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A Cost Effective Solution to Dynamic Economic Load Dispatch Problem Using Improved Chimp Optimizer

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The electricity sector has encountered several economic challenges in recent years. Increasing the expense of fossil fuels and environmental legislation such as the Kyoto Protocol and the Low Carbon Transition Plan have compelled governments to use renewable energy sources (RESs) more widely. In the proposed research, the dynamic economic load dispatch problem has been solved using improved chimp optimizer algorithm. The test systems consisting of 6, 7 and 10-unit generators has been taken into consideration along with significant contribution of renewable energy sources for effective research studies. The test systems has been evaluated for different cases considering renewable energy sources and electric vehicles using proposed algorithms. Experimentally, it has been observed that proposed optimizer yields better results as compared to other recently proposed optimizers.

Keywords: dynamic economic load dispatch, chimp optimizer, meta-heuristics search algorithms, renewable energy sources, green house gase

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1 INTRODUCTION

In recent years, the electrical power sector has faced a slew of economic issues which evoked a thought in Governments to encourage in adopting nonconventional energy sources noticing that the cost of fossil fuels has risen, the amount of fossil fuels has decreased, and the amount of Green House Gases (GHGs) emissions has increased. The Plug-in Electric Vehicles (PEVs) are a hybrid of Plug-in Hybrid Electric Vehicles (PHEVs) and Electric Vehicles (EVs) with a Vehicle to Grid (V2G) facility that looks to be a viable solution to the problem of GHG emissions. In (Kintner-Meyer et al., 2010) the impact of PEVs on the electrical system's overall economics and emissions is explained in depth. The benefits of PEVs have been discussed in (Kempton and Tomić, 2005a), (Kempton and Tomić, 2005b). The available energy from PEVs has been wisely planned in (Hutson et al., 2008). The effect of integrating PEVs in the power system for charging (G2V) and auxiliary backing (V2G) to the grid was detailed in (Gholami et al., 2014). RESs and PEVs are discussed in depth in (IEEE Std, 2011). The impact of PEVs/PHEVs on a power system, as well as the integration of RESs into that system, is explored in (Aghaei et al., 2016). The use of RESs by GVs to reduce the price and emissions in a power system was explored in (Saber and Venayagamoorthy, 2010).

Safari (2018) described a clear distinction between the mainstream of BEVs and a hypothetical group of BEVs that are technically on a par with internal combustion vehicles (ICVs). Chen et al. (2015) presented an improved particle swarm optimization for engine/motor hybrid electric vehicles to develop an online suboptimal energy management system. Richardson (2013) described to considerably reduce carbon emissions from both power generation and transportation sectors by offering the potential of electric vehicles and renewable energy sources. Manzetti and Mariasiu (2015) presented an assessment of green chemistries as novel green energy sources for the electric vehicle and microelectronics portable energy landscape which provides a cradle-to-grave analysis of the emerging technologies in the transport sector. Hu et al. (2016) examined the role of renewable energy and power train optimization in minimizing daily carbon emissions of plug-in hybrid vehicles. Li et al. (2017) presented India's ability to finance its ambitious renewable energy targets hinges on three significant factors. The first is based on how its regulatory framework can make the market attractive to finance providers. Second is in the context of effective implementation of RE policies. (Lopez-Behar et al., 2018, 2019) described the challenges and decision-making processes involved in the installation of EV charging infrastructure in Multi-Unit Residential Buildings in BC, from the perspective of different stakeholders. Yong et al. (2015) provided in-depth analyses on the current state, effects, and potential of EV deployment, as well as the most recent advancements in EV technology. Implementation of an incentive-based strategy to reduce the cost of EV purchases, the development of charging infrastructure, and improved public knowledge of environmental issues are all facilitators for expanded EV adoption (Li et al., 2021a), (Li et al., 2021b). Xu et al. (2015) presented a report on the multi-objective optimization problem of power train parameters for a predefined driving cycle regarding fuel economy and system durability. Yang et al. (2017) developed a revolutionary energy management technique for plug-in hybrid electric buses that optimizes the equivalent factor of each driving cycle segment. Liu et al. (2015) described the penetration of EVs is reshaping the transportation system. Clement-Nyns et al. (2011) presented PHEVs as they can provide storage to take care of the excess of produced energy and use it for driving or release into the grid at a later time would be a good combination. Tan et al. (2016) presented the optimization techniques to achieve different vehicle to grid objectives while satisfying multiple constraints and reviews the framework, benefits and challenges of vehicle to grid technology. Mwasilu et al. (2014) presented a review of the recent research and forecasting of electric vehicles (EVs) interaction with smart grid portraying the future electric power system model. The concept goal of the smart grid along with the future deployment of the EVs puts forward various challenges in terms of electric grid infrastructure, communication and control. Krishna et al. (2021a), (Krishna et al., 2021b) has developed two recent variants of pattern search algorithm to improve the local search capability of the existing Harris hawks optimizer and slime mould algorithm and had suggested to solve the economic load dispatch as future prospective. Arora et al. (2020) presented optimization methodologies for testing the Load Frequency Control for Interconnected multi area power system in smart grids. Nandi and Kamboj (2020) presented the a new solution approach for Profit Based Unit Commitment Problem Considering PEVs/BEVs and Renewable Energy Sources. Following an intensive review on advanced smart metering and communication infrastructures, the strategy for integrating the EVs into the electric grid is presented.

