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RISK MANAGEMENT AND PARTICIPATION OF ELECTRIC VEHICLE CONSIDERING TRANSMISSION LINE CONGESTION IN THE SMART GRIDS FOR DEMAND RESPONSE

Cyrous Beyzaee, Sara Karimi Marvi, Mahdi Zarif

Department of Electrical Engineering, Mashhad Branch, Islamic Azad University, Mashhad, Iran

Abstract. *Demand response (DR) could serve as an effective tool to further balance the electricity demand and supply in smart grids. It is also defined as the changes in normal electricity usage by end-use customers in response to pricing and incentive payments. Electric cars (EVs) are potentially distributed energy sources, which support the grid-to-vehicle (G2V) and vehicle-to-grid (V2G) modes, and their participation in time-based (e.g., time of use) and incentive-based (e.g., regulation services) DR programs helps improve the stability and reduce the potential risks to the grid. Moreover, the smart scheduling of EV charging and discharging activities supports the high penetration of renewable energies with volatile energy generation. This article was focused on DR in the presence of EVs to assess the effects of transmission line congestion on a 33-bit grid. A random model from the standpoint of an independent system operator was used to manage the risk and participation of EVs in the DR of smart grids. The main risk factors were those caused by the uncertainties in renewable energies (e.g., wind and solar), imbalance between demand and renewable energy sources, and transmission line congestion. The effectiveness of the model in a 33-bit grid in response to various settings (e.g., penetration rate of EVs and risk level) was evaluated based on the transmission line congestion and system exploitation costs. According to the results, the use of services such as time-based DR programs was effective in the reduction of the electricity costs for independent system operators and aggregators. In addition, the results demonstrated that the participation of EVs in incentive-based DR programs with the park model was particularly effective in this regard.*

Key words: *Electric Vehicles, Smart Grid, V2G, G2V, GAMS, Loss Function, Demand Response*

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Corresponding author: Cyrous Beyzaee
Department of Electrical Engineering, Mashhad Branch, Islamic Azad University, Mashhad, Iran
E-mail: mahaniranian1@gmail.com

1. INTRODUCTION

Electric vehicle (EV) sales are growing rapidly worldwide [1,2], with the amount exceeding one million. Several factors have been involved in this growing trend in the past few years, including the ability to replace fossil fuel vehicles with EVs, which results in the preservation of natural reservoirs. However, the increased number of EVs leads to increased grid demand. With the growth of domestic, industrial, and commercial demands, the power network must be capable of responding to all types of demands. The current power grids used in most countries are unable to fully respond to the large volume of EVs. In this regard, the simplest solution is to increase transmission lines and various power plants to supply the electricity required by the grid. Nonetheless, this solution requires unjustified large operating and economic costs. As such, the proper management of various parameters such as EVs, wind and solar power plants and new energies, programs to reduce consumption, increased grid sustainability and customer satisfaction, and operational costs of the system is of paramount importance.

In this context, one of the important topics is the transmission line congestion and management of grid demand response (DR) using EVs since the lack of management of EV charging may lead to issues such as increased grid demand, power loss, and voltage fluctuations [3].This article was focused on the management and participation of EVs in smart grid DR considering the impact of transmission line congestion in the form of time-based and incentive-based programs. To obtain our goals, we have first introduced EVs, their types, and DR in this field.

2. OVERVIEW OF EVS AND RENEWABLE ENERGY SOURCES AND DR

2.1. Evs [4-9]

There are different types of EVs, some of which use the electronic grid to supply their required energy, which increases the energy received from the grid, thereby causing more problems for the grid. In general, EVs are able to operate in frequency regulation, voltage regulation, spinning and non-spinning reserves, subsidiary services, and demand profile adjustment [4]. Compared to common vehicles (e.g., fossil fuel cars), EVs have a different propellant. The electric power required for EVs is provided by three main sources, including power plants, generators, and energy savers; however, most EVs are of the third type. In recent years, special attention has been paid to plug-in EVs (PEVs; especially battery EVs and hybrid PEVs) in the industrial and university sectors.

2.1.1. Battery EVs

Battery EVs encompass three parts, including an electronic engine, a battery, and a controller. The electronic motor uses the battery as the driving force. The two-input controller is only able to manage the power provided to the electric motor, which provides the driving force for the vehicle to move backward or forward. Simultaneously, a four-input controller supports the brake as well. Another important part of battery EVs is the power inverter, which is responsible for the conversion of the stored electrical energy in the battery from the DC into the AC mode. This is mainly due to the fact that most EVs have an AC engine, which has a simple, low-cost structure.

