

Vehicle-to-grid technology for cost reduction and uncertainty management integrated with solar power

Mehrjerdi, Hasan; Rakhshani, Elyas

DOI

[10.1016/j.jclepro.2019.05.023](https://doi.org/10.1016/j.jclepro.2019.05.023)

Publication date

2019

Document Version

Final published version

Published in

Journal of Cleaner Production

Citation (APA)

Mehrjerdi, H., & Rakhshani, E. (2019). Vehicle-to-grid technology for cost reduction and uncertainty management integrated with solar power. *Journal of Cleaner Production*, 229, 463-469. <https://doi.org/10.1016/j.jclepro.2019.05.023>

Important note

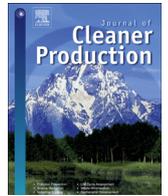
To cite this publication, please use the final published version (if applicable). Please check the document version above.

Copyright

Other than for strictly personal use, it is not permitted to download, forward or distribute the text or part of it, without the consent of the author(s) and/or copyright holder(s), unless the work is under an open content license such as Creative Commons.

Takedown policy

Please contact us and provide details if you believe this document breaches copyrights. We will remove access to the work immediately and investigate your claim.



Vehicle-to-grid technology for cost reduction and uncertainty management integrated with solar power

Hasan Mehrjerdi ^{a,*}, Elyas Rakhshani ^b

^a Electrical Engineering Department, Qatar University, Doha, Qatar

^b Electrical Sustainable Energy Department, Delft University of Technology, Delft, Netherlands

ARTICLE INFO

Article history:

Received 9 March 2019

Received in revised form

19 April 2019

Accepted 3 May 2019

Available online 3 May 2019

Keywords:

Energy price reduction

Small-scale charging station

Solar intermittency

Solar powered distribution grid

Vehicle-to-Grid

ABSTRACT

This paper optimizes the operation of electric vehicles in small charging stations deployed in electrical distribution networks. The grid is equipped with small-scale charging stations rather than one large-scale charging station. In addition, photovoltaic solar panels are installed on the grid to gain renewable energy benefits. The electric vehicles operate on vehicle-to-grid mode. The charging and discharging behavior of all the electric vehicles on all buses is optimized by the given method. The presented strategy optimizes the electric vehicles operation to damp out the renewable energy intermittency and energy cost reduction at the same time. And, it minimizes the charging-discharging cycles of the vehicles batteries in order to avoid battery degradation. The proposed problem is modeled as nonlinear stochastic programming including uncertainty of solar energy and solved by GAMS software. The results demonstrate that the suggested method can properly charge and discharge the vehicle-to-grid system. The vehicles are often charged on off-peak low-cost time periods and they are discharged at on-peak high-cost time-intervals. The Intermittency of solar cells is dealt with the achieved charging-discharging pattern for vehicle-to-grid system and cost of consumed energy is minimized by energy shifting. The results validate that the presented strategy can efficaciously achieve all the intended purposes at the same time.

© 2019 Elsevier Ltd. All rights reserved.

1. Introduction

Renewable energy resources (RESs) are promising solutions for energy issues (Mehrjerdi, 2019a). The electric vehicles (EVs) and vehicle-to-grid (V2G) technology are the proper supportive systems for RESs (Mehrjerdi et al., 2019a). Together with the progress of V2G technology, deployment of EVs charging stations on electrical distribution networks has faced new challenges. The V2G technologies have an bidirectional operation and they are able to inject power to the grid when necessary. The EVs are supported by battery storage pack and they operate like distributed energy resources in the electrical grids (Mehrjerdi et al., 2019b).

The V2G is the latest technology of EVs and it makes positive impacts on the operation and planning of EVs charging stations. The charging stations with the capability of V2G can take part in

energy management of the network and provide positive impacts on the grids.

The V2G can be properly utilized in home energy management as an storage unit in order to reduce the energy cost (Wu et al., 2016). The V2G is a promising solution for supporting renewable energy generation. To make a battery storage system cost-effectively viable for V2G applications, an efficient power-electronics converter should be designated and it must be supported by proper control strategy (Garcés Quílez et al., 2018). The battery degradation is one of the issues related to the V2G and considering battery degradation cost mainly reduce the economic benefits of V2G. The smart charging may be the proper solution for reducing the battery degradation cost (Ahmadian et al., 2018).

In the EVs, fast and safe charging protocols are essential for improving the feasibility of the batteries. It is mandatory to compromise between the charging time and health degradation subject to the electrical and thermal limitations (Perez et al., 2017). The battery degradation is associated with the energy output and it is highly sensitive to the depth of discharge. The V2G may need multiple battery pack substitutes over its lifespan (Bishop et al.,

* Corresponding author. Department of Electrical Engineering, Qatar University, Doha, Qatar.

E-mail addresses: hasan.mehrjerdi@qu.edu.qa (H. Mehrjerdi), E.rakhshani@tudelft.nl (E. Rakhshani).

2013), (Peterson et al., 2010).

The main contribution of V2G is to cut peak demand (Mehrjerdi, 2019b) and supply peak of demand through discharging the EVs. Such a procedure provides positive technical, environmental, and economic impacts on the EVs. The V2G would be applied for both peak shaving and valley filling simultaneously (Wang and Wang, 2013). The V2G can support the network from diverse point of views such as load shifting and congestion management. By the way, the economic impact of EVs on the grid is related to the charging facility power. The bigger rated power for charging facilities results in more economic benefits for the network (Tomić and Kempton, 2007).