2 PROBLEM FORMULATION

The basic purpose of single-area economic and dynamic load dispatch is to lower total fuel costs of power generating units while satisfying different constraints. The entire objective function for economic dispatch, taking into account PEVs, BEVs, and renewable energy sources, is as follows:

$$F\left(P^G\right) = \sum_{n=1}^{NG}\left[a_n\left(P_n^G\right)^2 + \left(b_n P_n^G + c_n\right)\right] \tag{1a}$$

The dispatch of power generating units for 'H' Hours may be represented as:

$$F\left(P^G\right) = \sum_{h=1}^{H}\left(\sum_{n=1}^{NG}\left[a_n\left(P_n^G\right)^2 + \left(b_n P_n^G + c_n\right)\right]\right) \tag{1b}$$

The actual mathematical formulation for *Dynamic Dispatch* was expressed by this **Eq. (1b)**. For time-varying load demand, the hour "h" can be changed from 1 to H hours.

2.1 Power Balance Constraint

The entire generation from all generators must meet the overall power demand and real power loss of the system.

$$\sum_{n=1}^{NG} P_n^G = P^{Demand} + P^{Loss} \tag{2}$$

where, P^{Demand} is the demand of power.

In **Eq. (2)** renewable energy source is integrated with generating units.

$$\sum_{n=1}^{NG} P_n^G + P^{\mathrm{Renewable}} = P^{Demand} + P^{Loss} \tag{3}$$

where, $P^{\mathrm{Renewable}}$ is the penetrated renewable energy source and P^{Loss} is loss in power.

Case-1: During Charging

The following **Eq. (4)** can be used to calculate the power balance constraints for PEVs, BEVs, and RES during the charging phase.

$$\sum_{n=1}^{NG} P_n^G + P^{\mathrm{Renewable}} = P^{Demand} + P^{Loss} + \sum_{n=1}^{NPEVs} P^{PEVs} + \sum_{n=1}^{NBEVs} P^{BEVs} \tag{4}$$

Case-2: During Discharging

The power balancing constraints for PEVs, BEVs, and RES during the discharging phase may be mathematically stated using the following eqns:

$$\sum_{n=1}^{NG} P_n^G + P^{\mathrm{Renewable}} = P^{Demand} + P^{Loss} - \sum_{n=1}^{NPEVs} P^{PEVs} - \sum_{n=1}^{NBEVs} P^{BEVs} \tag{5}$$

Where, P^{Loss} is loss in power.

$$P^{Loss} = \sum_{n=1}^{NG}\sum_{m=1}^{NG} P_n^G B_{nm} P_m^G \tag{6}$$

if B_{i0} and B_{00} matrices for loss coefficients are given, then the above equation can be modified as:

$$P^{Loss} = P_n^G B_{nm} P_m^G + \sum_{n=1}^{NG} P_n^G \times B_{i0} + B_{00} \tag{7}$$

The expanded version of the above equation may be represented as:

$$P^{Loss} = \Bigg[P_1 \quad P_2 \quad \ldots \quad p^{Loss} = \left[P_1 \quad P_2 \quad \cdots \quad P_{NG} \right]$$

$$\begin{bmatrix} B_{11} & B_{12} & \cdots & B_{1n} \\ B_{21} & B_{22} & \cdots & B_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ B_{n1} & B_{n2} & \cdots & B_{nn} \end{bmatrix} \begin{bmatrix} P_1 \\ P_2 \\ \vdots \\ P_{NG} \end{bmatrix} + \left[P_1 \quad P_2 \quad \cdots \quad P_{NG} \right] \begin{bmatrix} B_{01} \\ B_{02} \\ \vdots \\ B_{0NG} \end{bmatrix} + B_{00} \tag{8}$$

