load scheduling. For DELD, the load demand is divided into small durations during which the load is kept constant, which is a temporary steady-state [7]. Due to the quick dispatching nature of thermal and hydropower, they are considered the primary energy source. There are various optimization algorithms developed to optimize the power system operation [8].

This paper proposes an artificial electric field algorithm (AEFA) as an optimization technique to perform the DELD [9, 10]. AEFA provides (i) good performance for non-linear optimization problems [9], (ii) it has only two parameters to tune, (ii) faster convergence, (iii) better exploration and exploitation ability, and (iii) reduced computational effort [11]. The results are compared to differential evolution (DE) and particle swarm optimization (PSO). It shows that AEFA can provide better results than PSO and DE. With rising RES levels in the existing power, it is essential to study their impact on the power system scheduling for enhancing the operating efficiency of the overall power system. The information at different RES penetration levels in the power system is vital to identify which type of RES can be used at a site. The higher penetration level of RES in the power system faces some severe challenges [12–14]. An increment in penetration level affects the transient stability of power in the system [15]. There are significant issues faced by increasing RES penetration in the power system, such as Interconnection problems due to different voltage levels and topology [16, 17]. To determine the effect of higher penetration levels, a solution for the integrated DELD problem has been done considering different penetration levels with PSO, DE, and AEFA. The effect of a higher penetration level is discussed. The work presented in this work is primarily based on the work in reference [18]. However, it extended the work by analysing the penetration of RES in the system and application of AEFA for determining the solution. The contribution can be summarized as:

(a) Application of AEFA algorithm to solve DELD with RES and it performs better than PSO and DE, in terms of performance.
(b) Examination of the RES penetration and total savings considering variation of underestimation and overestimation costs associated with RES.

(c) Study of impact of increased RES penetration on thermal fuel and overall costs has been studied.
(d) The results show that the when RES penetration rises savings as well as net cost of RES rises.

The remaining paper is organized as, in Section 2, the problem formulation is discussed. In Section 3, the AEFA algorithm is elaborated. The results and discussions are presented in Section 4. Finally, conclusions are drawn in Section 5.

2 Problem Formulation

The problem includes three energy sources: thermal power generation, solar, and wind energy system as RES. These sources are modeled mathematically. The problem is formulated as a dispatch problem for thermal generation only and different penetration levels of RES, which is solved using AEFA, PSO, and DE. The complete process is shown in Figure 1. The mathematical model of the problem is presented below.

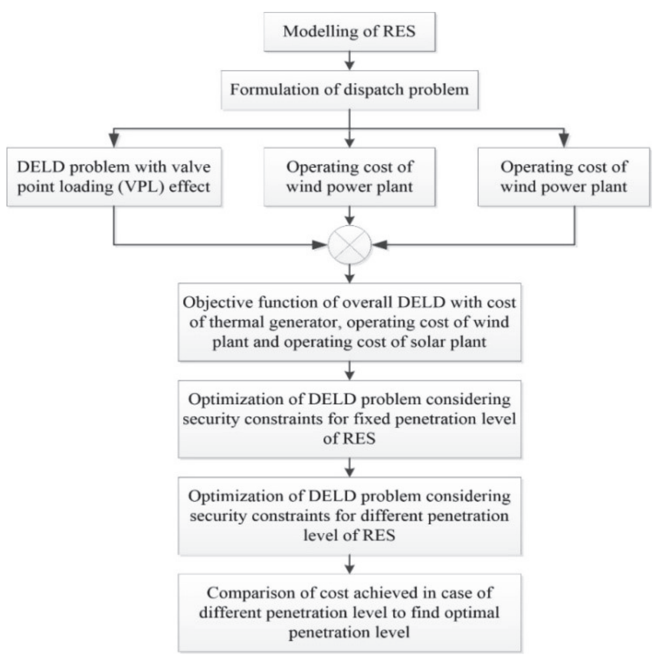

Figure 1 Flowchart of the methodology.

