

Multi-area economic/emission dispatch considering the impact of the renewable energy resources and electric vehicles

Rouhollah Abdollahzadeh Sangrodi^a, Mahmoud Samiei-Moghaddam^{a,*}, Amin Hajizadeh^b

^aDepartment of Electrical Engineering, Damghan Branch, Islamic Azad University, Damghan, Iran

^bAAU ENERGY, Aalborg University, Esbjerg, Denmark

(Communicated by Ehsan Kozegar)

Abstract

This paper proposed a model and method for multi-area economic/emission dispatch in the presence of renewable energy sources (RESs) and electric vehicles (EVs). The economic/Emission load dispatch model includes uncertain modeling of wind and solar renewable energy sources along with an uncertain model of electric vehicles and network demand with the objective of reducing economic and pollution costs of generation units. In this paper, the day-ahead electricity market is modeled on a 24-hour time period. Since it will be very difficult to solve the problem by increasing the time period and the number of generation units as well as considering the uncertainty, a meta-heuristic algorithm with the ability to solve large-scale problems and Investigate the concept of affordability based on the application of a thorough researched fast convergence has been presented. A modified particle swarm optimization (MPSO) algorithm has been proposed to solve the proposed problem due to the rapid convergence of hard optimization problems and achieve the optimal global result. A case study with four areas has been considered for the analysis of the proposed model and method, and two different approaches have been presented to illustrate the multi-area economic/emission dispatch and the results indicated the efficiency of the proposed model and method.

Keywords: Multi-Area economic dispatch, renewable energy, emission, uncertainty, electric vehicles, optimization
2020 MSC: 37N40, 91B74

1 Introduction

Soft computing methods have a wide range of applications [11, 13]. Solving the problem of economic dispatch (ED) is an important strategy for minimizing the total cost of generators and environmental pollution. In order to achieve this goal in an ED problem, the productive capacity of each of the sources involved in the load dispatching process should be properly adjusted. Today, RESs and EVs have become widespread and can therefore play a key role in solving the problem of ED in electric power networks. RESs were considered as a model for production planning under uncertainty; while EVs were used as a model for load planning under both uncertainty and deterministic. Recently, an optimal utilization of several renewable and fossil units (including two wind turbines, two photovoltaic units, two fuel cell units, and one micro turbine unit under a network division into three smaller subnets) has taken place in the form of combined heat and power (CHP) strategy. An optimal load dispatch model was considered based on the Imperialist

*Corresponding author

Email addresses: samiei352@yahoo.com (Mahmoud Samiei-Moghaddam), aha@energy.aau.dk (Amin Hajizadeh)

Competitive Algorithm (ICA) to minimize a two-objective function (e.g. minimizing exploitation costs and reducing greenhouse gas emissions) and also uncertainty for renewable and load units [9]. A multi-area economic dispatch was provided considering production under uncertainty in a 24-hour period to reduce costs by a linear programming method [1]. A multi-area economic dispatch model was considered based on the Frog Leaping Algorithm (FLA) to minimize a two-objective function (e.g. minimizing fuel costs and reducing emission) [8]. A modeling scheme was provided for the load dispatch problem to minimize the units' exploitation costs considering the power of charging and discharging small EVs [2]. An optimal scheduling model for energy resources in smart grids was presented to reduce the exploitation costs considering the load demand of vehicle-to-grid (V2G) network with distributed generation (DG) resources [14]. The optimization model was presented based on the Benders decomposition algorithm to minimize the total cost of exploitation and diffusion of pollution in distribution systems considering the large scale of EVs [17]. The ELD problem was solved using a hybrid algorithm based on Different Evolution (DE) and Partial Swarm Optimization (PSO) (DE-PSO algorithm) [3]. An economic/polluting load dispatch problem was solved considering the reservation of generators as well as two scenarios for solving the problems with dynamic and static approaches [3]. A Symbiotic Organisms Search (a new metaheuristic optimization) algorithm was proposed [10]. The authors in [12] proposed a decomposition and coordination algorithm based on the lagrangian relaxation for solved multi-area economic dispatch problem. In the reference [15], the authors proposed a hybrid Artificial Cooperative Search algorithm for multi objective economic emission load dispatch problem and the authors in [5] proposed genetic algorithm for solved to economic dispatch problems.

In this study, we present a solution to the multi-area economic dispatch problem considering RESs and load with EVs under uncertainty, which is implemented by a modified model of PSO algorithm. Contributions to this paper include:

- Present a multi-objective optimization for multi-area economic/emission dispatch with reducing pollution and economic costs by weighting coefficient method.
- Present a modified particle swarm optimization (MPSO) algorithm to solve the proposed multi-area multi-objective economic/emission dispatch.
- The uncertain model of renewable energy sources and electric vehicles in the proposed problem is considered.
- A large system with four areas with 24-hour modeling is considered.

The rest of this paper is structured as follows: In the second section, the modeling process includes target functions, problem constraints, and uncertainty model is determined, and then the model of the proposed algorithm is provided. The result of simulation and data analysis is presented in the third section. Finally, the conclusion is presented in the last section.