2.2 Generator Limit Constraint

Each generator's actual power output must be kept within its respective upper and lower operating limitations.

$$P_{n(\min)}^G \le P_n^G \le P_{n(\max)}^G \quad n = 1, 2, 3, \ldots, NG \tag{9}$$

where, $P_{n(\min)}^G$ represents the lowest real power allotted at unit n and $P_{n(\max)}^G$ presents the highest real power allotted at unit n.

2.3 Ramp Rate Limits

The output power of the generating unit is boosted between the lower and upper limits of active power generation.

1) As a result of an increase in generated power,

$$P_n^G - P_0^{G_o} \le UR_n \quad n = 1, 2, 3, \ldots, NG \tag{10}$$

2) By reducing the amount of generated power,

$$P_n^{G_o} - P_n^G \le DR_n \quad n = 1, 2, 3, \ldots, NG \tag{11}$$

As a result, the generator ramp rate is represented in the equation below.

$$\max\left[P_{n(\max)}^G, \left(UR_n - P_n^G\right)\right] \le P_n^G \le \min\left[P_{n(\max)}^G, \left(P_n^{G_o} - DR_n\right)\right] n = 1, 2, 3, \ldots, NG \tag{12}$$

where, P_n^G is the earlier outcome of nth generation unit's active power DR_n, UR_n are the lower and upper range for a nth generation unit ramp rate limits.

3 TEST SYSTEMS

The single area dynamic load dispatch problem has been described, considering plug-in electric vehicles, battery electric vehicles and renewable energy sources along with the system and physical limits of thermal generating units. The dynamic load dispatch problem has been solved and tested for 6-unit, 7-unit, and 10-unit systems. To validate the proposed algorithms, standard power systems consisting 6, 7, and 10 generating units have been considered.

4 RESULTS AND DISCUSSION

Proposed algorithms such as chimp optimizer, slime mould, improved chimp optimizer and improved slime mould algorithms fruitfully handle the electric power system's single area dynamic load dispatch problem. This section looks at how to solve the single area dynamic load dispatch problem using plug-in electric vehicles, renewable energy sources and combined plug-in electric vehicles and renewable energy sources for 6, 7 and 10 generating units, respectively. On an Intel corei3 processor laptop with a 7th generation CPU and 8GB RAM, the proposed approaches were evaluated using the MATLAB R2016a programme. For comparison reasons, the efficacy of the proposed algorithms is compared to that of other well-known evolutionary, heuristics, and meta-heuristics search techniques.

4.1 Dynamic Load Dispatch Using Chimp Optimizer Algorithm

In order to verify the chimp optimizer algorithm, the algorithm is accepted by search agents 50, 500 iterations and 30 maximum runs. The effectiveness of the proposed algorithm is tested on a variety of test systems, including plug-in electric vehicles, renewable energy sources, and combined plug-in electric vehicles and renewable energy sources as detailed in this section. This approach has been tested on a 6-unit, 7-unit and 10-unit test system.

4.1.1 Six Generator Test System (SADLD With EVs)

Chimp optimizer algorithm is suggested to get optimized outcomes for dynamic load dispatch with the effect of EVs as V2G and G2V. A six-generator test system is studied, with no valve point loading impact and a loss coefficient matrix of zero (Debnath et al., 2015). **Table 1** displays that the fuel price is **397294.1087** \$/day using the chimp optimizer algorithm.

4.1.2 Six Generator Test System (SADLD With RES)

Chimp optimizer algorithm is suggested to get optimized outcomes for dynamic load dispatch with the effect of RES. A six generator test system without valve point loading effect, with loss coefficient matrix as zero is considered (Debnath et al., 2015). The renewable energy sources wind and solar are incorporated. **Table 2** displays that the fuel price is **316498.35** \$/day using the chimp optimizer algorithm.

4.1.3 Six Generator Test System (SADLD With EVs and RES)

Chimp optimizer algorithm is suggested to get optimized outcomes for dynamic load dispatch with the combined effect

TABLE 1 | 6-unit generator Dynamic Load Dispatch with EVs (without valve point loading effect without losses) using Chimp optimizer Algorithm.