2.1.2. Hybrid PEVs

Hybrid EVs are classified into three categories of parallel, series, and two-part hybrids based on their engine type. The first category is recognized as the most common engines of such vehicles. PEVs often have two electronic and internal combustion engines as the propellant, which enables the vehicle to move in the no-charge and full-charge modes. Hybrid PEVs supply their propulsion energy from batteries. When the battery power levels are lower than a certain amount in the no-charge mode, the vehicle changes its status and switches to the use of the internal combustion engine as the propellant. In the full-charge mode, the vehicle uses a combination of electric engine and internal combustion engine for maximum efficiency in propulsion. Simultaneously, the controller controls the battery charge level and maintains it at a certain level.

2.2. Renewable energy sources

The increased awareness of environmental crises and reduction of fossil fuel use are leading to new directions for energy production and consumption. One of these issues is renewable energy sources with eco-friendly features, including the wind energy and solar energy.

2.3. Response demand

The necessity to define new electronic energy sources with quick response ability in the emergency situations of power network is ever-increasing due to the growing load of power networks, especially the increased loads sensitive to the changes in the power supply parameters by the network. Therefore, it is essential to address consumer management issues. Structural changes in the electricity industry have led to the emergence of new paradigms alongside consumer management. DR is one of these paradigms, which encompasses the consumer management methods that lead to changes in the consumption level of costumers caused by the changes in electricity prices in the market. According to the United States Department of Energy, DR is defined as the empowerment of industrial, commercial, and residential users to improve electronic energy consumption, so that appropriate costs could be established and the network exploitation conditions could be improved [10]. In other words, DR could change the form of electronic energy consumption, so that the maximum system demand would reduce and consumptions would be transferred to non-peak hours. The US Energy Regulatory Commission divides DR programs into two main groups of motivation-based and time-based DR [11]. In each classification, the DR programs are divided into several subcategories, which have been discussed in the following section [12]:

Incentive-based DR programs

1) Direct demand control programs
2) Demand reduction/cessation programs
3) Repurchase/demand sales programs
4) Emergency DR programs
5) Market capacity programs
6) Subsidiary service market programs

Time-based DR programs
1) Application-time pricing plans
2) Actual-time pricing plans
3) Critical peak-time pricing plans

3. Problem Statement and Model Presentation

With the increased prevalence of EVs and their use worldwide, there has been growing demand for attention and planning to exploit these vehicles. Owing to their numerous benefits, fuel fossil vehicles are being rapidly replaced by EVs. However, the increased number of EVs has resulted in higher demands in this regard. On the other hand, the electricity network must be able to respond to all types of demands with the ever-increasing growth of housing, industrial, and commercial demands. To this end, the simplest solution is to increase transmission lines and various power plants to supply the required electricity level. Nonetheless, this solution requires substantial operating and economic costs, which may not be economical. Therefore, the proper management of various network parameters such as EVs, wind and solar power plants, and new energies, various programs to reduce consumption, increased network stability, customer satisfaction, and system operating costs is of paramount importance.

One of the key topics in this regard is the discussion of transmission line congestion, grid demand response, and management using EVs. As such, the present study aimed to evaluate the management and participation of EVs in the demand response of smart grids, while considering transmission line congestion and its impact in time-based and motivation-based programs.

3.1. Time-based programs

These programs involve the use of global networks by consumers and grid demands. By pricing electricity at different hours (load peak, mean load, and low load), the consumption peak is divided into non-peak hours and may reduce. Therefore, there would be no transmission line congestion, and electricity purchase level would decrease significantly.

3.2. Motivation-based programs

Focusing on regulatory services and supplying the reserve amount are essential to the states of G2V and V2G, leading to demand-response balance and reduction of global network costs. Moreover, it results in increased profitability for customers and higher use of EVs. In this program, EVs are connected to the grid in the two states of G2V and V2G, experiencing smart discharging in addition to smart charging [13-15].

