Future Generation of Communication and Internet of Things (FGCIOT)

Journal homepage: http://fgciot.semnaniau.ac.ir/

Research paper

Presenting a New Method to Evaluate the Impact of Power Aggregators on the Congestion Management of Network Lines Considering the Demand Response Program

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Article Info

Article History:
Received: 15 October 2024
Revised 14 December 2024
Accepted 27 December 2024

Keywords:
Demand response,
Electric vehicle,
Demand side management,
Line flow.

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Extended Abstract

Background and Objectives: Power aggregators have different effects on network parameters, including line power. The effect of this equipment can cause congestion of network lines in peak load conditions.
Methods: In this paper, the effect of electric vehicle aggregators on power changes in grid lines is calculated using a method based on market analysis in low- and peak-load conditions. In addition, the demand response program is considered in this paper to reduce lane congestion in peak load conditions. The proposed method is implemented on a standard 24-bus network, and the results are analyzed.
Results: The results state that the effect of each aggregator has a different effect on the grid lines.
Conclusion: By using the proposed method, the network operator can prevent the formation of phenomena such as market power and line congestion.

Introduction

Today, the introduction of renewable energy and electric vehicles (EVs) has had a significant impact on changes in network congestion [1]. So that the lack of proper management of network congestion can cause phenomena such as market power and load unresponsiveness. On the other hand, demand-side management (DSM) is one of the most powerful tools to optimize energy consumption, the results of which include increased reliability, lower costs, fewer outages, and greater customer satisfaction [2]. Demand response (DR) is a type of demand-side management that uses methods such as load shifting and peak cutting [3]. One of the concerns created for subscribers and users of the network is how to properly manage controllable devices in order to participate in consumption management programs on the demand side. With the advancement of technology in the age of communication, the potential of implementing intelligent planning has been realized, but a suitable model that can take into account both the level of satisfaction of subscribers and achieve high flexibility for their participation has not yet been presented. In fact, the effective approach should be in such a way that by applying incentives, it provides the motivation of the subscribers to participate as much as possible in the demand response programs and on the other hand, it can provide conditions that the operator or the aggregator can ensure that the ability to control the consumption of equipment in residential houses is legally possible. Such accurate information can be very effective in the economic distribution of power for the next day. In this regard, the purpose of this paper is to provide a framework for planning the demand response of residential houses by considering the level of customer satisfaction.

Many studies have been presented in the field of demand response with different objective functions. For example, in [4], a new home equipment power management method has been used to plan electrical equipment by considering the current consumption with the aim of minimizing the cost of subscribers. In [5], convex programming has been used to plan the consumption of household equipment and storage systems. The method

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used in this study has been able to reduce the level of consumer dissatisfaction and the cost of electricity consumption. In [6], a method to reduce the cost of energy consumption with the help of intelligent integration of renewable energy and storage systems has been designed and has been used to minimize the ratio of electricity purchases during peak hours. However, in the mentioned studies, the limitations caused by the high volume of electric vehicle management on the distribution networks have not been investigated. In [7], a new method has been used to manage renewable energy from energy storage sources and electric vehicles, which significantly reduces the cost of network users with the help of energy produced by local renewable sources. However, the discharge mode of electric vehicles to minimize the energy costs is not considered in this study.

In [8–9], the authors have used the energy storage unit and electric vehicles on a larger scale, considering the bidirectional power distribution, to establish coordination between the load consumption timing operations of home users. In this study, they have proven that the proposed system is able to significantly reduce the electricity supply costs for large-scale smart homes. The authors have mentioned in [10] that the use of energy management systems in residential houses is a fundamental pillar for the beneficial use of energy produced in power plants and renewable sources. In this regard, a flexible management system is also provided that is able to manage multiple energy carriers in residential houses in an integrated manner.

In [11], energy management systems have been used to control and optimize the amount of energy consumption and help supply the required energy to the equipment. The purpose of this approach is to minimize the cost of operating costs. In [12], photovoltaic systems along with energy storage for commercial customers have been used to manage energy consumption. In addition, in order to provide the error of the difference between the requested energy and the produced amount, a gas microturbine has been used. In [13], an exact composite linear programming method has been proposed that aims to manage consumer satisfaction, equipment power consumption, and renewable resource performance. In fact, it provides optimal planning under dynamic constraints by considering the welfare conditions of subscribers. In addition, a method based on a new planning algorithm for managing household energy consumption costs by considering the uncertainty of household equipment operation and the intermittency of renewable resource production has been presented in [14]. In this study, evaluations have been done to determine the optimal capacity of a production system on the user side, which operates based on random variables such as wind speed and consumption load and reduces the energy consumption costs of subscribers. In [15], the authors have stated that the management systems placed on the common side are of great help in obtaining information on the amount of energy consumption; however, they cannot cause the participation of consumers in peak load reduction planning on a large scale. In this study, continuous monitoring is used to provide reports to users. In [16], the authors stated that in addition to reducing energy consumption and choosing to consume energy off-peak, consumers can be responsive by changing the type of energy consumed. In [17], a review of the literature on demand response and its advantages and disadvantages has been done. The benefits mentioned in this study include balancing the fluctuations of renewable generation, improving economic efficiency, and reducing production capacity.