2.1 Modelling of RES

Here the models the solar PV and wind energy are discussed. They aremodeled through Beta and Weibull probability density functions (PDFs) [17].

2.1.1 Wind power model

The stochastic nature of wind is developed using the two-parameter (scale and space) based Weibull distribution function [18]. The output power characteristics for the wind speed $v_t$can be taken as a simplified linear model, given as [19],

$$P_{W.t}(v_t) = \begin{cases} 0 & v_t < v_{in}, v_t > v_{cf} \\ P_W \dfrac{v_t - v_{in}}{v_r - v_{in}} & v_{in} \le v_t \le v_r \\ P_W & v_{in} \le v_t \le v_r \end{cases} \tag{1}$$

Using the discrete PDF, wind power PDF is expressed as (2)

$$\begin{aligned} P_r(P_{W.t} = 0) &= P_r(v_t < v_{in}) + P_r(v_t > v_{cf}) \\ &= 1 - \exp\left[-\left(\frac{v_{in}}{\sigma_t}\right)^{\theta_t}\right] + \exp\left[-\left(\frac{v_{cf}}{\sigma_t}\right)^{\theta_t}\right] \end{aligned} \tag{2}$$

The probability of occurrence of the event $P_{W,t} = P_W$ is

$$\begin{aligned} P_r(P_{W.t} = P_W) &= P_r(v_r < v_t < v_{cf}) \\ &= \exp\left[-\left(\frac{v_r}{\sigma_t}\right)^{\theta_t}\right] + \exp\left[-\left(\frac{v_{cf}}{\sigma_t}\right)^{\theta_t}\right] \end{aligned} \tag{3}$$

The wind speed energy feature is constant and linear ($v_{in} < v < v_{cf}$). The PDF of wind speed power for the interval of ($0 < P_{W,t} < P_W$) is given as

$$\begin{aligned} f_{pW.t}(P_{W.t}) &= \left(\frac{\theta_t h v_{in}}{\sigma_t P_W}\right)\left[\frac{\left(1 + h\frac{P_{W.t}}{P_W}\right) v_{in}}{\sigma_t}\right] \\ &\times \exp\left\{-\left[\frac{\left(1 + h\frac{P_{W.t}}{P_W}\right)}{\sigma_t}\right]^{\theta_t}\right\} \end{aligned} \tag{4}$$

where $h = (v_r - v_{in})/v_{in}$.

2.1.2 Solar power model

The solar power generated varies with the solar insolation, PV cell temperature, and type of PV modules. The output power of the PV module is calculated using solar temperature and solar irradiance [19]. The variation in solar energy can be estimated using the information about (i) orientation of the sun and (ii) availability time. The corresponding Beta distribution function $f_{S.t}(S_t)$ can be expressed as [20]

$$f_{S.t}(S_t) = \left\{ \frac{\Gamma(\delta_t + \partial_t)}{\Gamma(\delta_t)\Gamma(\partial_t)} \left(\frac{S_t}{S_{\max.t}} \right)^{\delta_t - 1} \left(1 - \frac{S_t}{S_{\max.t}} \right)^{\partial_t - 1} \right\},$$

$$0 \leq \left(\frac{S_t}{S_{\max.t}} \right) \leq 1,\ \delta_t, \partial_t > 0 \tag{5}$$

Where, *S* represents the solar irradiance, sub-script *t* and *max* denotes the time and maximum irradiance at the location. The Beta distribution parameters (δ_t, ∂_t) can be calculated using the mean (μ_t) and standard deviation $(\emptyset_t)$ [20]. The solar irradiance power PDF can be presented using the Beta distribution function [20].