2 Modeling the problem

2.1 Resource and load modeling

A multi-area economical load dispatch problem was presented in the previous section considering both production planning with RESs and load with EVs under uncertainty. The uncertainties are modelled in equations (2.1),(2.2),(2.3),(2.4),(2.5), including output power uncertainty of WT, output power uncertainty of PV, and uncertainty of EV, Then, the method of generating scenarios by Monte Carlo sampling (MCS) technique. Here, their modeling will be presented.

A) Photovoltaic resources: Modeling these resources as production planning under uncertainty is as follows [3]:

$$P_{PV,s}^{t,n} = P_{STC,s}^{t,n} \frac{G_{ING}^s}{G_{STC}^s} [1 + k(T_c - T_{STC})], \quad \forall t \in T \quad (2.1)$$

where $P_{PV,s}^{t,n}$ is output power of $PV(kw)$ at time t and unit n for the s th scenario, $P_{STC,s}^{t,n}$ is rated power of PV cells under standard test condition (kw) for the s th scenario, G_{STC}^s is light intensity of PV cells under standard test condition (Lux) for the s th scenario, G_{ING}^s is actual light intensity of PV cells (Lux) for the s th scenario, k is power generation temperature coefficient of PV , T_c is actual temperature of PV cells (K) and T_{STC} is temperature of PV cells under STC (K).

B) Wind resources: Modeling these resources as production planning under uncertainty for a 24-hour period is as follows [7]:

$$P_{WT,s}^{t,n} = \begin{cases} a \times V^3 - b \times P_r & \text{if } V_{ci} < V \leq V_r \\ P_r & \text{if } V_r < V \leq V_{co} \\ 0 & \text{if } V \leq V_{ci} \\ 0 & \text{if } V \geq V_{co} \end{cases} \quad (2.2)$$

$$a = \frac{P_r}{V_r^3 - V_{ci}^3}, \quad b = \frac{V_{ci}^3}{V_r^3 - V_{ci}^3} \quad (2.3)$$

where $P_{WT,s}^{t,n}$ is actual output power of the WT (kW) at time t and unit n for the s th scenario, V_r is rated wind speeds (m/s), V_{ci} is cut-in wind speeds (m/s), V_{co} is cut-out wind speeds (m/s).

C) Electric Vehicles: Modeling EVs is based on daily mileage analysis, charging time and charge capacity. Modeling the probability distribution for the EVs mileage is as follows [4, 16]:

$$f_s(x) = \frac{1}{\sqrt{2\pi\sigma_s x}} \exp\left(-\frac{(\ln x - \mu_s)^2}{2\sigma_s^2}\right) \quad (2.4)$$

where $\mu_s = 3.2$, $\sigma_s = 0.88$.

The charging model of EVs in each of the designated areas in the system is considered as a normal distribution. The distribution function for vehicles arrival in a 24-hour period is as follows [6, 7]:

$$f_{t_1}(x) = \begin{cases} \frac{1}{\sqrt{2\pi\sigma_{t_1}}} \exp\left(-\frac{(x+24-\mu_{t_1})^2}{2\sigma_{t_1}^2}\right) & 0 < x \leq \mu_{t_1} - 12 \\ \frac{1}{\sqrt{2\pi\sigma_{t_1}}} \exp\left(-\frac{(x-\mu_{t_1})^2}{2\sigma_{t_1}^2}\right) & \mu_{t_1} - 12 < x \leq 24 \end{cases} \quad (2.5)$$

In this study, MCS technique is applied to generate the multiple scenarios of wind speed, light intensity and power charging of EV.

2.2 Optimization algorithm

In this study, the PSO algorithm was used. In this model, identifying a bad personal experience and removing it from the search space accelerates convergence and achieves the optimal global solution. The mathematical modeling for this modified model is as follows [16]:

$$v_{ij}^{t+1} = w \times v_{ij}^t + C_1^g \times r_1 \times (P \text{ best}_{ij}^t - s_{ij}^t) + C_1^b \times r_2 \times (s_{ij}^t - P \text{ worst}_{ij}^t) + C_2 \times r_3 \times (G \text{ best}_{ij}^t - s_{ij}^t) \quad (2.6)$$

$$s_{ij}^{t+1} = s_{ij}^t + v_{ij}^{t+1} \quad (2.7)$$

where v_{ij}^{t+1} is dimension i of the velocity of particle j at iteration t , s_{ij}^{t+1} is dimension i of the position of particle j at iteration t and $P \text{ worst}_{ij}^t$ is dimension i of the own worst position of particle j until iteration t .