In [18], the authors have reviewed the demand response literature and identified some of the key barriers to deployment and demand response challenges. In this regard, suggestions about evaluation methods have been presented. In [19], the flexibility of the load response program for the integration of renewable energy sources in Al-Elem has been investigated based on two proposed steps. Reference [20] introduces the tools that electric companies use to encourage their consumers to reprogram their energy consumption patterns. Then, it examines the mathematical models in this field from previous studies and suggests more effective solutions to address this issue. In [21], to reduce costs and greenhouse gas emissions using wind turbines, photovoltaic units have been used in an improved micro-energy grid. In addition, incentive programs for network users to achieve better performance on behalf of consumers are considered in this study. Also, in order to achieve more accurate results, the uncertainty of wind and solar energy has been considered. Reference [22] has proposed a two-level optimization in which consumers who are equipped with their own energy sources can manipulate electricity market prices by implementing a demand response program to meet the needs of electricity, heating, and cooling simultaneously. Reference [23] presents a method for multi-energy optimization in central buildings in the presence of active demand response programs. In [24], incentive and price-based incentive programs are used to encourage microgrids to transact electricity, heating, and cooling carriers. In this study, a two-level optimization method is used for future planning. In [25], a motivation-based model has been used in order to reach a certain level of response on the consumption side, which is based on two-stage planning.

In [26], one of the methods based on demand response based on price encourages consumers to use household appliances during low load hours instead of peak load conditions. Reference [27] used mathematical modelling using demand-side management to optimize microgrid performance. This study has used the load response program to design the microgrid from the customers' point of view. In [28], a simulation method has been used to minimize electricity consumption and cost. In addition, the time-based program is used in the optimization problem in this study. In [29], a new method of pricing based on quality of service is presented so that owners of electric vehicles can cope with travel uncertainties. In this study, different prices offered by electric vehicles have been used. In [30], the level of consumer load in response to the price of electricity is presented by an optimization model. The main goal of this study is to maximize the consumer's profit. Reference [31] describes the structural barriers to the correct implementation of load response and introduces several solutions that will make it perform better in the future.

A general classification of demand response management is reviewed in [32], which breaks down the different parts of demand response management. In [33], mathematical modelling has been developed considering load response, which is based on price elasticity and user profit. As mentioned, many studies have been conducted in the field of demand response with different objectives. On the other hand, the presence of electric vehicles as power generators has attracted the attention of many countries that have been less studied in this field. Accordingly, this paper evaluates responsive load management in the presence of electric vehicles. The proposed method in this paper is based on mathematical modelling that is completely analytical. Among the advantages of the proposed method, the following can be mentioned:

- Calculation of the contribution of each network load to changes in the congestion of network lines in low and peak network load conditions
- Considering different steps of demand response to reduce congestion on congested lines
- Evaluating the behavior of electric vehicles in low and peak load conditions
- There is no need to perform consecutive power flows to calculate the contribution of each load to line flow changes
- High computational speed due to the analytical nature of the problem

The whole paper is divided into five sections. The basic formulation and the formulation of the proposed method are presented in Section 2. Then, the results of the proposed method are analyzed in Section 4. Finally, the conclusion of the paper is made in Section 5.

Problem formulation

In this section, first, the basic formulation of the problem is presented. Then, the proposed formulation related to the impact of electric vehicles on line congestion in peak and low load conditions is presented by considering the demand response program. The objective function of the problem is the cost of generation units, which, according to (1), is a quadratic function.

$$Min\sum_{i=1}^{N_u}(m_i.Pu_i+\frac{1}{2}n_i.Pu_i^2) \tag{1}$$

which Pu_i is the generation power of the unit i, and m_i and n_i are the cost function coefficients of the ith unit. In addition, N_u is the number of generation units. The equality constraints of the problem include equality and inequality constraints. According to (2) and (8), equality constraints include generation and demand constraints and flow passing through network lines.