2.2 DELD Cost Function

The overall DELD objective function using thermal generator fuel cost, wind power plant operational cost, and solar power plant operational cost is given [21].

$$C = \sum_{t=1}^{H} \left(\sum_{i=1}^{N_G} C(P_{Gi,t}) + \sum_{j=1}^{N_W} C(P_{Wj,t}) + \sum_{K=1}^{N_{PV}} C(P_{PVK,t}) \right) \tag{6}$$

A thermal generator's cost is determined by a quadratic non-convex objective function [22], which includes the valve point effect (VPL) [23].

The cost of running a wind-powered generator is divided into three parts: (i) Direct cost: This is the price of a wind turbine. This expense is ignored if the system operator owns it. (ii) Cost of Underestimation: This is the cost of not utilizing available wind power. (iii) Cost of overestimation: If available wind power is less than scheduled power [24].

The cost of operating a solar-PV module also consists of three parts: (i) Direct cost: It is the cost of scheduled solar power, (ii) Underestimation cost, and (iii) Overestimation cost. The underestimation and overestimation costs are similar to that of the wind operation cost [24].

2.3 Constraints

The power system operational constraints included in the DELD are (i) power balance constraint, (ii) ramp rates, (iii) power inequality constraints, and (iv) prohibited operating zones (POZs).

The power balance constraint is given as

$$\sum_{i=1}^{N_G} P_{Gi,t} + \sum_{j=1}^{N_W} P_{Wj,t} + \sum_{K=1}^{N_{PV}} P_{PVK,t} = P_{load,t} + P_{loss,t} \tag{7}$$

The thermal generation boundaries articulated as high and low as for a stable operation are

$$P_{Gi}^{\min} \leq P_{Gi,t} \leq P_{Gi}^{\max} \tag{8}$$

Likewise, RES production limits must be limited to certain levels to enable the system to operate optimally [23].

$$P_{Wj}^{\min} \leq P_{Wj,t} \leq P_{Wj}^{\max} \tag{9}$$

$$P_{PVK}^{\min} \leq P_{PVK,t} \leq P_{PVK}^{\max} \tag{10}$$

The ramp rates and the POZ are modeled using [25].

3 Artificial Electric Field Algorithms

AEFA is an electrostatic force based on Coulomb's law optimization algorithm. Charged particles represent the set of solutions, and the strength of each particle is determined by its charge. The electrostatic force of attraction or repulsion acts on the particles. The most effective solution, i.e., the charged particle, will attract all the lower charge particles to converge effectively in the hyperspace [9]. The algorithm's comprehensive mathematical model can be found in [9]. Figure 2 depicts the algorithm for the same.

4 Result and Discussion

The main aim of DELD is to get an optimal mix of energy sources at least operating cost while meeting the load demand. The energy sources consist of (i) wind energy, (ii) solar energy, and (iii) thermal power plants. Using the model of these sources discussed in Section above, the performance is tested on two systems [25], (i) Test system-I: 6 unit system, and (ii) Test

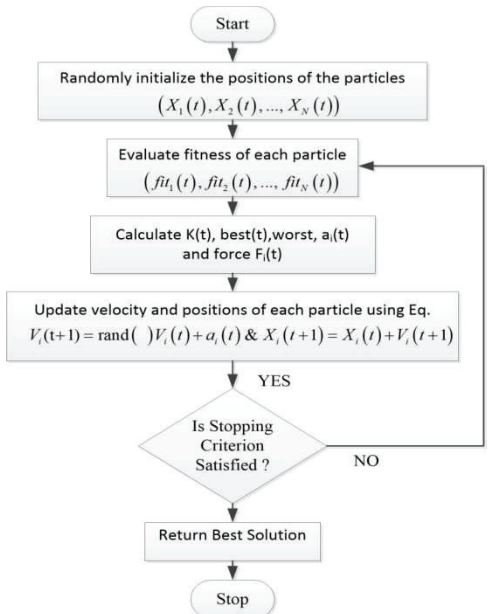

Figure 2 Flowchart of the AEFA.

system: 15 unit system. The experimentation is performed in two cases for each system, (i) Case-I: Without RES and (ii) Case-II: With RES. Initially, the simulation is performed for thermal power plants, only, i.e., without RES. The results for Case-I are used as a reference system. Thereafter, the impact on the system cost is observed for increasing penetration of RES in the system. For each system, the convergence characteristics of the optimization algorithm, namely, AEFA, PSO, and DE, are considered. The complete system is analyzed on the MATLAB[§] platform. The system uses Weibull and Beta parameters [18] to model the RES. The other parameters for the wind used in the study are tabulated in Table 1 and solar PV parameters are available in [18]. The constraint values are available in [25].