The solution of RESs intermittency (Saboori et al., 2017) is the other advantage found by V2G systems (Dallinger and Wietschel, 2012). In such strategies, the EVs charge the surplus of RESs during off-peak times and send this energy back to the network when renewable energy goes down. The uncertainty of solar and wind energies could be efficiently dealt with V2G technology. This technology can also be applied to operate under unbalance (Knezović et al., 2017) and uncertain (Tabar et al., 2017) conditions.

The EVs have been modeled and studied in the electricity market as an ancillary service. The EVs operate like a flexible demand. Properly management of their charging–discharging operation provides significant benefits for both the network and vehicle owners. The operation of EVs makes an impact on the market prices and consequently influences the charging–discharging arrangement itself (Liu et al., 2018).

1.1. The main contributions and novelty

This paper presents an optimal paradigm for the operation of V2G in electrical distribution grids. The grid is supported by photovoltaic solar panels and the upstream network. The V2G is optimally scheduled to deal with solar energy intermittency, energy cost, and peak loading. The problem is expressed as nonlinear optimization programming and solved by GAMS software. The main innovations and contributions of the paper are listed below;

- o The distribution grid is installed with multiple small-scale charging stations for EVs.
- o The EVs operate on V2G mode and the proposed model deals with solar energy uncertainty and reduces the energy cost and shaves the peak loading by optimal charging–discharging of V2G.
- o The batteries on the EVs are operated with minimum possible charging–discharging cycles to avoid battery degradation.
- o The uncertainties of the model are considered in stochastic programming and nonlinear optimization problem solved by GAMS software.

1.2. Assumptions and limitations in the proposed model

Some assumptions and limitations are considered in the proposed model as follows;

- o Each 24-h is subdivided into 96 time-periods each one 15-min (Luo et al., 2018).
- o In every time-interval, the variations of load demand, EVs energy, and prices are ignored. In other words, every time-interval is modeled as a deterministic scenario where number of vehicles, powers, prices, and the other parameters are constant (Luo et al., 2018).
- o The locations of the charging stations are constant and their sites have been determined in advance.

- o The charging time of EVs is assumed to be less than two hours.
- o The uncertain parameters in the model are expressed by normal and uniform distributions.

2. The proposed model for V2G

2.1. V2G for planning and operation of charging stations

The V2G can be properly utilized for improving both the planning and operation of EVs charging stations. In this paper, the V2G is applied for improving the operation of EVs charging stations. In other words, the locations of EVs charging stations are predefined on the grid and the V2G is optimally operated to reduce the system cost. However, the V2G can make positive impacts on the deployment and planning of EVs charging stations in the electrical grids. The V2G technology for planning of EVs charging stations is not studied in the current paper, but it has already been investigated in the literature (Loisel et al., 2014). It is also suggested as future work further to the current work.

2.2. Modeling the V2G operation

The objective function of the planning shows the annualized cost of energy as presented by (1). This cost is modeled as expected value of cost to cope with uncertainties caused by solar energy.

$$AEC = \left(\sum_{s \in S} \sum_{k \in K} \left[\sum_{t \in T} (P_{line}^{s,i,j,k,t} \times E_{price}^t) \times T_p^s \right] \times H_{pro}^s \right) \quad (1)$$

$\forall s \in S, k \in K, t \in T, i \in I, j \in J$

The rated power for charging facilities of the charging stations is given by (2) and (3). At all intervals of time, the charging and discharging powers of each vehicle must be less than the rated power of charging infrastructure (Hemmati et al., 2017).

$$P_c^{t,i,cdt} \leq P_r^i \quad (2)$$

$\forall t \in T, i \in I, cdt \in CDT$

$$P_d^{t,i,cdt} \leq P_r^i \quad (3)$$

$\forall t \in T, i \in I, cdt \in CDT$

The energy of EVs at each time-interval is calculated by (4). At the first time-interval, the initial energy of the EVs is included in the planning as (5). The initial energy of the EVs shows the energy inside of the battery of EVs when it arrives at the charging station to start the charging–discharging process (Hemmati, 2018).

$$E_{ve}^{t,i,cdt} = E_{ve}^{t,i,cdt-1} + (P_c^{t,i,cdt} - P_d^{t,i,cdt}) \times T_p^t \quad (4)$$

$\forall t \in T, i \in I, cdt \in CDT$

$$E_{ve}^{t,i,cdt} = E_0^{t,i} + (P_c^{t,i,cdt} - P_d^{t,i,cdt}) \times T_p^t \quad (5)$$

$\forall t \in T, i \in I, cdt = 1$

The EVs eventually gets fully charged after several time-intervals shown by ‘*cdt*’ as expressed in (6). The energy of EVs must be less than the full capacity of the vehicle at every time-interval as specified by (7).

$$E_{ve}^{t,i,cdt} = E_{full}^i \quad (6)$$

$\forall t \in T, i \in I, cdt = cdt^n$

$$E_{ve}^{t,i,cdt} \leq E_{full}^i \quad (7)$$

$\forall t \in T, i \in I, cdt \in CDT$

Total power of each charging station at each time-interval is calculated by (8). The power through each line of the network is also denoted by (9). The capacity of each line is limited as (10) and the equality of power on all buses is passed by (11) (Hemmati, 2017).