$$C_u\times P_u-C_L\times P_L=P_B \tag{2}$$

which are defined as follows:

$$P_u=\left(\begin{bmatrix}P_{u1} & \cdots & P_{ui} & \cdots & P_{Nu}\end{bmatrix}_{1\times Nu}\right)^T \tag{3}$$

$$P_L=\left(\begin{bmatrix}P_{L1} & \cdots & P_{Li} & \cdots & P_{NL}\end{bmatrix}_{1\times NL}\right)^T \tag{4}$$

$$P_B=\left(\begin{bmatrix}P_{B1} & \cdots & P_{Bi} & \cdots & P_{NB}\end{bmatrix}_{1\times NB}\right)^T \tag{5}$$

The matrices C_u and C_L, which represent the location of generation units and network lines, are defined as follows:

$$C_u=\begin{bmatrix}0\text{ or }1 & \cdots & 0\text{ or }1\\ \vdots & \ddots & \vdots\\ 0\text{ or }1 & \cdots & 0\text{ or }1\end{bmatrix}_{NB\times Nu} \tag{6}$$

$$C_L=\begin{bmatrix}0\text{ or }1 & \cdots & 0\text{ or }1\\ \vdots & \ddots & \vdots\\ 0\text{ or }1 & \cdots & 0\text{ or }1\end{bmatrix}_{NB\times NL} \tag{7}$$

In which, 0 means the absence of equipment and 1 means the presence of equipment. Another equality constraint related to the flow of the line is presented in (8).

$$P_{Li}-(\theta_a-\theta_b)x_{ab}^{-1}=0 \tag{8}$$

Also, the unequal constraints of the problem, which include the generation power of the units and the power of crossing the lines, must be in their minimum and maximum ranges.

$$P_u^{Min}\le P_u\le P_u^{Max} \tag{9}$$

$$-P_{Li}^{Max}\le P_{Li}\le P_{Li}^{Max} \tag{10}$$

In the next step, using the Lagrange function and the method used in [1], the influencing factors on the power changes of the network lines are defined as follows:

$$dflow = \Psi_{flow} \times dq \tag{11}$$

which $dflow$ is the power change matrix of the line network, and dq is defined as follows:

$$dq_{Nz\times 1} = \left(\begin{bmatrix} da_{mrg} & dP_u^{\min} & dP_u^{\max} & dP_B & dP_{Li}^{\max} \end{bmatrix}_{1\times Nz}\right)^T \tag{12}$$

Which Nz are all factors influencing the power changes of the lines. In addition, the matrix Ψ_{flow} is defined as follows:

$$\Psi_{flow} = \begin{bmatrix} \delta^{mrg} & \delta^{\min} & \delta^{\max} & \delta^{B} & \delta^{\max,\,\mathrm{Li}} \end{bmatrix}_{NL\times Nz} \tag{13}$$

Which δ^B is the network load influence matrix on the power changes of the network lines, which is defined as follows:

$$\delta^B = \left[\delta^B_{i,j}\right]_{NL\times NB} \tag{14}$$

Which $\delta^B_{i,j}$ is the power change of line i by 1 MW for load increase in bus j. As a result, power changes due to load changes on each bus are defined as follows:

$$dflow^{B} = \delta^B \times dP_B \tag{15}$$

In this section, the formulation related to the electric vehicle as a power aggregator in peak load and low load conditions is presented. In addition, uncertainty is used to determine the capacity of the power aggregator, which will be discussed further. As mentioned, uncertainty is used to determine the capacity of electric vehicle aggregators. The uncertainty used includes Nm samples, and the capacity of the aggregators is determined as follows:

$$dq_{EV_i} = \frac{\sum_{j=1}^{Nm} \lambda^i_{fixed} \pm \lambda^i_{rand\,(j)}}{Nm} \tag{16}$$

which λ^i_{fixed} is the fixed capacity for electric vehicle i and $\lambda^i_{rand\,(j)}$ is a random value for uncertainty for electric vehicle i. Finally, dq_{EV_i} is the obtained capacity for the aggregator of electric vehicle i. The behavior of electric vehicles in low-load conditions is similar to network load. Therefore, their impact is calculated through the matrix δ^B mentioned in (14), which is as follows:

$$\delta^{EV}_{low} = \delta^B\left(EV_i\right) = \left[\delta^{EV}_{i,j}\right]_{NL\times NEV} \tag{17}$$