4.1 Case-I

For Test system-1 and Test system-2 all constraints are considered. The maximum number of iterations is set to 300, and the population size is 100. A total of 50 trial runs are executed, after which the best, worst, and average results are recorded. First, a single load of 935 MW is considered, only to be met using the thermal power plants. The optimal cost obtained using for Test

Table 1 System Parameters used in the study [18]

Parameter	Value
Wind's direct cost($/MWh)	8
Wind penalty cost	1.5
Wind reserve cost coefficient	10
Solar's direct cost($/MWh)	9
Solar penalty cost	1.5
Solar reserve cost coefficient	11
Peak wattage ($\mathrm{PV}^{\max}$)	340 W
Nominal cell temperature (N_{OT})	46°C

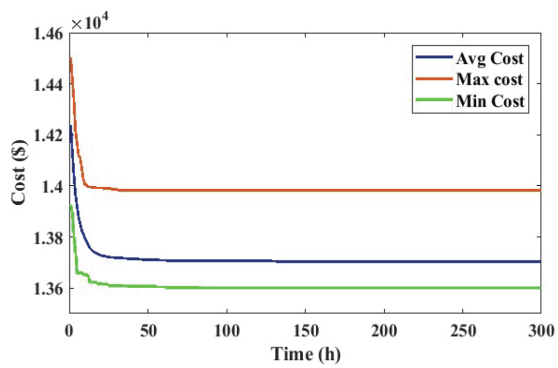

Figure 3 Convergence characteristics for 935 MW load.

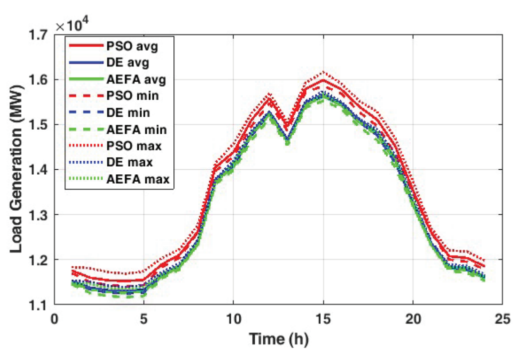

Figure 4 Different load and active power generation with AEFA.

System-I is optimal cost for 935 MW is around 13600.26$. The convergence plot for the same is shown in Figure 3.

For DELD, the load data is shown in Figure 4. For Test-system-1 with all thermal units, the results for DELD are shown in Table 2 using AEFA.

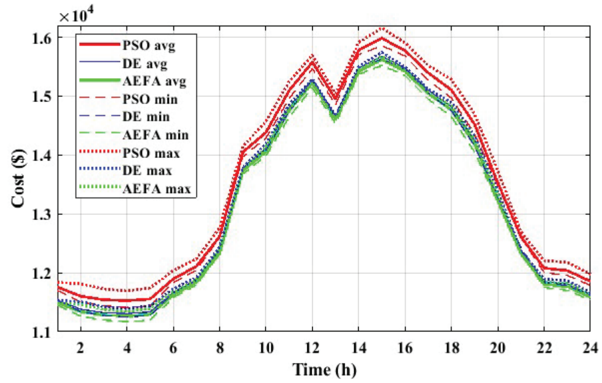

Figure 5 Cost comparison for six units without RES.