$$T_p^{t,i} = (P_c^{t,i,cdt} - P_d^{t,i,cdt}) + \sum_{\substack{cdt \in CDT \\ cdt < t}} (P_c^{t-cdt,i,cdt+cdt} - P_d^{t-cdt,i,cdt+cdt})$$

$$\forall t \in T, i \in I, cdt \in CDT, cdt \leq t \tag{8}$$

$$P_{line}^{s,i,j,k,t} = A_d^{ij} \times (V_{\theta}^{s,i,k,t} - V_{\theta}^{s,j,k,t})$$

$$\forall s \in S, k \in K, t \in T, i \in I, j \in J \tag{9}$$

$$|P_{line}^{s,i,j,k,t}| \leq P_{max}^{ij}$$

$$\forall s \in S, k \in K, t \in T, i \in I, j \in J \tag{10}$$

$$T_p^{t,i} + P_{load}^{s,i,k,t} + \sum_{j \in J} P_{line}^{s,i,j,k,t} - P_{pv}^{s,i,k,t} = 0$$

$$\forall s \in S, k \in K, t \in T, i \in I \tag{11}$$

3. Illustrative test system

A typical distribution grid known as IEEE 33-bus distribution network is adopted as a test network to simulate the given approach and implement the introduced strategy. Fig. 1 shows the network topology installed with 10 small charging stations and one solar system. The network is radial and the data of network can be found in (Saboori et al., 2015). The base parameters of the network for the per-unit system are 12.66 kV and 10 MVA. The network is equipped with 500 kW solar panels on bus 6 (Hemmati and Saboori, 2017). The loading and solar profile for network are depicted in Fig. 2 (Hemmati, 2018). The time period in one day is divided into 96 time-intervals that each one is 15-min (Luo et al., 2018). The peak loading is seen in time-intervals 50 and 90. The solar energy is also increased during daytime and goes on zero for nighttime.

The network is equipped with 10 small-scale charging station.

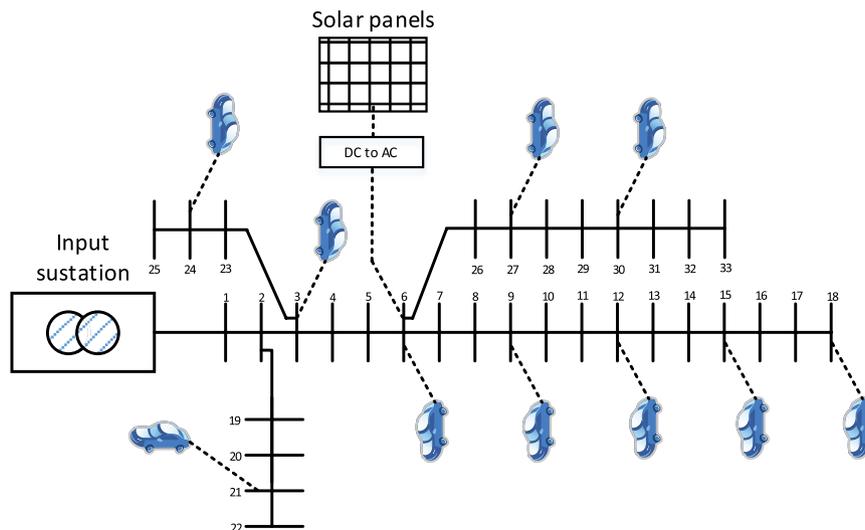


Fig. 1. IEEE 33-bus network installed with charging stations and solar system.

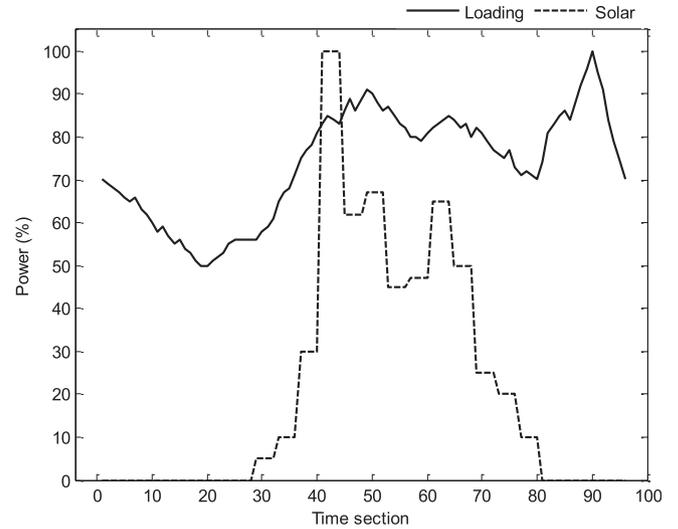


Fig. 2. Loading and solar energy profile for network.

Each charging station has capacity for 8 EVs and one EV arrives at the station at each time-interval. Table 1 shows the initial energy of EVs that arrive at the charging stations on different buses at various time-intervals. It is clear that the charging stations are on buses 3-6-9-12-15-18-21-24-30. The capacity of each EVs is 50 kWh and it is assumed that each EVs can stay for a maximum of two hours to get fully charged. The initial energy is between zero and full capacity (50 kWh) and is generated by random sampling from an uniform distribution (Luo et al., 2018).

The time-of-use energy pricing is defined in Table 2 and the seasonal profile for loading and solar energy are assumed in Table 3. The time-of-use energy pricing comprises three levels as 0.05, 0.07, and 0.10 (\$/kWh). The seasonal loading profile also shows peak loading in the summer and off-peak loading in the spring. The seasonal solar energy profile shows maximum energy production in the summer and minimum energy production in the winter.

4. Numerical results and discussions

The proposed model is simulated on the given test case and

Table 1
Initial energy of EVs on different buses at various time-intervals (per kWh).