Which δ^{EV}_{low} is the matrix of aggregating coefficients of electric vehicles on line power changes in low load condition. $\delta^{EV}_{i,j}$ is the power change of line i per electric vehicle placed in bus j, and NEV is the number of electric vehicles in the network. As a result, the number of changes in the power of grid lines caused by electric vehicles is defined as follows:

$$dflow^{EV}_{low} = \delta^{EV}_{low} \times dq_{EV} \tag{18}$$

In peak conditions, electric vehicles inject the power stored in them into the grid due to the high price of electricity. In this paper, the amount of power injected by electric vehicles into the network is represented by γ, which can be a number between 0 and 1. Also, since the power is injected into the network, its impact is associated with the network load matrix with a negative sign, which is defined as follows:

$$\delta^{EV}_{peak} = \left(-1\times\gamma\right)\times\,\delta^B\left(EV_i\right) = \left(-1\times\gamma\right)\times\left[\delta^{EV}_{i,j}\right]_{NL\times NEV} \tag{19}$$

Which δ^{EV}_{peak} is the matrix of aggregating coefficients of electric vehicles on line power changes in peak load conditions. Similarly, power changes caused by electric vehicles in high load conditions are as follows:

$$dflow^{EV}_{peak} = \delta^{EV}_{peak} \times dq_{EV} \tag{20}$$

Demand response means the ability of subscribers to transfer load from peak load periods to low load periods to improve the power consumption pattern. In this paper, the modified load model is used for the demand response program [34].

$$\overline{L(t)} = \begin{cases} M & \mathrm{t} \in \Lambda \\ L(t) + C & \mathrm{t} \in \Pi \end{cases} \tag{21}$$

which $\overline{L(t)}$ and $L(t)$ are the modified load at time t and the instantaneous load at low load time ($\mathrm{t} \in \Pi$). In addition, M is the maximum load during peak load, and C is the amount of added load at low load, which is defined as follows [34]:

$$C = \mu \left(\frac{\sum_{t \in \Lambda} (L(t) - M)}{Number\ of\ low\ load\ hours} \right) \quad (22)$$

which μ is the percentage of the load removed in the high load period and added in the low load period. In the following, the results obtained from the proposed method will be presented.

Results and Discussion

In this section, first, the standard 24-bus network information is presented, including network line data and network load in low-load and peak-load conditions. Then, the results of the proposed method are analyzed in low and peak-load conditions. The optimal answer is obtained by quadratic programming in MATLAB software. As shown in Table 1, the information about network lines (location, reactance, and capacity of each line) is as follows:

Table 1: Network line data

Line	From bus	To bus	X	Capacity (MW)
1	1	2	0.01	1.75
2	1	3	0.21	1.75
3	1	5	0.08	1.75
4	2	4	0.13	1.75
5	2	6	0.19	1.75
6	3	9	0.12	1.75
7	24	3	0.08	4
8	9	4	0.10	1.75
9	10	5	0.09	1.75
10	10	6	0.06	1.75
11	7	8	0.06	1.75
12	9	8	0.17	1.75
13	10	8	0.17	1.75
14	11	9	0.08	4
15	12	9	0.08	4
16	11	10	0.08	4
17	12	10	0.08	4
18	13	11	0.05	5
19	14	11	0.04	5
20	13	12	0.05	5
21	23	12	0.10	5
22	23	13	0.09	5
23	16	14	0.06	5
24	16	15	0.02	5
25	21	15	0.05	5
26	21	15	0.05	5
27	15	24	0.05	4.5
28	17	16	0.03	5
29	16	19	0.02	5
30	18	17	0.01	5
31	22	17	0.11	5
32	21	18	0.03	5
33	21	18	0.03	5
34	20	19	0.04	5
35	20	19	0.04	5
36	23	20	0.02	5
37	23	20	0.02	5
38	22	21	0.07	5

Also, network load data is defined in Table 2 for low and peak network conditions:

Table 2: Networl load data in low and peak load conditions

Bus	Low load (MW)	Peak load (MW)
1	0.86	2.16
2	0.77	1.94
3	1.44	3.60
4	0.59	1.48
5	0.56	1.42
6	1.08	2.72
7	1.00	2.50
8	1.36	3.42
9	1.40	3.50
10	1.56	3.90
11	0.00	0.00
12	0.00	0.00
13	2.12	5.30
14	1.55	3.88
15	2.53	6.34
16	0.80	2.00
17	0.00	0.00
18	2.66	6.66
19	1.44	3.62
20	1.02	2.56
21	0.00	0.00
22	0.00	0.00
23	0.00	0.00
24	0.00	0.00