Table 2 Generator scheduling for 24 hours

	Units					
Time (in Hrs)	1	2	3	4	5	6
0000	440	170	200	150	190	110
0100	380	125.55	205.1	95.73	116.93	50
0200	350	125.94	209.35	102.93	120.1	51.49
0300	380	118.78	196.72	92.14	115.28	50.02
0400	350	128.4	210	98.22	110..81	50
0500	350	127.49	210	100.33	113.66	51.09
0600	380	122.42	210	105.79	113.21	50.19
0700	389.31	130.86	210	101.09	120.1	57.47
0800	397.54	140	210	110	126.56	59.89
0900	418.88	140	240	131.96	150	70.41
1000	426.11	160	243.58	136.01	140	70.33
1100	436.815	165.31	249.1	143.1	150	85
1200	442.28	173.1	256.59	148.89	159.1	85
1300	433.47	162.56	240	144.74	150	86.88
1400	451.21	182.1	260.57	145.07	158.04	85
1500	450.44	179.64	261.08	149.83	162.25	91.2
1600	451.49	179.55	257.37	150	157.27	85
1700	442.2	167.1	264.04	134.07	152.17	91.23
1800	431.9	164.65	253.02	141.32	153.57	85
1900	428.11	160	242.78	139.44	139.95	75
2000	415.12	140	240	110	136.13	75
2100	399.94	140	210	110	123.98	60.05
2200	385.75	130.05	210	104.73	119.86	53.16
2300	383.95	131.39	210	100.38	116.76	51.82
2400	350	134.83	210	110	119.57	53.84

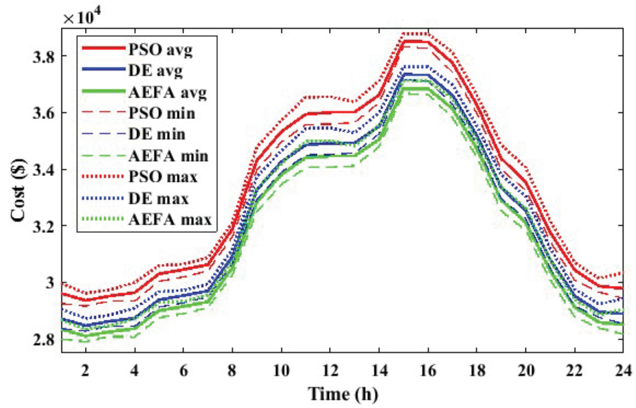

Figure 6 Cost Comparison for 15 units without RES.

Table 3 Result Comparison without RES for 6-unit

Test System	Method	Best Cost ($)	Worst Cost ($)	Average Cost ($)
1	PSO	**321164.878**	**326819.44**	**323338.536**
	DE	**316604.3363**	**318420.1815**	**317162.7697**
	AEFA	314388.299	317112.99	316024.618
2	PSO	**789264.1233**	**805256.4464**	**796412.7687**
	DE	**765357.313**	**780961.8594**	**772337.2107**
	AEFA	755404.6924	770807.5756	762302.4099

The maximum power generation for all intervals is presented in Figure 4. The comparative variation of total fuel cost with AEFA, PSO, and DE is shown in Figure 5. The statistical analysis of this variation, using the best, worst, and average fuel cost, is tabulated in Table 3. It shows that AEFA provides the optimal fuel cost in comparison to another complementary algorithm. Similar results are observed for Test-system-2, as shown in Figure 6. The results obtained with all thermal operations are considered the base case for analyzing the addition of RES. It shows that the AEFA can provide a better solution than PSO and DE in both cases; the cost remains the lowest.