Time-interval	Bus 3	Bus 6	Bus 9	Bus 12	Bus 15	Bus 18	Bus 21	Bus 24	Bus 27	Bus 30	Time-interval	Bus 3	Bus 6	Bus 9	Bus 12	Bus 15	Bus 18	Bus 21	Bus 24	Bus 27	Bus 30
1	9	34	30	49	21	18	1	27	2	1	49	22	29	35	44	8	10	10	48	29	50
2	3	18	4	29	10	16	40	41	5	24	50	10	19	11	44	19	9	5	18	33	27
3	28	25	10	4	48	3	50	35	26	4	51	4	14	4	12	12	41	28	5	37	43
4	34	9	21	5	7	48	31	44	46	13	52	6	50	24	16	2	3	9	45	48	45
5	50	6	9	49	24	4	18	29	13	30	53	22	33	20	21	10	30	1	20	16	35
6	45	29	45	23	43	48	49	34	33	8	54	20	20	13	10	13	36	28	8	38	26
7	8	19	46	45	13	12	44	2	4	21	55	13	6	39	10	50	46	32	33	15	23
8	5	18	22	46	22	5	22	38	1	45	56	33	16	49	8	33	15	20	2	46	20
9	18	5	7	49	50	37	8	9	27	43	57	33	3	5	43	6	43	29	4	34	2
10	43	50	26	39	47	38	33	28	33	28	58	32	20	39	47	42	21	5	27	15	11
11	36	22	40	48	3	45	9	27	20	24	59	2	37	10	39	37	50	26	46	17	5
12	9	39	30	34	28	31	16	16	20	8	60	13	39	1	8	36	31	5	9	36	40
13	10	38	35	36	1	25	8	36	19	25	61	36	6	21	37	28	49	13	7	10	21
14	47	44	24	7	37	17	9	48	38	29	62	37	46	8	10	20	2	9	1	23	3
15	14	41	36	5	31	24	13	28	31	18	63	45	35	27	23	18	10	2	39	19	16
16	3	27	15	6	19	23	25	13	12	21	64	27	6	28	43	5	6	44	37	11	44
17	33	13	2	19	15	30	22	2	47	9	65	10	38	35	7	11	10	3	43	27	47
18	20	45	25	49	3	37	45	38	20	42	66	39	38	44	31	5	44	24	13	42	22
19	36	43	10	19	36	50	15	1	19	34	67	31	41	1	32	38	31	31	31	24	44
20	4	2	49	47	45	42	16	14	17	10	68	47	30	35	38	4	38	18	3	32	25
21	47	4	39	5	37	14	29	28	46	31	69	25	29	50	13	30	28	23	6	10	46
22	13	35	31	7	30	42	39	7	24	36	70	18	42	50	28	15	10	40	18	50	13
23	34	14	20	25	48	27	46	23	26	2	71	41	49	23	47	27	39	41	24	1	27
24	13	2	46	47	19	1	19	8	40	27	72	17	3	18	48	49	9	16	4	31	13
25	48	30	27	7	5	38	16	44	7	13	73	49	9	50	31	35	44	13	35	42	42
26	17	2	38	8	25	43	31	28	11	26	74	19	42	25	41	21	42	20	27	21	27
27	47	6	21	17	9	12	25	30	10	49	75	5	1	16	16	6	38	9	26	45	18
28	14	19	18	23	13	23	13	27	1	41	76	2	33	20	14	21	37	38	48	26	13
29	43	1	38	1	1	45	44	43	43	43	77	27	43	1	22	28	27	4	7	49	9
30	33	24	41	21	39	5	27	26	1	45	78	5	19	26	38	12	46	5	33	31	30
31	32	6	20	10	39	25	37	37	1	15	79	46	37	7	24	1	15	47	43	34	41
32	15	36	39	44	1	12	21	43	43	45	80	37	20	16	50	28	6	30	18	47	43
33	33	34	26	28	7	6	37	6	39	13	81	23	47	13	43	44	18	43	4	23	43
34	49	28	20	44	5	23	36	22	43	10	82	14	24	1	17	19	6	20	1	32	12
35	36	29	20	3	4	2	15	15	47	10	83	42	27	39	9	42	31	19	1	11	26
36	18	24	45	26	30	12	5	44	1	44	84	3	2	34	43	8	18	15	15	29	34
37	38	19	37	8	25	25	31	4	10	23	85	28	12	20	44	31	29	5	11	6	5
38	15	2	39	22	25	18	24	31	35	20	86	30	41	26	6	42	31	33	16	15	28
39	24	44	25	23	33	30	48	18	49	42	87	16	6	31	39	17	37	47	30	28	15
40	38	49	21	16	43	12	17	14	29	11	88	19	23	7	7	21	28	28	29	10	20
41	28	46	44	47	1	45	35	29	29	45	89	50	34	15	31	21	23	34	11	14	27
42	41	38	13	37	43	29	24	7	48	23	90	31	24	42	40	29	18	47	20	12	22
43	8	15	1	32	39	42	13	7	35	9	91	41	2	44	11	7	4	29	17	28	12
44	11	17	5	48	15	9	24	47	17	14	92	31	35	3	2	6	23	46	38	28	2
45	39	24	41	37	36	16	31	17	18	27	93	3	12	25	41	8	12	47	19	32	2
46	15	29	50	27	46	29	23	10	47	39	94	3	11	42	2	22	37	15	22	1	14
47	25	31	25	33	48	7	5	4	16	20	95	22	5	46	38	24	38	48	29	10	35
48	32	12	22	37	14	34	49	46	2	3	96	35	28	41	17	35	14	41	30	24	17

Table 2
Time-of-use energy pricing scheme.