In this paper, four aggregators of EVCS are considered, which are placed in the buses of 3, 9, 16, and 22. The capacity of each aggregator of EVCS is calculated using the average of 500 considered samples, which is shown in Fig. 1. Therefore, the capacity of EVCSs 1 to 4 is equal to 0.502 MW, 0.500 MW, 0.498 MW, and 0.500 MW. In the following, the impact of the EVCS aggregator on peak load conditions is investigated. In peak load conditions, EVCS aggregators act as power generators because the price of electricity is high during these hours. The power of network lines in peak load conditions is shown in Fig. 2. In addition, Fig. 3 shows the state of each line in terms of density, indicating that lines 10, 23, and 28 are congested. As mentioned, electric vehicle accumulators inject their excess power into the grid in peak load conditions. The effect of the aggregator of the electric vehicle 1, which is placed in bus 3, is shown in Fig. 4. It can be clearly seen that the greatest effect of this aggregator is on line 6, with a value of 1.83 MW, which increases the power of this line. In addition, the negative effect of this aggregator on lines 7 and 27 has a value of 1.94 MW. In other words, it reduces the power of these lines.

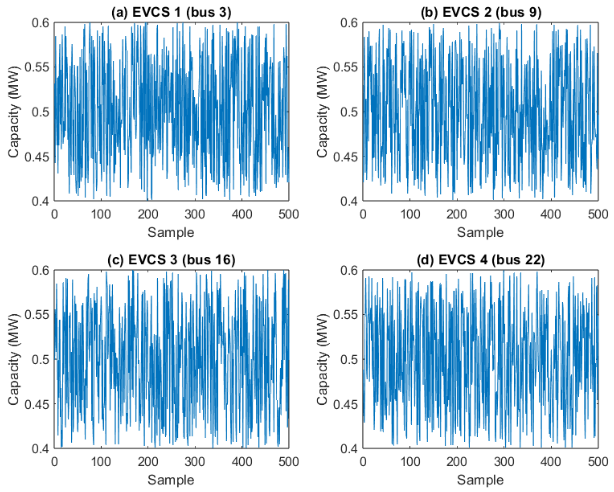

Fig. 1: The capacity of EVCSs in specific buses

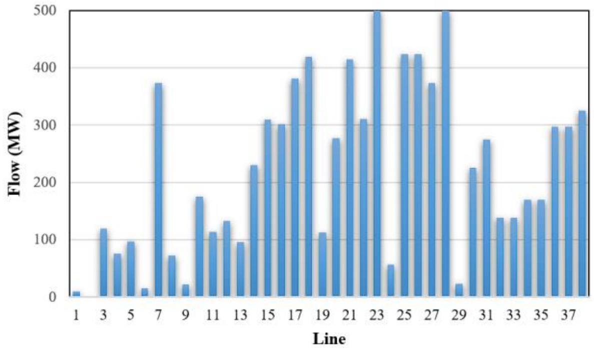

Fig. 2: Power of network lines in peak load conditions

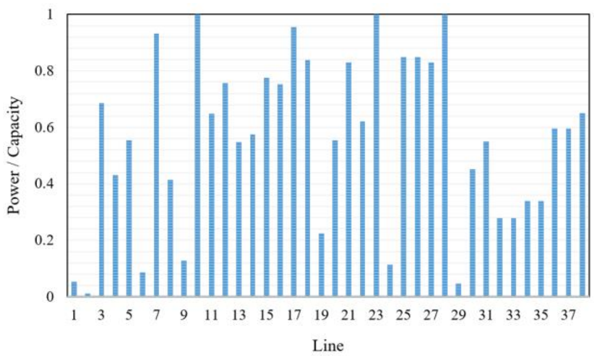

Fig. 3: The condition of network lines in terms of density

In addition, the effect of aggregator 2, which is placed in bus 9, on the power changes of the grid lines is shown in Fig. 5. The greatest and most optimal impact of this aggregator is on lines 12 and 15, with values of 0.87 MW and -1.5 MW, respectively.

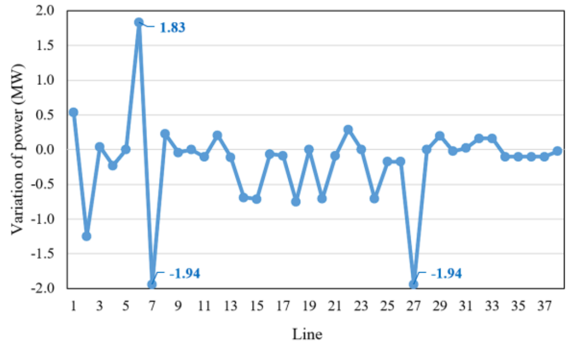

Fig. 4: Changes in the power of network lines caused by the aggregator of EVCS 1 in peak load condition

Similarly, the effect of aggregators 3 and 4, which are placed in buses 16 and 22, respectively, has been shown in Figs. 6 and 7.