4.2 Case-2

In this case, the DELD is performed for the two test systems with RES. The results obtained are shown in Table 4. The same load profile as used in Case-1 is used here. PSO, DE, and AEFA obtained the best, worst, and average of different costs. It shows that the AEFA provides the lowest cost operation

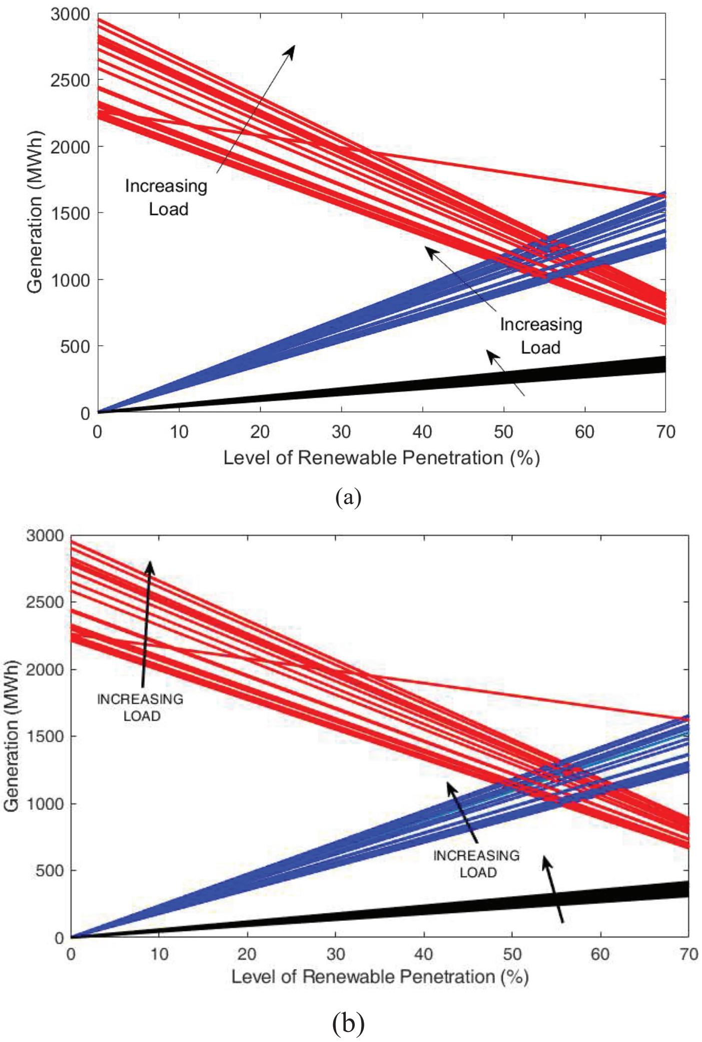

Figure 7 Generation variation with change in the penetration level and load variation (a) 6 unit, and (b) 15 unit (red-thermal, blue- wind, black- solar generation).

in all circumstances. As the penetration of RES increases, the system's total operating cost decreases to 65%, then after the cost suddenly increases. This generation variation with change in the penetration level and load variation is shown in Figures 7(a) and 7(b) for Test-system: 1 and Test system 2, respectively. This increase can be attributed to the violation of constraints by

Table 4 Result for Case-2: with RES

Test System				Penetration Level (%)							
				5%	15%	25%	35%	45%	55%	65%	70%
1	**Thermal Cost ($)**	**Best**	**PSO**	316694	294368	272628	253257	238209	228415	222123	16965740
			DE	311660	289665	268258	249218	234502	225040	219079	16962862
			AEFA	**308543**	**286769**	**265575**	**246726**	**232157**	**222790**	**216888**	**16793234**
		Worst	**PSO**	316801	294448	272779	253382	238298	228458	222165	16965751
			DE	311767	289745	268408	249343	234591	225083	219121	16962874
			AEFA	**308649**	**286848**	**265724**	**246850**	**232245**	**222832**	**216930**	**16793245**
		Average	**PSO**	316727	294406	272669	253302	238238	228429	222129	16965743
			DE	311767	289745	268408	249343	234591	225083	219121	16962874
			AEFA	**308576**	**286806**	**265616**	**246770**	**232186**	**222803**	**216895**	**16793236**
	Total RES Cost ($)			13543	36946	60377	83837	107327	130846	154394	166179
	Net Cost ($)	**Best**	**PSO**	330237	331313	333005	337094	345537	359261	376517	17131919
			DE	325203	326611	328635	333055	341829	355886	373473	17129042
			AEFA	**322087**	**323714**	**325952**	**330563**	**339484**	**353636**	**371282**	**16959413**
		Worst	**PSO**	330344	331393	333155	337219	345625	359304	376559	17131931
			DE	325310	326691	328785	333180	341918	355929	373515	17129053
			AEFA	**322193**	**323793**	**326101**	**330687**	**339572**	**353678**	**371324**	**16959424**
		Average	**PSO**	330270	331351	333046	337139	345565	359275	376523	17131922
			DE	325310	326691	328785	333180	341918	355929	373515	17129053
			AEFA	**322119**	**323752**	**325992**	**330607**	**339513**	**353649**	**371289**	**16959415**