Time (hr)	PD (MW)	G1 (MW)	G2 (MW)	G3 (MW)	G4 (MW)	G5 (MW)	G6 (MW)	Electric Vehicles (MW)	Fuel Cost ($)/hr
1	700	352.72	99.50	190.13	50	89.41	50	−131.76	9834.43
2	750	352.94	103.28	190.89	50	87.89	50	−85	9873.09
3	850	367.15	112.59	202.17	61.72	98.87	50	−42.5	10564.56
4	950	379.67	125.64	210.36	72.99	111.34	50	0	11267.25
5	1000	392.20	129.99	220.79	82.53	124.48	50	0	11887.03
6	1100	410.35	146.03	241.79	102.77	147.31	51.75	0	13152.39
7	1150	429.15	156.35	243.49	109.17	150.81	61.02	0	13796.10
8	1200	442.53	162.73	252.15	112.86	156.85	72.87	0	14447.13
9	1300	458.22	175.35	266.64	127.04	178.34	94.51	0.102	15770.06
10	1400	471.82	189.10	282.36	148.41	200	110.45	2.142	17147.01
11	1450	493.87	200.00	300.00	150	200	120	13.872	17994.97
12	1500	500.00	200.00	360.00	150	200	120	34.782	82862.50
13	1400	481.45	194.92	290.51	150	200	117.90	34.782	17593.33
14	1300	459.73	179.90	273.89	137.39	176.69	86.28	13.872	15954.50
15	1200	435.49	165.65	254.57	116.05	157.44	72.94	2.142	14474.65
16	1050	404.57	141.65	229.31	97.25	127.46	50	0.2359	12519.09
17	1000	394.07	133.14	221.89	81.52	127.20	50	−7.8157	11984.77
18	1100	420.10	146.04	236.48	104.81	149.68	61.10	18.207	13386.30
19	1200	439.09	169.25	264.32	120.43	174.31	78.24	45.6514	15046.90
20	1400	485.09	198.46	293.46	150	200	118.64	45.6514	17742.83
21	1300	453.77	179.75	274.54	135.34	181.10	93.70	18.207	16011.99
22	1100	412.30	147.43	239.59	103.30	147.36	52.83	2.8114	13188.22
23	900	366.69	114.45	205.11	65.21	104.77	50	−6.2411	10731.43
24	800	354.79	103.67	193.05	50	90.99	50	−42.5	9962.79
								Fuel Cost ($) per day	**397294.1087**

Bold represents better fuel cost as compared to others methods.

TABLE 2 | 6-unit generator Dynamic Load Dispatch with RES (without valve point loading effect without losses) using Chimp optimizer algorithm.

Time (hr)	PD (MW)	G1 (MW)	G2 (MW)	G3 (MW)	G4 (MW)	G5 (MW)	G6 (MW)	Wind (MW)	Solar (MW)	Fuel Cost ($)/hr
1	700	309.00	69.42	157.92	50	53.13	50	10.54	0	8179.70
2	750	320.37	78.89	166.32	50	62.15	50	22.27	0	8616.48
3	850	350.83	99.31	187.58	50	86.78	50	25.5	0	9747.97
4	950	377.02	117.10	205.77	67.94	106.68	50	25.5	0	10954.23
5	1000	385.10	127.32	217.71	75.00	119.37	50	25.5	0	11569.88
6	1100	409.18	144.40	230.65	99.02	140.64	50.61	25.5	0	12826.62
7	1150	421.25	150.65	241.41	107.80	151.42	51.87	25.5	0.09	13465.98
8	1200	423.39	157.55	246.61	107.19	156.87	65.44	25.5	17.46	13887.15
9	1300	449.19	162.95	259.82	122.80	166.97	81.32	25.5	31.45	15012.68
10	1400	466.73	184.46	268.37	133.98	182.57	102.38	25.5	36.01	16285.31
11	1450	467.03	189.68	260.91	150	194.41	104.40	25.5	38.06	16933.40
12	1500	481.88	199.54	290.33	150	200	116.82	25.5	35.93	17645.39
13	1400	458.76	184.28	282.49	133.35	179.83	99.01	25.5	36.78	16274.79
14	1300	443.73	167.61	263.77	116.13	175.20	77.14	24.82	31.59	15019.99
15	1200	421.90	158.40	253.73	113.22	155.60	66.71	20.74	9.7	14049.95
16	1050	398.47	135.26	228.68	84.67	125.39	50	14.62	12.92	12168.47
17	1000	382.01	127.84	212.25	78.99	123.41	50	25.5	0	11570.27
18	1100	411.24	144.79	236.41	97.02	136.50	54.99	19.04	0	12908.99
19	1200	432.81	157.70	254.21	107.49	156.84	65.45	25.5	0	14114.10
20	1400	464.17	187.80	282.86	143.34	200	103.82	18.02	0	16873.02
21	1300	446.59	173.49	259.03	128.95	178.31	88.13	25.5	0	15429.22
22	1100	406.31	147.27	233.23	96.61	141.69	53.47	21.42	0	12878.69
23	900	368.74	114.97	199.24	64.31	102.74	50	0	0	10655.64
24	800	342.42	94.59	181.44	50	79.01	50	2.55	0	9427.80
									Fuel Cost ($) per day	**316498.35**