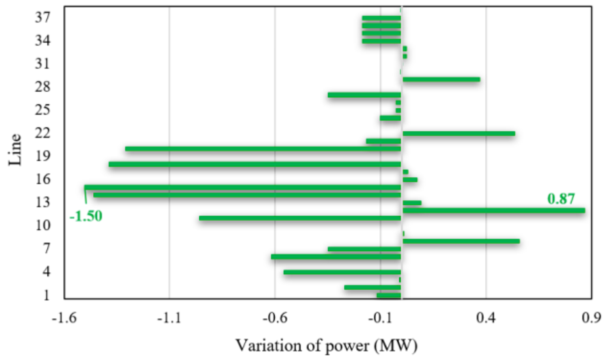

Fig. 5: Changes in the power of network lines caused by the aggregator of EVCS 2 in peak load condition

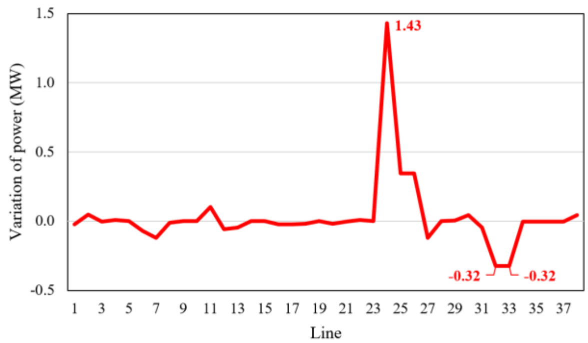

Fig. 6: Changes in the power of network lines caused by the aggregator of EVCS 3 in peak load condition

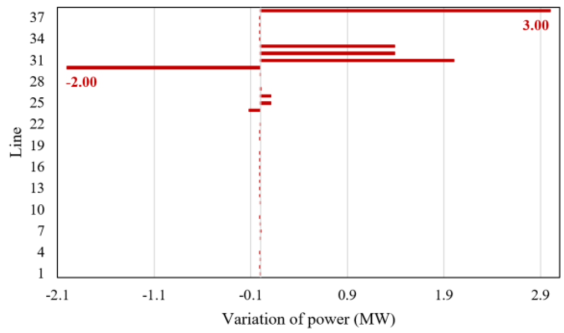

Fig. 7: Changes in the power of network lines caused by the aggregator of EVCS 4 in peak load condition

The greatest impact of the two aggregates is on lines 24 and 38, with values of 1.43 MW and 3.00 MW, respectively. On the other hand, the least impact of these two aggregators is on lines 32, 33, and 30, with values of -0.32 MW and -2.00 MW, respectively.

Table 3 shows the density of network lines for different percentages of load reduction in peak hours and adding to low load hours. For example, the density of line 11 has increased for different μ. In other words, the transfer of load from peak to low load hours has increased the density of line 11. On the other hand, the density of line 12 decreases for different percentages of μ. In other words, the load shift from peak to off-peak hours reduces the density of this line. Therefore, the changes in the density of network lines for different percentages of load transfer from peak load to low load are shown in this table: some lines have decreased density and some lines have increased density.

Table 3: Density of grid lines in peak load condition

Line	μ = 0	μ = 0.05	μ = 0.1	μ = 0.15	μ = 0.2
1	0.053	0.054	0.054	0.055	0.055
2	0.010	0.009	0.008	0.007	0.007
3	0.685	0.685	0.685	0.685	0.685
4	0.431	0.431	0.431	0.430	0.430
5	0.554	0.544	0.544	0.544	0.544
6	0.086	0.088	0.089	0.091	0.090
7	0.933	0.934	0.936	0.937	0.936
8	0.415	0.415	0.415	0.415	0.415
9	0.127	0.127	0.127	0.127	0.127
10	1.000	1.000	1.000	1.000	1.000
11	0.649	0.713	0.776	0.840	0.957
12	0.757	0.725	0.693	0.662	0.603
13	0.549	0.517	0.485	0.453	0.394
14	0.574	0.568	0.561	0.555	0.543
15	0.775	0.768	0.760	0.752	0.738
16	0.753	0.747	0.741	0.734	0.722
17	0.955	0.947	0.939	0.932	0.918
18	0.838	0.881	0.924	0.966	1.000
19	0.244	0.224	0.224	0.224	0.224
20	0.555	0.599	0.644	0.688	0.724
21	0.829	0.836	0.842	0.849	0.855
22	0.621	0.604	0.587	0.570	0.556
23	1.000	1.000	1.000	1.000	1.000
24	0.113	0.075	0.038	0.000	0.000
25	0.848	0.850	0.853	0.855	0.857
26	0.848	0.850	0.853	0.855	0.857
27	0.830	0.831	0.832	0.833	0.832
28	1.000	1.000	1.000	1.000	1.000
29	0.046	0.035	0.025	0.015	0.007
30	0.451	0.513	0.575	0.637	0.699
31	0.549	0.554	0.558	0.562	0.567
32	0.278	0.273	0.268	0.264	0.259
33	0.278	0.273	0.268	0.264	0.259
34	0.339	0.334	0.349	0.355	0.359
35	0.339	0.344	0.349	0.355	0.359
36	0.595	0.600	0.605	0.611	0.615
37	0.595	0.600	0.605	0.611	0.615
38	0.651	0.646	0.642	0.638	0.633