Time-interval	Price (\$/kWh)	Time-interval	Price (\$/kWh)
1 to 4	0.07	5 to 35	0.05
36 to 39	0.07	40 to 70	0.10
71 to 82	0.07	83 to 92	0.10
93 to 96	0.07	–	–

Table 3
Seasonal profile for loading and solar powers.

	Spring	Summer	Autumn	Winter
Loading power percentage	40	100	50	60
Solar power percentage	80	100	70	50

results are presented here. The total cost of consumed energy is achieved equal to 6382280.70 (\$/year) which has been minimized by the planning. As it was stated, the proposed model minimizes

Table 4
Maximum number of charging-discharging operations for the vehicles.

	Number of charging times	Number of discharging times
Bus 3	3	2
Bus 6	3	2
Bus 9	3	3
Bus 12	3	3
Bus 15	2	2
Bus 18	3	3
Bus 21	3	2
Bus 23	2	2
Bus 27	2	2
Bus 30	3	2

energy cost while it utilizes the batteries of EVs with minimum possible charging-discharging cycles. The maximum number of charging-discharging operations for the vehicles on all buses are listed in Table 4 and it is demonstrated that the maximum charging-discharging cycles are equal to 3 for avoiding battery

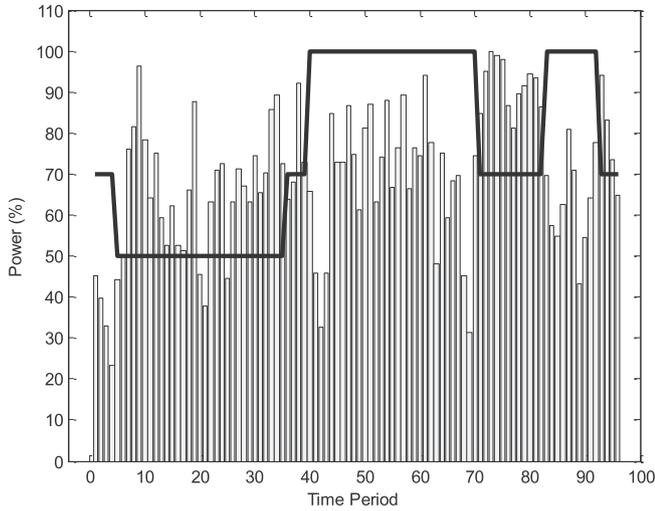


Fig. 3. Received power by grid and energy price (bars: Received power; solid line: energy price).

degradation. Such optimal charging-discharging operation increases the battery lifetime and reduces the requirement for battery replacement over the EVs lifespan.

Fig. 3 represents the received power by the grid and the energy price at different time periods. In this figure, the bars show the received power by the grid and the solid line indicates the energy price at various time-intervals. The results emphasize the precious trend of the proposed strategy. The planning has shifted energy from high-price time-intervals such as 40–70 to the low-price time periods such as 70–80. Such energy arbitraging results in two benefits including peak load cutting and energy cost reduction.

In order to demonstrate the charging-discharging operation of charging stations, the power of three charging stations are depicted in Figs. 4–6. It is clear that the charging stations often consume energy in the low-price time-intervals and discharge energy during high-price time-periods. Such optimal charging-discharging pattern achieved by the EVs helps network to operate on minimum energy cost and deals with peak loading demand. As well, the results indicate that the V2G system often discharges energy when solar energy reduces or goes to zero. On the other hand, V2G often charges energy when solar energy is on its highest levels. Such

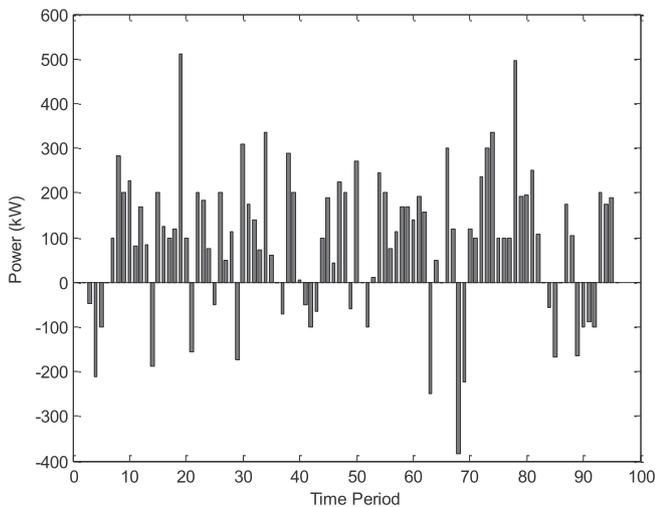


Fig. 4. Power of charging station on bus 3.

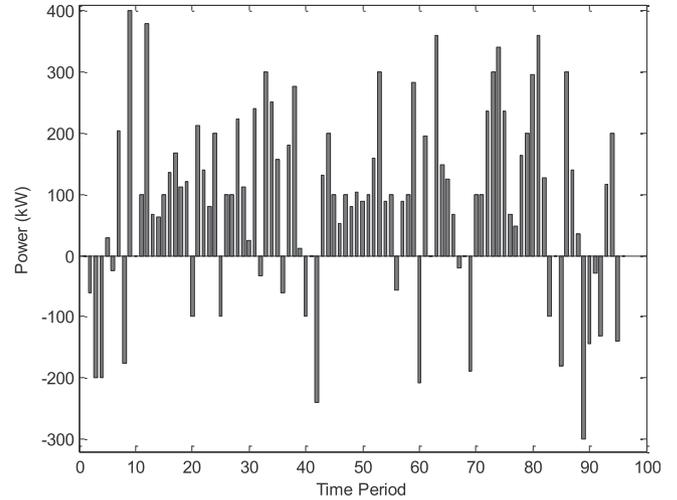


Fig. 5. Power of charging station on bus 21.

procedure efficiently deals with solar energy intermittency.