2.3 Objective functions and the constraints of the problem

This study aims to minimize fuel costs and emissions of greenhouse gases as follows:

$$\min f = f_{fuel} + w f_{emission} \quad (2.8)$$

$$f_{fuel} = \sum_{i \in n} a_i + b_i p_i + c_i p_i^2 \quad (2.9)$$

$$f_{emission} = \sum_{i \in n} \alpha_i + \beta_i p_i + \gamma_i p_i^2 \tag{2.10}$$

In which, f_{fuel} is a fuel cost (\$/kwh) and $f_{emission}$ is emission of greenhouse gasses (g/kwh); a , b and c are a cost coefficients, while α , β and γ are coefficients for emission of greenhouse gasses and w is weight factor, that computed based on [4]:

$$w = \frac{\max\{f_{fuel}\}}{\min\{f_{emission}\} \times 10^3}, \quad s.t \ w > 0 \tag{2.11}$$

The constraints considered in this study include:

1. Power balance:

$$\sum_{i=1}^n P_{i,t} + P_{PV,t}^s + P_{WD,t}^s = P_{d,t} + P_{EV,t}^s \quad \forall i \in n, t \in T, s \in S \tag{2.12}$$

where $P_{i,t}$ is output power of i th fossil energy in period t (deterministic generation), $P_{PV,t}^s$ is output power of i th PV source in period t for the s th scenario (uncertainty generation), $P_{WD,t}^s$ is output power of i th wind generation in period t for the s th scenario (uncertainty generation), $P_{d,t}$ is deterministic load in period t , and $P_{EV,t}^s$ is charging power of i th electric Vehicles in period t for the s th scenario (uncertainty load).

2. Output power limit of the deterministic resource:

$$P_{i,t}^{min} \leq P_{i,t} \leq P_{i,t}^{max} \tag{2.13}$$

where $P_{i,t}$ is generation power of i th deterministic resource in period t for the s th scenario, that should satisfy its lower and upper power limit.

3. Charging power of EV:

$$P_{EV,t}^{min} \leq P_{EV,t} \leq P_{EV,t}^{max} \tag{2.14}$$

where $P_{EV,t}$ should satisfy its lower and upper power capacity limit.

3 Numerical results

In order to analyze the proposed model, four different areas were considered in relation to the wind and solar RESs (production planning under uncertainty), different loads (different load factors under certainty) and EVs (load planning under uncertainty). Modeling the uncertainty of EVs was carried out based on the Monte Carlo simulation. The diagram of the four different areas is shown in Fig. 1. The data for the first area as shown in Figure 1, as well as the certain loads and sources in all four areas are presented in tables 1 until 12 respectively.

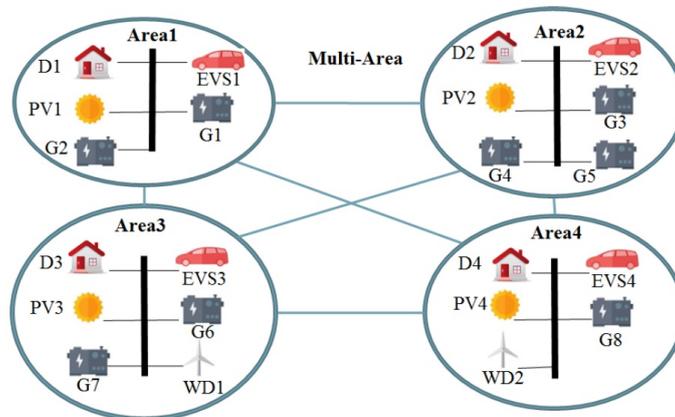


Figure 1: Multi-Area system

The first area: As shown in Fig. 1, two certain power supplies (e.g. Gen 1 and Gen 2), a deterministic load (D1), an EV parking (EV1) with load planning under uncertainty and an uncertain power supply (PV1) are in this area. Information on power supplies, hourly certain load and uncertain load (EVs) are presented in Tables 1, 2 and 3, respectively.

Table 1: GENERATION DATA OF AREA 1

	Min	Max	a	b	c	α	β	γ
Gen1	50	400	20	5	0.01	10	3	0.005
Gen2	70	500	10	3	0.07	5	1	0.02
PV1	0	100	0	0	0	0	0	0

Table 2: LOAD DATA OF AREA 1

Hour	1	2	3	4	5	6	7	8	9	10	11	12
kW	200	250	270	300	310	320	340	330	300	320	350	400
Hour	13	14	15	16	17	18	19	20	21	22	23	24
kW	420	460	510	550	570	590	610	640	660	600	520	310

Table 3: EV DATA OF AREA 1

Car Number	30000
Charge kW	2.5
Per km power	0.1
Capacity kW	10

The second area: As shown in Fig. 1, three certain power supplies (e.g. Gen 3, Gen 4 and Gen 5), a deterministic load (D2), an EV parking (EV2) with load planning under uncertainty and an uncertain power supply (PV2) are in this area. Information on power supplies, hourly certain load and uncertain load (EVs) are presented in Tables 4, 5 and 6, respectively.

Table 4: GENERATION DATA OF AREA 2

	Min	Max	a	b	c	α	β	γ
Gen3	50	400	20	5	0.01	10	3	0.005
Gen4	70	500	10	3	0.07	5	1	0.02
Gen5	40	350	8	2	0.005	2	0.5	0.01
PV2	0	350	0	0	0	0	0	0

Table 5: LOAD DATA OF AREA 2

Hour	1	2	3	4	5	6	7	8	9	10	11	12
kW	280	350	378	420	434	448	476	462	420	448	490	560
Hour	13	14	15	16	17	18	19	20	21	22	23	24
kW	588	644	714	770	798	826	854	896	924	840	728	434

Table 6: EV DATA OF AREA 2

Car Number	15000
Charge kW	5
Per km power	0.2
Capacity kW	20

The third area: As shown in Fig. 1, two certain power supplies (e.g. Gen 6 and Gen 7), a deterministic load (D3), an EV parking (EV3) with load planning under uncertainty and two uncertain power supplies (PV3 and WD1) are in this area. Information on power supplies, hourly certain load and uncertain load (EVs) are presented in Tables

7, 8 and 9, respectively.