In the following, the impact of electric vehicle aggregators in low-load conditions is investigated. In general, electric vehicle aggregators play the role of network load in low-load conditions. In other words, they try to get power from the network during these hours. Fig. 8 shows the power of network lines in low-load conditions, where only line 28 is dense.

The effect of electric vehicle aggregator 1 on line power changes in low load conditions is shown in Fig. 9. It can be clearly seen that the greatest impact of this equipment is on lines 7 and 27, with a value of 2.33 MW. In addition, the most optimal effect of this equipment is on line 6, with a value of -1.83 MW. On the other hand, it can be determined that the mentioned equipment has no effect on the power changes of lines 11 and 28.

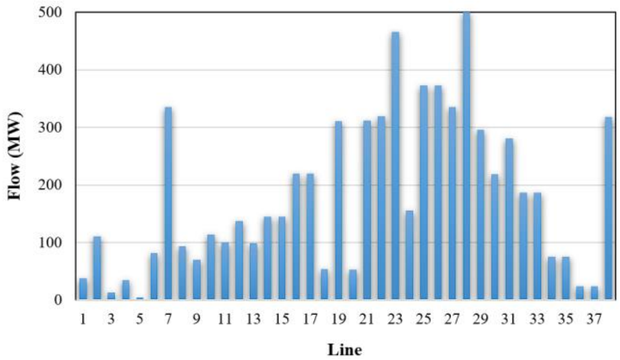

Fig. 8: Power of network lines in low load conditions

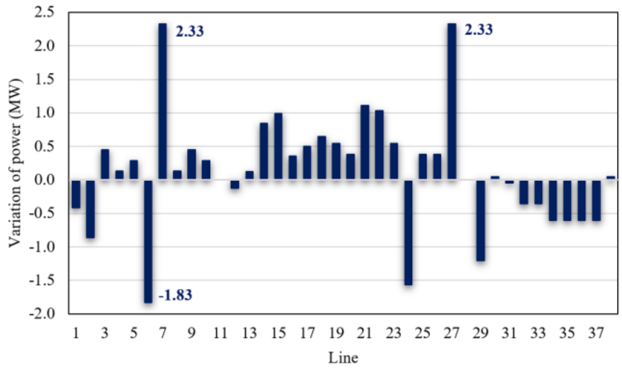

Fig. 9: Changes in the power of network lines caused by the aggregator of EVCS 1 in low load condition

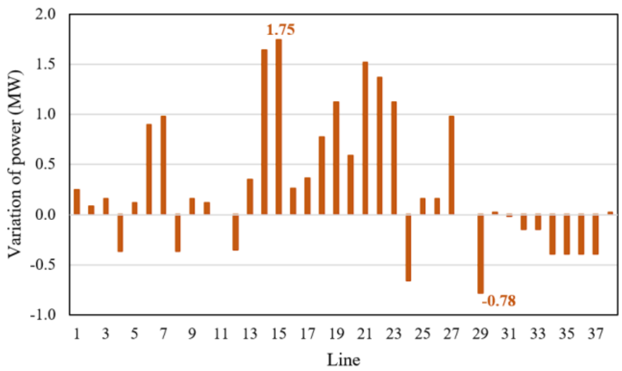

Fig. 10: Changes in the power of network lines caused by the aggregator of EVCS 2 in low load condition

As shown in Fig. 10, electric vehicle aggregator 2 similarly does not affect the power changes of lines 11 and 28. The greatest and most optimal effect of this equipment is on lines 15 and 29, with values of 1.75 MW and -0.78 MW, respectively. Finally, the effect of two electric vehicle aggregators on the changes in grid lines is shown in Fig. 11. Also, the maximum and minimum impact of each piece of equipment can be clearly seen. It can be clearly seen that EVCS 4 has not had any effect on most of the network lines. In low-load conditions, where the amount of load in each bus is presented in Table 3, the effect of load shifting from peak.