TABLE 3 | 6-unit generator Dynamic Load Dispatch with EVs and RES (without valve point loading effect without losses) using Chimp optimizer algorithm.

Time (hr)	PD (MW)	G1 (MW)	G2 (MW)	G3 (MW)	G4 (MW)	G5 (MW)	G6 (MW)	EV (MW)	Wind (MW)	Solar (MW)	Fuel Cost ($)/hr
1	700	350.24	97.80	186.27	50	86.91	50	−131.76	10.54	0	9709.02
2	750	344.96	97.62	184.78	50.16	85.21	50	−85	22.27	0	9608.30
3	850	359.51	106.26	194.76	57.73	99.74	50	−42.5	25.5	0	10256.61
4	950	372.78	120.23	205.71	67.58	108.20	50	0	25.5	0	10954.22
5	1000	383.01	127.24	218.11	79.68	116.46	50	0	25.5	0	11569.94
6	1100	409.02	143.86	236.27	93.19	142.17	50	0	25.5	0	12826.49
7	1150	417.06	148.15	244.83	101.58	151.96	60.83	0	25.5	0.09	13465.81
8	1200	428.13	152.75	249.06	109.70	157.18	60.22	0	25.5	17.46	13887.30
9	1300	440.61	164.96	257.23	123.89	173.75	82.71	0.102	25.5	31.45	15013.97
10	1400	457.48	182.88	278.01	131.23	188.01	103.02	2.142	25.5	36.01	16313.87
11	1450	473.02	191.47	286.18	150	194.31	105.33	13.872	25.5	38.06	17121.97
12	1500	500	200	300	150	200	120	34.782	25.5	35.93	21432.50
13	1400	468.45	186.09	280.11	150	185.29	102.57	34.782	25.5	36.78	16744.58
14	1300	448.76	165.92	266.40	122.57	173.09	80.72	13.872	24.82	31.59	15203.01
15	1200	427.99	160.56	252.19	105.90	157.80	65.27	2.142	20.74	9.7	14077.55
16	1050	398.94	136.71	224.02	87.38	125.65	50	0.2359	14.62	12.92	12171.36
17	1000	388.61	128.71	215.44	76.95	122.6	50	−7.8157	25.5	0	11666.95
18	1100	415.78	146.47	242.20	95.85	148.87	50	18.207	19.04	0	13141.91
19	1200	440.44	161.39	258.05	124.73	161.67	73.87	45.6514	25.5	0	14711.13
20	1400	477.54	194.43	291.21	150	200	114.45	45.6514	18.02	0	17495.19
21	1300	446.15	173.83	271.08	128.58	181.13	91.95	18.207	25.5	0	15671.44
22	1100	413.93	144.92	239.56	95.98	137.00	50	2.8114	21.42	0	12914.46
23	900	367.76	113.85	204.95	67.53	102.15	50	−6.2411	0	0	10731.49
24	800	355.82	102.10	191.71	50	90.32	50	−42.5	2.55	0	9932.21
										Fuel Cost ($) per day	**326625.6**

Bold represents better fuel cost as compared to others methods.

TABLE 4 | 7-unit generator Dynamic Load Dispatch with EVs (without valve point loading effect without losses) using Chimp Optimizer Algorithm.