Table 7: GENERATION DATA OF AREA 3

	Min	Max	a	b	c	α	β	γ
Gen6	20	200	25	9	0.03	15	4	0.015
Gen7	30	300	19	7	0.04	8	2	0.03
PV3	0	200	0	0	0	0	0	0
WD1	1	80	0	0	0	0	0	0

Table 8: LOAD DATA OF AREA 3

Hour	1	2	3	4	5	6	7	8	9	10	11	12
kW	160	200	216	240	248	256	272	264	240	256	280	320
Hour	13	14	15	16	17	18	19	20	21	22	23	24
kW	336	368	408	440	456	472	488	512	528	480	416	248

Table 9: EV DATA OF AREA 3

Car Number	35000
Charge kW	2.5
Per km power	0.1
Capacity kW	10

The fourth area: As shown in Fig. 1, a deterministic power supply (e.g. Gen 8), a certain load (D4), an EV parking (EV4) with load planning under uncertainty and two uncertain power supplies (PV4 and WD2) are in this area. Information on power supplies, hourly certain load and uncertain load (EVs) are presented in Tables 10, 11 and 12, respectively.

Table 10: GENERATION DATA OF AREA 4

	Min	Max	a	b	c	α	β	γ
Gen8	30	500	10	3	0.07	5	1	0.02
PV4	0	150	0	0	0	0	0	0
WD2	1	80	0	0	0	0	0	0

Table 11: LOAD DATA OF AREA 4

Hour	1	2	3	4	5	6	7	8	9	10	11	12
kW	140	175	189	210	217	224	238	231	210	224	245	280
Hour	13	14	15	16	17	18	19	20	21	22	23	24
kW	294	322	357	385	399	413	427	448	462	420	364	217

Table 12: EV DATA OF AREA 4

Car Number	2000
Charge kW	2
Per km power	0.2
Capacity kW	8

The total load of the areas is shown in Fig. 2. The distribution function for photovoltaic, wind energy sources and EV charging are shown in Figures 3, 4, and 5.

Two scenarios have been presented to illustrate the effectiveness of a multi-area economic dispatching model. The first scenario is related to the application of the economical load dispatching model separately for each of the four areas and, finally, the aggregation of cost functions for the four areas. The second scenario is related to the application

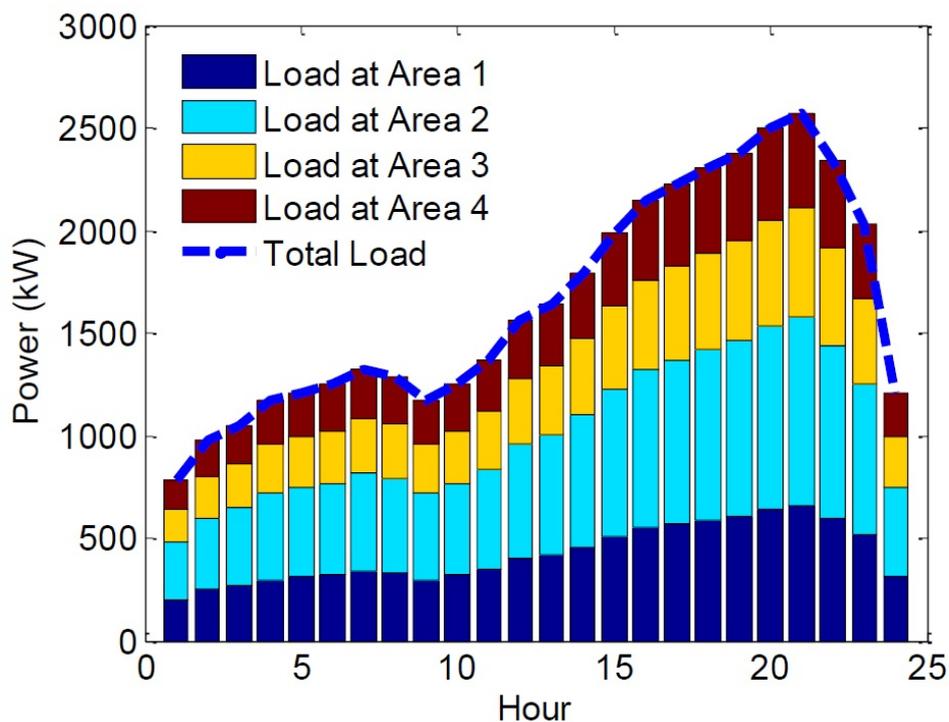


Figure 2: deterministic loads at each area.