Fig. 4 shows that the charging station on bus 3 when receives its maximum power (about 500 kW) at time-intervals 19 and 79 and injects its maximum power (about 400 kW) at time-interval 69. Fig. 5 demonstrates that the charging station on bus 21 receives its maximum power (about 400 kW) at time-intervals 9 and injects its maximum power (about 300 kW) at time-interval 89. Fig. 6 shows that the charging station on bus 30 receives its maximum power (about 380 kW) at time-intervals 9 and injects its maximum power (about 250 kW) at time-interval 68. All the charging-discharging patterns show that the charging stations receive their maximum power during off-peak time-intervals and inject their maximum power during on-peak time-intervals in order to shift the energy and minimize the energy cost.

For more details, Fig. 7 shows the energy of vehicles that arrive at time-interval 65 to the charging stations on buses 3–6–9. Two plots are presented to provide more details to the readers. In Fig. 7.a and Fig. 7.b, it is clear that the energy of the vehicles is discharged from time-interval 65 to 69 and their energies reach to zero at time period 69. Then they are charged again at time-interval 70 to 72 and they get fully charged at time-interval 72. Such a charging-discharging operation helps the charging station to deal with

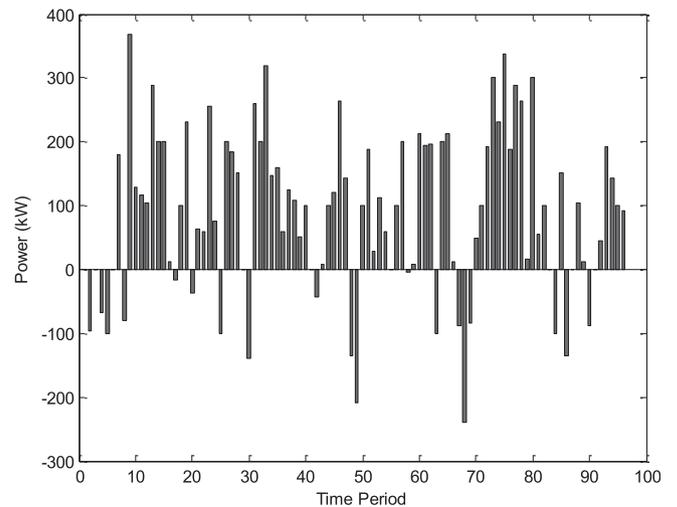


Fig. 6. Power of charging station on bus 30.

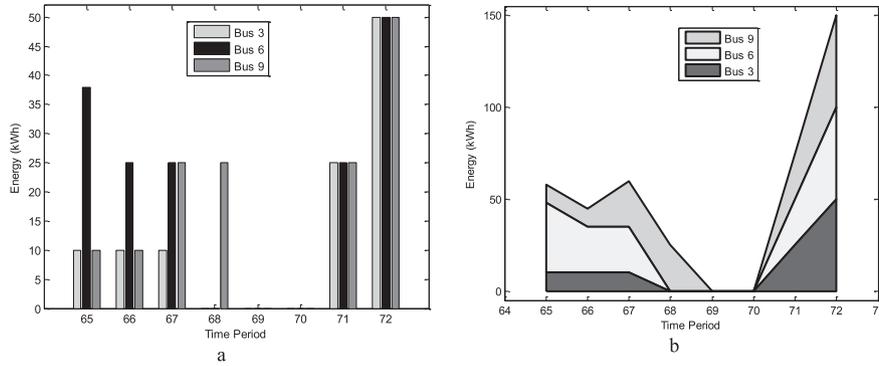


Fig. 7. Energy of vehicles that arrive at time-interval 65 to charging stations on buses 3-6-9.

peak cutting and energy cost reduction. The energy profile in Fig. 7.b indicates that each EVs is charged up to 50 kWh and the energy of all three vehicles reach to 150 kWh after fully charged. As well, the EVs arrive at the charging station with different initial energy. For instance, the EVs that arrive at the charging stations on buses 3 and 9 have 10 kWh energy inside their batteries, while the EVs that arrives at the charging station on bus 6 has about 47 kWh energy inside its battery. Fig. 8 depicts the charging-discharging regime of the mentioned vehicles.

4.1. Comparative study

In order to show the impacts of the charging-discharging regime on the planning, several cases are simulated and results are listed in Table 5. The cases are defined as follows;

Case 1. EVs are able to operate on both charging and discharging states and the vehicle stays in the charging station 8 time-intervals (nominal case adopted by this paper).

Case 2. EVs are able to operate only on charging state and the vehicle stay in the charging station 8 time-intervals.

Case 3. EVs are able to operate on both charging and discharging states and the vehicle stays in the charging station 4 time-intervals.

Case 4. EVs are able to operate on both charging and discharging states and the vehicle stays in the charging station 2 time-intervals.