Time (hr)	PD (MW)	G1 (MW)	G2 (MW)	G3 (MW)	G4 (MW)	G5 (MW)	G6 (MW)	G7 (MW)	EV (MW)	Fuel Cost ($)/hr
1	800	311.40	71.56	140	50	100	50	100	−22.96	10018.49
2	780	297.66	61.43	140	50	100	50	100	−19.09	9749.63
3	750	280.68	50	134.98	50	100	50	100	−15.66	9380.535
4	750	283.69	51.09	137.38	50	100	50	100	−22.16	9451.726
5	720	269.15	50	126.00	50	100	50	100	−25.15	9158.026
6	700	253.61	50	112.92	50	100	50	100	−17.52	8863.511
7	700	251.67	50	112.41	50	100	50	100	−14.08	8827.264
8	700	259.68	50	118.64	50	100	50	100	28.32	8977.915
9	800	314.05	74.15	140	50	100	50	102.87	31.07	10110.78
10	900	347.29	98.74	140	50	100	50	137.74	23.77	11189.39
11	1000	378.52	100	140	73.24	111.24	50	167.56	20.56	12360.18
12	1200	443.99	100	140	100	169.76	82.77	236.59	73.1	15583.27
13	1400	487.25	100	140	100	207.41	100	280.37	15.03	17499.22
14	1500	522.49	100	140	100	237.98	100	316.29	16.76	18929.83
15	1750	575.00	100	140	100	340.08	100	410	15.08	22644.93
16	1800	574.99	100	140	100	396.44	100	410	−21.43	23568.64
17	1500	529.56	100	140	100	243.45	100	324.32	−37.33	19225.17
18	900	345.06	96.20	140	50	100	50	135.01	−16.27	11100.5
19	850	327.92	84.17	140	50	100	50	117.25	19.34	10550.8
20	800	321.44	79.37	140	50	100	50	109.92	50.73	10335.9
21	780	301.05	63.93	140	50	100	50	100	24.98	9815.545
22	750	280.64	50	134.95	50	100	50	100	−15.59	9379.77
23	700	263.56	50	126.66	50	100	50	100	−35.22	9051.488
24	800	323.50	80.63	140	50	100	50	112.15	−56.28	10399.8
									Fuel Cost ($) per day	**296174.3**

of EVs and RES. A six generator test system without valve point loading effect, with loss coefficient matrix as zero is considered (Debnath et al., 2015). The Electric vehicles and renewable energy sources wind and solar are incorporated. **Table 3** displays that the fuel price is **326625.6** $/day using the chimp optimizer algorithm.

4.1.4 Seven Generator Test System (SADLD With EVs)

Chimp optimizer algorithm is suggested to get optimized outcomes for dynamic load dispatch with the effect of EVs as V2G and G2V. A seven generator test system without valve point loading effect, with loss coefficient matrix as zero is considered (Tariq et al., 2020), (Gholami et al., 2014). **Table 4** displays that the fuel price is **296174.3087** $/day using the chimp optimizer algorithm.

5 CONCLUSION

In the proposed research, dynamic load dispatch problem has been solved using chimp optimizer algorithm. The test systems consisting of 6, 7 and 10-unit generators when incorporated with only electric vehicles, only renewable energy sources, and combined electric vehicles and renewable energy sources have been successfully tested using proposed algorithms. The results of the test systems with EVs and RES have been compared without EVs and RES results. The simulation results show that the suggested methods found satisfactory load dispatch at a reasonable cost. These dominating algorithms may also be used to solve the problem of multi-area dynamic load dispatch in electrical power networks.

DATA AVAILABILITY STATEMENT

The original contributions presented in the study are included in the article/Supplementary Material, further inquiries can be directed to the corresponding author.

AUTHOR CONTRIBUTIONS

JX put forward the main research points; AL, YQ, GX, and YT completed manuscript writing and revision; AL, YQ, and GX completed simulation research; YQ, GX, and YT collected relevant background information; AL, GX, and YT revised grammar and expression. All authors contributed to manuscript revision, read, and approved the submitted version.