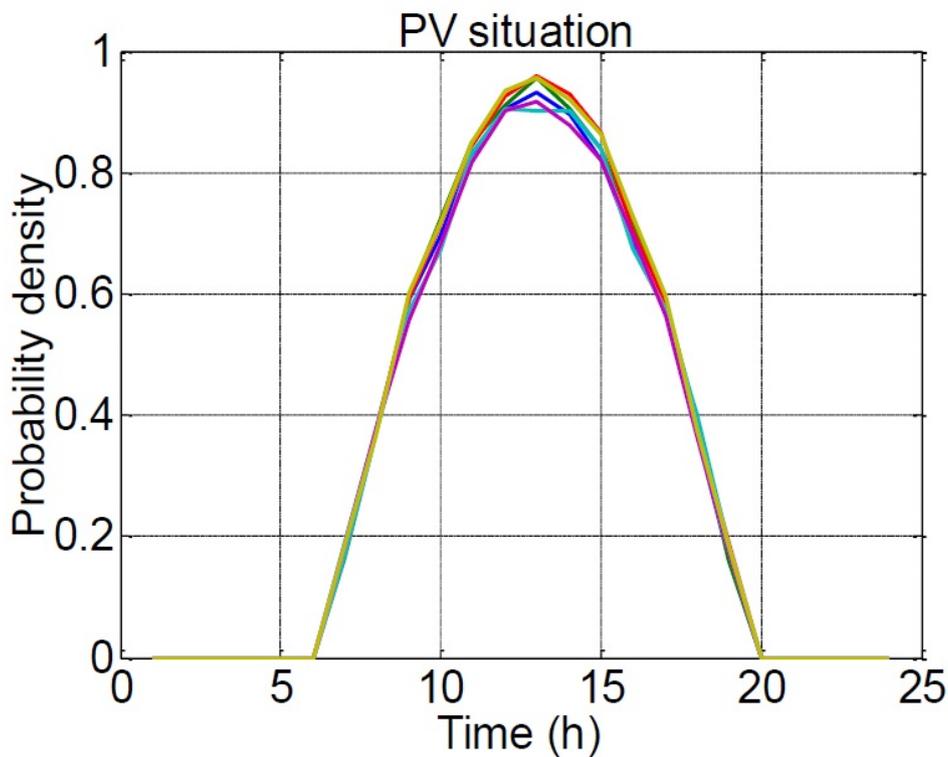


Figure 3: probability density of PV.

of the multi-area economical dispatching model simultaneously for all areas and ultimately the achievement of the overall cost function.

The first scenario: The economical load dispatching model is applied individually to all areas, and eventually

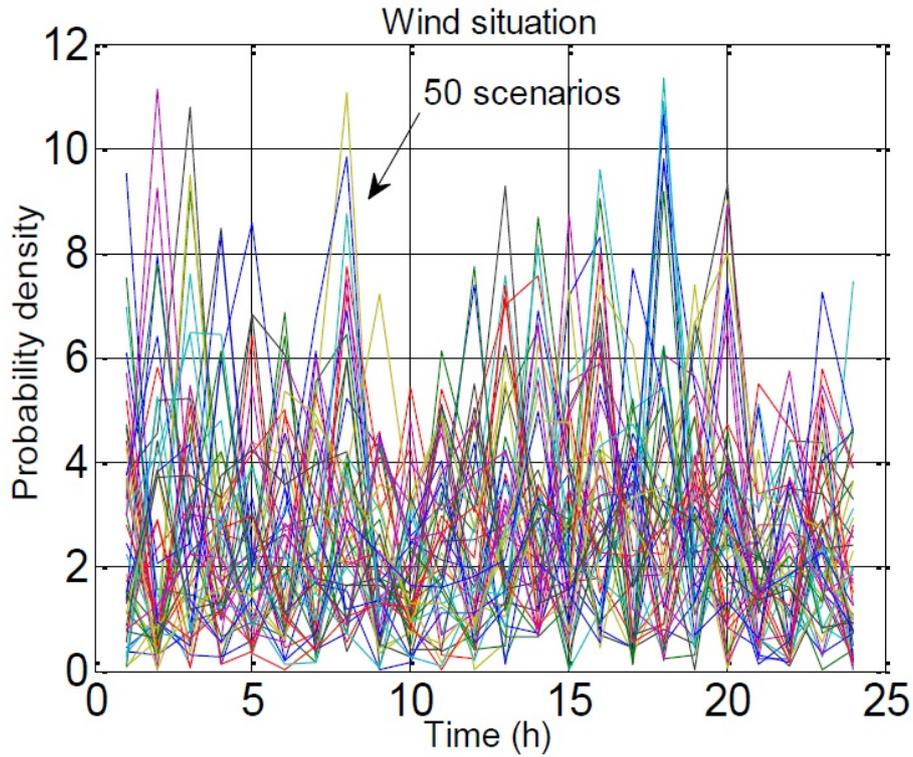


Figure 4: Probability density of wind velocity for 50 scenarios.