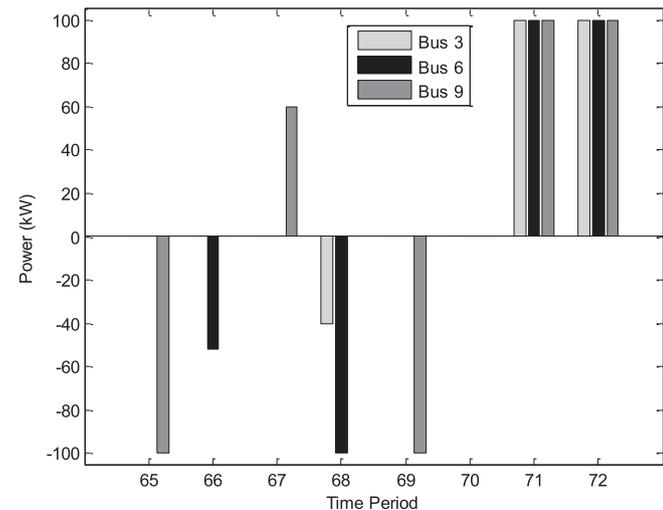


Fig. 8. Charging-discharging of vehicles arriving at time-interval 65 to stations on buses 3-6-9.

Table 5 Simulation of the model under various cases.

	Cost (\$/year)
Case 1	6382280.70
Case 2	6668523.90
Case 3	6765248.70
Case 4	6964472.70

The results confirm that Case 1 (the nominal case) comprises the minimum cost. In Case 2, the EVs can only store energy and they cannot inject power to the grid. However, the charging times are optimized by the planning. But the cost increases because the V2G capability is not included. As a result, the planning flexibility reduces and consequently the planning cost increases. In Case 3, the flexibly of charging-discharging regime reduces and the vehicles stay in the charging station only 4 time-intervals. It is denoted that such process increases the planning cost compared to the nominal case. Eventually, case 4 shows that more reduction in charging-discharging flexibility results in further growth in the planning cost.

5. Conclusions

This paper optimizes the operation of V2G technology in the distribution grid. Ten EVs charging stations are installed on the grid and the grid is also supported by solar panels. The EVs are modeled for V2G operation. The optimization programming is presented to minimize the operational cost of the network. The uncertainties of the model are included by stochastic programming. The implemented stochastic programming is solved by GAMS software. The introduced model optimally utilizes the V2G technology to schedule the EVs charging stations. The V2G technology properly deals with solar energy uncertainty, peak loading, and energy cost at the same time. The V2G technology is operated with minimum charging-discharging cycle to avoid battery degradation. The results demonstrate that the total cost of consumed energy by the network is 6382280.70 (\$/year). The results verify the model minimizes the energy cost by minimum charging-discharging cycles in order to avoid battery degradation. Furthermore, the V2G system often discharges energy when solar energy decreases and charges energy when solar energy rises. Such method usefully tackles solar energy uncertainty. It is also addressed that limiting the time-intervals of the charging-discharging regime (i.e., the time duration that the operator is allowed to keep the EVs inside charging station) reduces the planning flexibility and will increase the planning cost. As well, the vehicles without the capability of operation under V2G mode increase the cost compared to the

operation under V2G manner.

Further to this work, the following items are suggested as future work: considering the shorter time-intervals for simulation (e.g., one-minute time-intervals); including the other energy resources in the model such as wind turbine and diesel generator, and investigating the impacts of V2G system on the resiliency and self-healing for the network.

Acknowledgement

This publication was made possible by NPRP Grant no. 11S-1125-170027 from the Qatar National Research Fund (a member of Qatar Foundation). The statements made herein are solely the responsibility of the authors.

Appendix A

Nomenclature

Indexes

cdt	Index of charging-discharging time period
I_j	Index of buses
k	Index of seasons
s	Index of scenarios
t	Index of time periods

Sets

CDT	Set of charging-discharging time periods
I_j	Set of buses
K	Set of seasons
S	Set of scenarios
T	Set of time periods

Parameters

A_{ij}^d	Admittance of line from bus i to bus j (p.u.)
AEC	Annualized cost of energy consumed by the grid (\$/year)
cdt^n	Last charging-discharging time-interval in set CDT, $CDT = [1, 2, \dots, cdt^n]$
E_0^i	Initial energy of EVs that arrives to bus i at time-interval t (kWh)
$E_{full}^{t,i}$	Full capacity of EVs that arrives to bus i at time-interval t (kWh)
E_{price}^t	Electricity price (\$/kWh)
$E_{ve}^{t,i,cdt}$	Energy of EVs at time-interval t , bus i , charging-discharging time period cdt (kWh)
H_{pro}^s	Probability of scenario s
$P_c^{t,i,cdt}$	Charged power to EVs at time-interval t , bus i , charging-discharging time period cdt (kW)
$P_d^{t,i,cdt}$	Discharged power from EVs at time-interval t , bus i , charging-discharging time period cdt (kW)
$P_{line}^{s,i,j,k,t}$	Power through line between buses i - j , under scenario s , at season k , at time-interval t (p.u.)
$P_{load}^{s,i,k,t}$	Load on bus i , under scenario s , season k , time-interval t (p.u.)
P_{max}^{ij}	Maximum permitted power of line from bus i to bus j (p.u.)
$P_{pv}^{s,i,k,t}$	Produced power by solar panels on bus i , under scenario s , season k , time-interval t (p.u.)
P_r^i	Rated power of charging facility in the charging station on bus i (kW)
T_p^s	Time duration for seasons equal to 90 days

$T_p^{t,i}$	Total power of charging station on bus i at time-interval t (kW)
$V_{\theta}^{s,i,k,t}$	Voltage angle on bus i , under scenario s , season k , time-interval t (Rad)