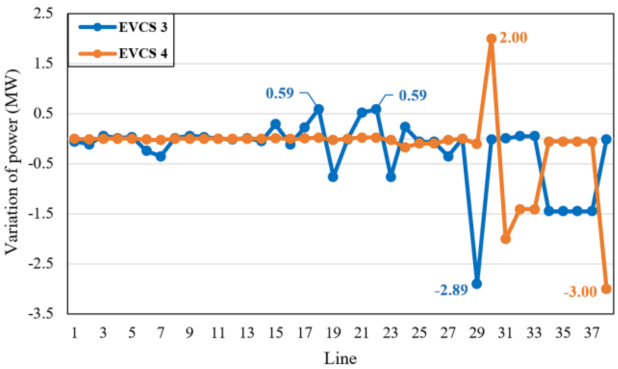

Fig. 11: Changes in the power of network lines caused by the aggregator of EVCS 3 and EVCS4 in low load condition

Table 3: Density of grid lines in low load condition

Line	μ = 0	μ = 0.05	μ = 0.1	μ = 0.15	μ = 0.2
1	0.215	0.217	0.220	0.222	0.225
2	0.631	0.636	0.642	0.647	0.653
3	0.077	0.074	0.071	0.068	0.066
4	0.198	0.198	0.197	0.196	0.195
5	0.029	0.027	0.025	0.024	0.022
6	0.465	0.477	0.488	0.500	0.512
7	0.839	0.847	0.854	0.862	0.869
8	0.537	0.536	0.535	0.534	0.533
9	0.402	0.399	0.396	0.393	0.390
10	0.651	0.649	0.647	0.645	0.643
11	0.571	0.571	0.571	0.571	0.571
12	0.785	0.786	0.786	0.787	0.788
13	0.567	0.567	0.566	0.565	0.564
14	0.362	0.360	0.359	0.357	0.356
15	0.362	0.359	0.355	0.351	0.347
16	0.549	0.549	0.549	0.549	0.549
17	0.549	0.547	0.545	0.542	0.540
18	0.107	0.117	0.126	0.136	0.146
19	0.621	0.631	0.642	0.652	0.663
20	0.106	0.119	0.132	0.145	0.158
21	0.623	0.631	0.638	0.646	0.654
22	0.637	0.639	0.640	0.642	0.643
23	0.931	0.942	0.952	0.963	0.973
24	0.310	0.330	0.349	0.368	0.388
25	0.745	0.744	0.744	0.744	0.744
26	0.745	0.744	0.744	0.744	0.744
27	0.671	0.677	0.683	0.689	0.695
28	1	1	1	1	1
29	0.590	0.599	0.608	0.617	0.626
30	0.437	0.462	0.487	0.511	0.536
31	0.562	0.564	0.566	0.568	0.570
32	0.373	0.372	0.371	0.371	0.370
33	0.373	0.372	0.371	0.371	0.370
34	0.150	0.155	0.159	0.164	0.168
35	0.150	0.155	0.159	0.164	0.168
36	0.048	0.052	0.057	0.061	0.066
37	0.048	0.052	0.057	0.061	0.066
38	0.637	0.635	0.633	0.631	0.629

load hours to low load hours is presented in Table 4. You can clearly see the density changes of grid lines for different μ. For example, the density of lines 1 and 2 increases with the increase in load shift. So that the density of line 1 at μ =0 is equal to 0.215, and $\mu = 0.2$ is equal to 0.225. In other words, the density of line 1 at $\mu = 0$ and $\mu = 2$ increases by 0.215 MW and 0.225 MW, respectively. Therefore, some lines have an increase in density and some lines have a decrease in density for different values of μ, which can be seen in the table. As a result, the contribution of each electric vehicle aggregator to changes in line density can be calculated with the help of the proposed method, which can be a suitable tool for the network operator.

Conclusion

The presence of power aggregators in the network causes a change in the density of the network lines, so that it brings the possibility of densification of the network lines. On the other hand, the demand response program is one of the most effective ways to reduce network line congestion during peak hours. In this paper, using a method based on market analysis, the effect of electric vehicle power aggregators on line power changes in the presence of a demand response program is investigated. The obtained results are analyzed under two conditions: low load and peak load. In addition, uncertainty has been used by EVCSs to bring the problem closer to reality. The proposed method can be a suitable tool for the network operator to predict the future state of the network. In other words, the network operator can avoid phenomena such as congestion of lines and the formation of market power.

Conflict of Interest

The author declares that there is no conflict of interests regarding the publication of this manuscript. In addition, the ethical issues, including plagiarism, informed consent, misconduct, data fabrication and/or falsification, double publication and/or submission, and redundancy have been completely observed by the authors.

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