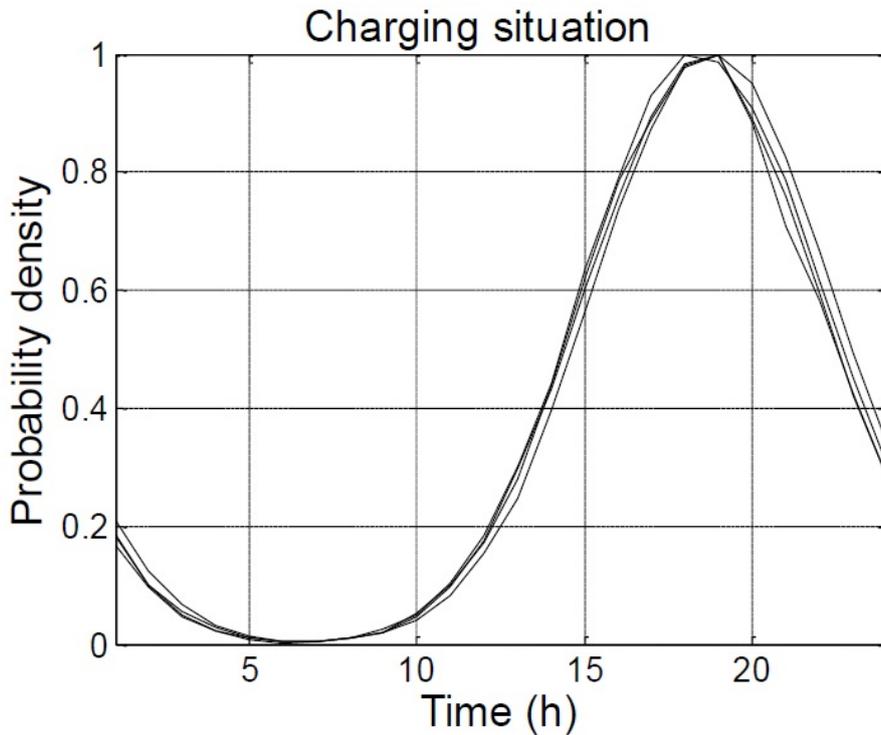


Figure 5: Probability density of EV charging.

the cost functions will be aggregated. Economical load dispatching results are presented in tables 13, 14, 15 and 16, respectively. The replication numbers and population of the PSO algorithm is 500 and 60, respectively. The results of the aggregation of fuel cost and emission for all four areas are presented in Table 17.

Table 13: economic dispatch in area 1 ($w = 0.23$)

Area 1							
Time	Gen1	Gen2	PV1	Time	Gen1	Gen2	PV1
1	148	70	0	13	287	70	93
2	190	70	0	14	343	70	91
3	205	70	0	15	399	90	82
4	232	70	0	16	400	158	69
5	241	70	0	17	400	203	58
6	251	70	0	18	400	251	38
7	252	70	18	19	400	293	18
8	232	70	38	20	400	330	0
9	174	70	58	21	400	337	0
10	185	70	70	22	400	260	0
11	207	70	82	23	400	163	0
12	257	70	91	24	269	70	0
Total f=159419.5825 Emission=48316.3143 g/kw Fuel Cost=111103.2682\$							

Table 14: economic dispatch in area 2 ($w = 0.17$)

Area 2									
Time	Gen3	Gen4	Gen5	PV2	Time	Gen3	Gen4	Gen5	PV2
1	50	70	195	0	13	50	70	203	326
2	50	70	247	0	14	95	70	245	319
3	52	70	265	0	15	147	70	325	294
4	50	70	305	0	16	259	70	350	245
5	50	70	316	0	17	356	70	350	202
6	50	70	328	0	18	400	142	350	133
7	50	70	293	63	19	400	239	350	63
8	50	70	211	133	20	400	328	350	0
9	50	70	102	203	21	400	332	350	0
10	50	70	93	245	22	400	214	350	0
11	50	70	95	294	23	397	70	350	0
12	50	70	157	319	24	72	70	350	0
Total f=146611.9298 Emission=52601.2446 g/kw Fuel Cost=94010.6852 \$/kw									

Table 15: economic dispatch in area 3 ($w = 0.2$)

Area 3									
Time	Gen6	Gen7	PV3	WD1	Time	Gen6	Gen7	PV3	WD1
1	119	115	0	6	13	139	140	186	4
2	114	122	0	9	14	200	170	182	10
3	110	121	0	9	15	200	300	168	10
4	95	148	0	8	16	20	30	140	9
5	139	110	0	5	17	20	30	116	9
6	115	139	0	4	18	20	30	76	8
7	132	101	36	6	19	20	30	36	8
8	76	107	76	9	20	20	30	0	8
9	84	49	116	3	21	200	300	0	4
10	54	79	140	7	22	200	300	0	5
11	57	99	168	3	23	200	300	0	5
12	141	68	182	10	24	200	176	0	3
Total f=123065.2019 Emission=40949.9964 g/kw Fuel Cost=82115.2054 \$/kw									

The second scenario: The economic dispatch model is applied simultaneously to all areas. The results of the multi-area economic dispatch model are presented in Table 18.