References

- Ahmadian, A., Sedghi, M., Mohammadi-ivatloo, B., Elkamel, A., Golkar, M.A., Fowler, M., 2018. Cost-benefit analysis of V2G implementation in distribution networks considering PEVs battery degradation. *IEEE Trans. Sustain. Energy* 9 (2), 961–970.
- Bishop, J.D.K., Axon, C.J., Bonilla, D., Tran, M., Banister, D., McCulloch, M.D., 2013. Evaluating the impact of V2G services on the degradation of batteries in PHEV and EV. *Appl. Energy* 111, 206–218.
- Dallinger, D., Wietschel, M., 2012. Grid integration of intermittent renewable energy sources using price-responsive plug-in electric vehicles. *Renew. Sustain. Energy Rev.* 16 (5), 3370–3382.
- Garcés Quilez, M., Abdel-Monem, M., El Baghdadi, M., Yang, Y., Van Mierlo, J., Hegazy, O., 2018. Modelling, analysis and performance evaluation of power conversion unit in g2v/v2g application—a review. *Energies* 11 (5), 1082.
- Hemmati, R., 2017. Technical and economic analysis of home energy management system incorporating small-scale wind turbine and battery energy storage system. *J. Clean. Prod.* 159, 106–118.
- Hemmati, R., 2018. Optimal design and operation of energy storage systems and generators in the network installed with wind turbines considering practical characteristics of storage units as design variable. *J. Clean. Prod.* 185, 680–693.
- Hemmati, R., Saboori, H., 2017. Stochastic optimal battery storage sizing and scheduling in home energy management systems equipped with solar photovoltaic panels. *Energy Build.* 152, 290–300.
- Hemmati, R., Saboori, H., Jirdehi, M.A., 2017. Stochastic planning and scheduling of energy storage systems for congestion management in electric power systems including renewable energy resources. *Energy* 133, 380–387.
- Knezović, K., Soroudi, A., Keane, A., Marinelli, M., 2017. Robust multi-objective PQ scheduling for electric vehicles in flexible unbalanced distribution grids. *IET Generation, Transm. Distrib.* 11 (16), 4031–4040.
- Liu, Z., Wu, Q., Huang, S., Wang, L., Shahidehpour, M., Xue, Y., 2018. Optimal day-ahead charging scheduling of electric vehicles through an aggregative game model. *IEEE Trans. Smart Grid* 9 (5), 5173–5184.
- Loisel, R., Pasaoglu, G., Thiel, C., 2014. Large-scale deployment of electric vehicles in Germany by 2030: an analysis of grid-to-vehicle and vehicle-to-grid concepts. *Energy Policy* 65, 432–443.
- Luo, L., Gu, W., Zhou, S., Huang, H., Gao, S., Han, J., et al., 2018. Optimal planning of electric vehicle charging stations comprising multi-types of charging facilities. *Appl. Energy* 226, 1087–1099.
- Mehrjerdi, H., 2019. Optimal correlation of non-renewable and renewable generating systems for producing hydrogen and methane by power to gas process. *Int. J. Hydrogen Energy* 44 (18), 9210–9219.
- Mehrjerdi, H., 2019. Multilevel home energy management integrated with renewable energies and storage technologies considering contingency operation. *J. Renew. Sustain. Energy* 11 (2), 025101–025109.
- Mehrjerdi, H., Bornapour, M., Hemmati, R., Ghiasi, S.M.S., 2019. Unified energy management and load control in building equipped with wind-solar-battery incorporating electric and hydrogen vehicles under both connected to the grid and islanding modes. *Energy* 168, 919–930.
- Mehrjerdi, H., Hemmati, R., Farrokhi, E., 2019. Nonlinear stochastic modeling for optimal dispatch of distributed energy resources in active distribution grids including reactive power. *Simulat. Model. Pract. Theor.* 94, 1–13.
- Perez, H.E., Hu, X., Dey, S., Moura, S.J., 2017. Optimal charging of Li-ion batteries with coupled electro-thermal-aging dynamics. *IEEE Trans. Veh. Technol.* 66 (9), 7761–7770.
- Peterson, S.B., Apt, J., Whitacre, J.F., 2010. Lithium-ion battery cell degradation resulting from realistic vehicle and vehicle-to-grid utilization. *J. Power Sources* 195 (8), 2385–2392.
- Saboori, H., Hemmati, R., Jirdehi, M.A., 2015. Reliability improvement in radial electrical distribution network by optimal planning of energy storage systems. *Energy* 93 (Part 2), 2299–2312.
- Saboori, H., Hemmati, R., Ghiasi, S.M.S., Dehghan, S., 2017. Energy storage planning in electric power distribution networks—A state-of-the-art review. *Renew. Sustain. Energy Rev.* 79, 1108–1121.
- Tabar, V.S., Jirdehi, M.A., Hemmati, R., 2017. Energy management in microgrid based on the multi objective stochastic programming incorporating portable renewable energy resource as demand response option. *Energy* 118, 827–839.
- Tomić, J., Kempton, W., 2007. Using fleets of electric-drive vehicles for grid support. *J. Power Sources* 168 (2), 459–468.
- Wang, Z., Wang, S., 2013. Grid power peak shaving and valley filling using vehicle-to-grid systems. *IEEE Trans. Power Deliv.* 28 (3), 1822–1829.
- Wu, X., Hu, X., Moura, S., Yin, X., Pickert, V., 2016. Stochastic control of smart home energy management with plug-in electric vehicle battery energy storage and photovoltaic array. *J. Power Sources* 333, 203–212.