(*Continued*)

Table 4 Continued

Test System				Penetration Level (%)							
				5%	15%	25%	35%	45%	55%	65%	70%
2	**Thermal Cost ($)**	**Best**	**PSO**	763867	720310	678380	638413	605668	580563	564239	48625690
			DE	737393	695572	655379	617148	586140	562771	548184	48610503
			AEFA	**727807**	**686530**	**646859**	**609125**	**578520**	**555455**	**541058**	**47978566**
		Worst	**PSO**	768498	723070	681361	642061	608068	582564	565675	48627865
			DE	742024	698332	658360	620796	588540	564772	549620	48612678
			AEFA	**732378**	**689254**	**649801**	**612726**	**580889**	**557430**	**542475**	**47980714**
		Average	**PSO**	766407	721832	679772	640344	606802	581810	565505	48626834
			DE	739933	697094	656771	619079	587274	564018	549450	48611647
			AEFA	**730313**	**688032**	**648233**	**611031**	**579639**	**556686**	**542307**	**47979695**
	Total RES Cost ($)			29331	84407	139642	195037	250591	306304	362177	390173
	Net Cost ($)	**Best**	**PSO**	793199	804717	818023	833449	856259	886867	926416	49015863
			DE	766725	779979	795022	812185	836731	869076	910361	49000676
			AEFA	**757138**	**770937**	**786502**	**804162**	**829111**	**861759**	**903235**	**48368740**
		Worst	**PSO**	797830	807477	821003	837097	858658	888868	927852	49018038
			DE	771356	782739	798002	815833	839130	871077	911797	49002852
			AEFA	**761709**	**773661**	**789444**	**807762**	**831479**	**863735**	**904652**	**48370887**
		Average	**PSO**	795738	806239	819414	835380	857393	888114	927682	49017007
			DE	769264	781501	796413	814116	837865	870322	911627	49001820
			AEFA	**759645**	**772439**	**787875**	**806068**	**830230**	**862990**	**904484**	**48369869**

the parameters. In other words, with an increase in the penetration of RES, the generation associated with RES increases, which may violate the constraints. Thus, the cost associated increases.

5 Conclusion

In this work, DELD is performed for a system consisting of the thermal power plant and RES. DELD problem has been solved for two test systems, 6 generation units and 15 generation units, using AEFA, PSO, and DE. The results show that AEFA provides better results than PSO and DE. The problem has also been solved for the different penetration levels of RES in conventional thermal power plant based power systems. It has been observed that at a higher penetration level, proper RES scheduling is required. Based on this, the following observations are drawn

i. The net cost increases with the increased penetration level, mainly caused by underestimation and overestimation cost of wind and solar.
ii. Though net cost increases with RES penetration, higher penetration leads to a reduction in the thermal unit's fuel cost.
iii. At 65% RES penetration, 28.19% savings are observed in the thermal generators' fuel cost. However, the total cost rose by 16.4%. At this level of penetration, 21.15% of increment in net cost is caused by underestimation and overestimation of wind and solar; the significant increment is caused by wind overestimation of almost 94%.

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