Table 16: economic dispatch in area 4 ($w = 0.34$)

Area 4							
Time	Gen8	PV4	WD2	Time	Gen8	PV4	WD2
1	30	0	74	13	30	52	114
2	30	0	83	14	30	101	98
3	30	0	85	15	30	126	114
4	30	0	93	16	70	105	130
5	55	0	70	17	120	87	121
6	44	0	85	18	178	57	111
7	30	3	103	19	217	27	115
8	30	51	52	20	253	0	112
9	30	55	37	21	298	0	60
10	30	66	37	22	246	0	68
11	30	78	42	23	203	0	62
12	30	32	116	24	125	0	37
Total f=43834.7473 Emission=10025.5194 g/kw Fuel Cost=33809.2279 \$							

Table 17: TOTAL COST AND EMISSION OF ALL AREA IN FIRST SCENARIO

Total Fuel Cost of All Area	321038.3867 \$
Total Emission of All Area	151893.0747 g/kw
Total f of All Area	472931.4615

Table 18: results of multi area economic dispatch at second scenario ($w = 0.2$)

Multi Area														
Time	Area-1			Area-2				Area-3				Area-4		
	Gen1	Gen2	PV1	Gen3	Gen4	Gen5	PV2	Gen6	Gen7	PV3	WD1	Gen8	PV4	WD2
1	90	70	0	89	70	289	0	20	30	0	49	30	0	54
2	112	70	0	143	73	350	0	20	30	0	53	30	0	62
3	146	70	0	163	70	350	0	20	30	0	55	30	0	60
4	188	70	0	257	70	322	0	20	30	0	49	30	0	54
5	241	70	0	247	70	350	0	22	30	0	29	30	0	32
6	269	70	0	240	70	350	0	22	30	0	35	30	0	38
7	230	70	14	224	70	350	63	20	30	36	45	30	27	17
8	155	70	37	50	70	350	133	20	30	76	54	30	57	59
9	50	70	58	50	70	233	203	20	30	116	33	30	87	37
10	57	70	70	50	70	199	245	20	30	140	38	30	105	42
11	50	70	84	50	70	193	294	20	30	168	49	30	126	54
12	50	70	91	55	70	322	319	20	30	182	56	30	137	61
13	50	70	93	136	70	315	326	20	30	186	62	30	140	70
14	154	70	91	214	70	350	319	20	30	182	61	30	137	66
15	252	70	84	400	70	350	294	20	30	168	57	47	126	62
16	400	70	70	363	90	350	245	135	48	140	53	105	105	58
17	400	114	58	400	84	350	203	200	137	116	38	109	87	46
18	400	70	38	400	178	350	133	200	295	76	46	176	57	43
19	400	198	18	400	214	348	63	200	222	36	42	320	27	52
20	400	280	0	400	290	350	0	200	290	0	46	324	0	50
21	400	399	0	400	301	350	0	200	299	0	25	329	0	17
22	400	200	0	400	299	350	0	200	292	0	15	202	0	31
23	389	166	0	373	126	350	0	200	250	0	20	143	0	23
24	315	70	0	265	70	350	0	20	30	0	53	81	0	17
Fuel Cost:300186.3366\$ Emission:148515.2812 g/kw Total f:448701.6178														

For example, based on the table 18 and at 15:00 PM, the production of Gen 1 (from area 1), Gen 3 (from area 2), Gen 6 (from area 3) and Gen 8 (from area 4) is 252, 400, 20 and 47 kW, respectively. At the same time, provided that

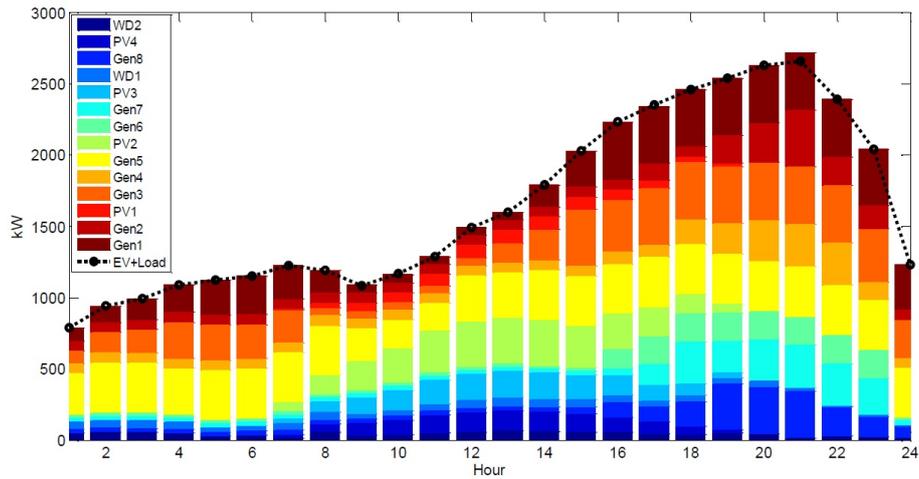


Figure 6: Optimal power of generation with multi area economic dispatch

the areas are considered separately, the above values will be 399, 147, 200, and 30 kW, respectively. In terms of cost function, based on the table 17, if the economical load dispatching model for each of the areas is applied separately, then the total f (multi objective function) will be equal to 472931; while in the multi-area economical load dispatching model, based on the table 18, the total f will be 448701. This suggests that the cost has fallen by 5.12%. As a result, the multi-area economical load dispatching model has a high performance. This f difference is well illustrated in Table 19. Note that the 5.12% cost reduction is for a 24-hour period. This will certainly be much higher for a one-year period. The output of resources power is shown in Figure 6 after applying the multi-area economical load dispatching model.