REFERENCES

Aghaei, J., Nezhad, A. E., Rabiee, A., and Rahimi, E. (2016). Contribution of Plug-In Hybrid Electric Vehicles in Power System Uncertainty Management. *Renew. Sustain. Energy Rev.* 59 (99), 450–458. doi:10.1016/j.rser.2015.12.207

Arora, K., Kumar, A., Kamboj, V. K., Prashar, D., Jha, S., Shrestha, B., et al. (2020). Optimization Methodologies and Testing on Standard Benchmark Functions of Load Frequency Control for Interconnected Multi Area Power System in Smart Grids. *Mathematics* 8 (6), 980. doi:10.3390/math8060980

Chen, S.-Y., Hung, Y.-H., Wu, C.-H., and Huang, S.-T. (2015). Optimal Energy Management of a Hybrid Electric Powertrain System Using Improved Particle Swarm Optimization. *Appl. Energy* 160, 132–145. doi:10.1016/j.apenergy.2015.09.047

Clement-Nyns, K., Haesen, E., and Driesen, J. (2011). The Impact of Vehicle-To-Grid on the Distribution Grid. *Electr. Power Syst. Res.* 81 (1), 185–192. doi:10.1016/j.epsr.2010.08.007

Debnath, U. K., Ahmad, I., Habibi, D., and Saber, A. Y. (2015). Energy Storage Model with Gridable Vehicles for Economic Load Dispatch in the Smart Grid. *Int. J. Electr. Power & Energy Syst.* 64, 1017–1024. doi:10.1016/j.ijepes.2014.09.004

Gholami, A., Ansari, J., Jamei, M., and Kazemi, A. (2014). Environmental/economic Dispatch Incorporating Renewable Energy Sources and Plug-in Vehicles. *IET Generation, Transm. Distribution* 8 (12), 2183–2198. doi:10.1049/iet-gtd.2014.0235

Hu, X., Zou, Y., and Yang, Y. (2016). Greener Plug-In Hybrid Electric Vehicles Incorporating Renewable Energy and Rapid System Optimization. *Energy* 111, 971–980. doi:10.1016/j.energy.2016.06.037

Hutson, C., Venayagamoorthy, G. K., and Corzine, K. A. (2008). "Intelligent Scheduling of Hybrid and Electric Vehicle Storage Capacity in a Parking Lot for Profit Maximization in Grid Power Transactions," in 2008 IEEE Energy 2030 Conf. ENERGY 2008, Atlanta, GA, USA, 17-18 Nov. 2008, 1–8. doi:10.1109/energy.2008.47810512008

IEEE Std (2011). .2030-2011, *IEEE Guide For Smart Grid Interoperability Of Energy Technology And Information Technology Operation With the Electric Power System (EPS), End-Use Appl. Loads*, September

Kempton, W., and Tomić, J. (2005). Vehicle-to-grid Power Fundamentals: Calculating Capacity and Net Revenue. *J. Power Sources* 144 (1), 268–279. doi:10.1016/j.jpowsour.2004.12.025

Kempton, W., and Tomić, J. (2005). Vehicle-to-grid Power Implementation: From Stabilizing the Grid to Supporting Large-Scale Renewable Energy. *J. Power Sources* 144 (1), 280–294. doi:10.1016/j.jpowsour.2004.12.022

Kintner-Meyer, M., Nguyen, T. B., Jin, C., Balducci, P., and Secrest, T. (2010). "Impact Assessment of Plug-In Hybrid Vehicles on the U.S. Power Grid," in The 25th World Battery, Hybrid and Fuel Cell Electric Vehicle Symposium & Exhibition, Shenzhen, China, November 5–9, 2010 Vol. EVS25, 1–6.

Krishna, A. B., Saxena, S., and Kamboj, V. K. (2021). A Novel Statistical Approach to Numerical and Multidisciplinary Design Optimization Problems Using Pattern Search Inspired Harris Hawks Optimizer. *Neural Comput. Applic* 33, 7031–7072. doi:10.1007/s00521-020-05475-5

Krishna, A. B., Saxena, S., and Kamboj, V. K. (2021). A Novel Statistical Approach to Numerical and Multidisciplinary Design Optimization Problems Using Pattern Search Inspired Harris Hawks Optimizer. *Neural Comput. Applic* 33 (12), 7031–7072. doi:10.1007/s00521-020-05475-5

Li, H., Deng, J., Feng, P., Pu, C., Arachchige, D. D. K., and Cheng, Q. (2021). Short-Term Nacelle Orientation Forecasting Using Bilinear Transformation and ICEEMDAN Framework. *Front. Energy Res.* 9, 780928. doi:10.3389/fenrg.2021.780928

Li, H., Deng, J., Yuan, S., Feng, P., and Arachchige, D. D. K. (2021). Monitoring and Identifying Wind Turbine Generator Bearing Faults Using Deep Belief Network and EWMA Control Charts. *Front. Energy Res.* 9, 799039. doi:10.3389/fenrg.2021.799039