Table 19: Comparing between multi area and separate area number of iterations =1500, number of runs=20 in the best solution

case	fuel cost \$	emission g/kw	cpu time (min)
Multi Area	300186	148515	66
Area 1	111103	48316	26
Area 2	94010	52601	25
Area 3	82115	40949	22
Area 4	33809	10026	23
Total			
multi area	300186	148515	66
All of the separate area	321037	151892	96

Table 20: Result of solutions at the multi area economic dispatch number of iterations =1500, number of runs=20

case	best value	mean value	worst value
fuel cost \$	300186	301151	302908
emission g/kw	148515	149032	150299

4 Conclusion

In this paper, using a modified version of PSO algorithm, a multi-area economic dispatch model was proposed to minimize the fuel cost of the certain grid generators and reduce pollution, considering photovoltaic and wind energy (as RESs) as a model for production planning under uncertainty, and also EVs as a model for load planning under both uncertainty and certainty, in a 24-hour period. The results showed that the simultaneous use of the multi-area economical load dispatching model for all areas significantly reduced the cost of production process.

References

- [1] M. Alipour and B. Mohammadi-ivatloo, *Stochastic scheduling of renewable and CHP based microgrids*, IEEE Trans. Ind. Inf. **10** (2015), no. 8, 1–11.
- [2] C. Battistelli, L. Baringo and A.J. Conejo, *Optimal energy management of small electric energy systems including V2G facilities and renewable energy sources*, Elec. Power Syst. Res. **92** (2012), 50–59.
- [3] M. Ghasemi, J. Aghaei, E. Akbari, S. Ghavidel and L. Li, *A differential evolution particle swarm optimizer for various types of multi-area economic dispatch problems*, Energy **107** (2016), 182–195.
- [4] Y. Huang, C. Guo, L. Wang, Y. Bao, S. Dai and Q. Ding, *A cluster-based dispatch strategy for electric vehicles considering user satisfaction*, Autom. Electr. Power Syst. **39** (2015), 183–191.
- [5] X. Lei, E. Lerch and D. Povh, *Genetic algorithm solution to economic dispatch problems*, Eur. Trans. Electric. Power **9** (1999), no. 6.
- [6] X. Lu, K. Zhou and S. Yang, *Multi-objective optimal dispatch of microgrid containing electric vehicles*, J. Clean. Prod. **165** (2017), 1572–1581.
- [7] M. Motevasel and A.R. Seifi, *Expert energy management of a micro-grid considering wind energy uncertainty*, Energy Convers. Manag. **83** (2014), 58–72.
- [8] H. Narimani, S.-E. Razavi, A. Azizivahed, E. Naderi, M. Fathi, M.H. Ataei and M.R. Narimani, *A multi-objective framework for multi-area economic emission dispatch*, Energy **154** (2018), 126–142.
- [9] N. Nikmehr and S. Najafi-Ravadanegh, *Optimal operation of distributed generations in micro-grids under uncertainties in load and renewable power generation using heuristic algorithm*, IET Gener. Transm. Distrib. **9** (2016), no. 8, 982–990.
- [10] M. Pandit, K. Jian, H.M. Dubey and R. Singh, *Large scale multi-area static/dynamic economic dispatch using nature inspired optimization*, J. Inst. Eng. India Ser. B **98** (2017), no. 2, 221–229.
- [11] A. Rahmani, J. Haddadnia and A. Sanai, *Intelligent detection of electrical equipment faults in the overhead substations-based machine vision*, 2nd Int. Conf. Mech. Electron. Engin., IEEE, **2** (2010), V2–141.
- [12] Y. Ren, Y. Tian and H. Wei, *Parameter evaluation of auxiliary problem principle for large-scale multi-area economic dispatch*, Int. Trans. Electr. Energ. Syst. **24** (2014), 1782–1790.
- [13] O.R. Seryasat and J. Haddadnia, *Assessment of a novel computer aided mass diagnosis system in mammograms*, Biomed. Res. **28** (2017), no. 7.
- [14] J. Soares, H. Morais, T. Sousa, Z. Vale and P. Faria, *Day-ahead resource scheduling including demand response for electric vehicles*, IEEE Trans. Smart Grid **4** (2013), 596–605.
- [15] M.S. Turgut and G.K. Demir, *Quadratic approximation-based hybrid artificial cooperative Search algorithm for economic emission load dispatch problems*, Int. Trans. Electr. Energ. Syst. **27** (2017), no. 4, p. e2284.
- [16] A. Vyas and D. Santini, *Use of national surveys for estimating 'full' PHEV potential for oil use reduction [EB/OL]*, <http://www.docin.com/p-486955039.html>, (2008).
- [17] A. Zakariazadeh, S. Jadid and P. Siano, *Multi-objective scheduling of electric vehicles in smart distribution system*, Energy Convers. Manag. **79** (2014), 43–53.