Li, L., Zhou, L., Yang, C., Xiong, R., You, S., and Han, Z. (2017). A Novel Combinatorial Optimization Algorithm for Energy Management Strategy of Plug-In Hybrid Electric Vehicle. *J. Frankl. Inst.* 354 (15), 6588–6609. doi:10.1016/j.jfranklin.2017.08.020

Liu, L., Kong, F., Liu, X., Peng, Y., and Wang, Q. (2015). A Review on Electric Vehicles Interacting with Renewable Energy in Smart Grid. *Renew. Sustain. Energy Rev.* 51, 648–661. doi:10.1016/j.rser.2015.06.036

Lopez-Behar, D., Tran, M., Froese, T., Mayaud, J. R., Herrera, O. E., and Merida, W. (20182019). Charging Infrastructure for Electric Vehicles in Multi-Unit Residential Buildings: Mapping Feedbacks and Policy Recommendations. *Energy Policy* 126, 444–451. doi:10.1016/j.enpol.2018.10.030

Manzetti, S., and Mariasiu, F. (2015). Electric Vehicle Battery Technologies: From Present State to Future Systems. *Renew. Sustain. Energy Rev.* 51, 1004–1012. doi:10.1016/j.rser.2015.07.010

Mwasilu, F., Justo, J. J., Kim, E.-K., Do, T. D., and Jung, J.-W. (2014). Electric Vehicles and Smart Grid Interaction: A Review on Vehicle to Grid and Renewable Energy Sources Integration. *Renew. Sustain. Energy Rev.* 34, 501–516. doi:10.1016/j.rser.2014.03.031

Nandi, A., and Kamboj, V. K. (2020). A New Solution to Profit Based Unit Commitment Problem Considering PEVs/BEVs and Renewable Energy Sources. *E3S Web Conf.* 184, 01070. doi:10.1051/e3sconf/202018401070

Richardson, D. B. (2013). Electric Vehicles and the Electric Grid: A Review of Modeling Approaches, Impacts, and Renewable Energy Integration. *Renew. Sustain. Energy Rev.* 19, 247–254. doi:10.1016/j.rser.2012.11.042

Saber, A. Y., and Venayagamoorthy, G. K. (2010). Efficient Utilization of Renewable Energy Sources by Gridable Vehicles in Cyber-Physical Energy Systems. *IEEE Syst. J.* 4 (3), 285–294. doi:10.1109/jsyst.2010.2059212

Safari, M. (2018). Battery Electric Vehicles: Looking behind to Move Forward. *Energy Policy* 115 (December 2017), 54–65. doi:10.1016/j.enpol.2017.12.053

Tan, K. M., Ramachandaramurthy, V. K., and Yong, J. Y. (2016). Integration of Electric Vehicles in Smart Grid: A Review on Vehicle to Grid Technologies and Optimization Techniques. *Renew. Sustain. Energy Rev.* 53, 720–732. doi:10.1016/j.rser.2015.09.012

Tariq, F., Alelyani, S., Abbas, G., Qahmash, A., and Hussain, M. R. (2020). Solving Renewables-Integrated Economic Load Dispatch Problem by Variant of Metaheuristic Bat-Inspired Algorithm. *Energies* 13 (23), 6225. doi:10.3390/en13236225

Xu, L., Mueller, C. D., Li, J., Ouyang, M., and Hu, Z. (2015). Multi-objective Component Sizing Based on Optimal Energy Management Strategy of Fuel Cell Electric Vehicles. *Appl. Energy* 157, 664–674. doi:10.1016/j.apenergy.2015.02.017

Yang, C., Du, S., Li, L., You, S., Yang, Y., and Zhao, Y. (2017). Adaptive Real-Time Optimal Energy Management Strategy Based on Equivalent Factors Optimization for Plug-In Hybrid Electric Vehicle. *Appl. Energy* 203, 883–896. doi:10.1016/j.apenergy.2017.06.106

Yong, J. Y., Ramachandaramurthy, V. K., Tan, K. M., and Mithulananthan, N. (2015). A Review on the State-Of-The-Art Technologies of Electric Vehicle, its Impacts and Prospects. *Renew. Sustain. Energy Rev.* 49, 365–385. doi:10.1016/j.rser.2015.04.130

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