3.3. Studied system

The system assessed in the present study is illustrated in Figure 1 [16].The independent system operator plays a pivotal role in this system, managing the market by collecting and exporting information among the market members, such as power plants, demand centers, and EV aggregators. The independent system operator aims to reduce the operational costs of the system. However, the balance between supply and demand remains constant at all times. The power system encompasses the energy distribution of various manufacturing units, such as conventional power generators and renewable energy systems (wind and solar power). Considering the limited capacity of electric car batteries, the contribution of each battery separately to the grid is negligible. Previous studies have indicated the inefficiency of planning for small-scale consumer participation in wholesale electricity market [11]. Therefore, it is essential to control the charging and discharging of numerous EVs by an aggregator to participate in tenders and coordinate the charging and discharging activities of EVs. Notably, the aggregator units cover both V2G and G2V models. Vehicle owners announce their battery capacity and traffic route to the aggregator units by considering the additional time and distance and possible parameters for the proper and accurate planning of EVs. On the other hand, the aggregator units inform the independent system operator on the available and anticipated capacity of the state of charge (SOC) in order to participate in the demand level and frequency tuning services.

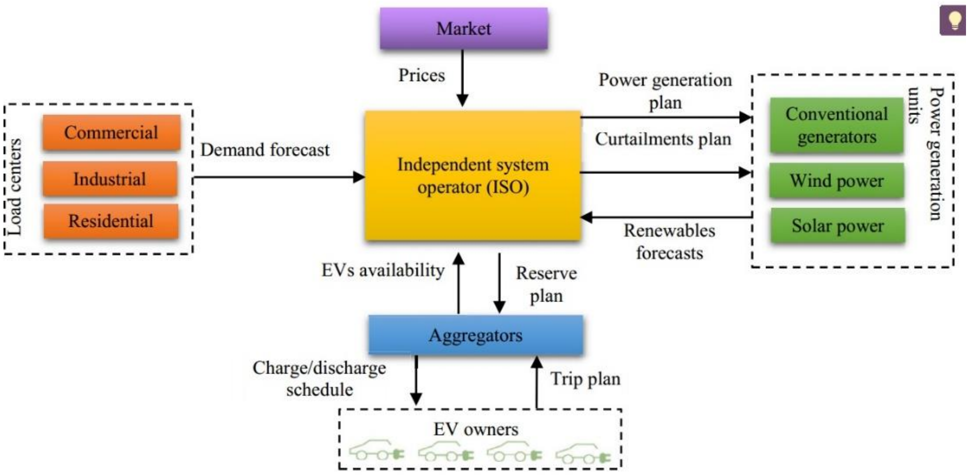

Fig. 1 An Overview of studied system [16]

The aggregators support both the time-based and motivation-based states in demand response programs. In this article, the time of use was selected as the time-based program to supply the demand service provision. The vehicles participating in the program were required with different costs at various times (e.g., load peak or low load) [17-20].

The aggregators often participate in the motivation-based programs of the demand response to supply the required V2G and G2V for regulatory services. These services have two classifications in terms of the costs for the independent system operator, which involve paying the reserving capacity costs and energy costs to the aggregators [21-22].The reserve capacity costs are equal to the maximum capacity supplied by each aggregator during the contract. The energy costs are associated with the costs of energy transfer from the V2G state to the G2V state. In addition, a specific number of EVs is required for the rapid responding to the demand, as well as saving the excess energy or compensating for its shortage. The level of emergency storage must also be set correctly. Moreover, the decision-makings in this regard are mainly focused on the charging and discharging of electric cars, and the plan of producing electricity from various sources often has to be precise. Decisions should be made by considering various risk factors for the possible future scenarios. In this regard, the risk in the mentioned conditions is the possible imbalance between demand and power supplies (supply and demand). In the current research, the model presented for the management of the participation of EVs in demand response programs was based on the DC OPF model.

$$min \sum_{k=1}^{k} C_g^{Gen} P_g + C_k^{ul} Z_k \tag{1}$$

$$\sum_{l=1}^{L} H_{l,k} f_l + P_g + Z_k = \lambda_k \forall k \tag{2}$$

$$f_l = B_l\big(\theta_{\alpha(l)} - \theta_{\beta(l)}\big)\forall l \tag{3}$$

$$-F_l^{max} \leq F_l \leq F_l^{max} \tag{4}$$

$$P_g^{min} \leq P_g \leq P_g^{max} \tag{5}$$

Equations 1-5 show the main formula of OPF, which minimizes the costs associated with various generating units and the current load in terms of the technical limitations of the electricity grid. In addition, Equations 2 and 3 demonstrate the load balance per bus and power flux per line. The heat flux limit and generator capacity are shown in Equations 4 and 5. The OPF model presented above has been corrected for the integration of dynamic issues into our model. In this respect, the main goal was to manage the level of necessary reservation for the V2G and G2V states, as well as the anticipated costs in the future system vision. The modified model was presented for the management of the cooperation of EVs in Equations 5 and 6. The first part of the target function shown in Equation 6 is related to the reservation capacity costs of EVs to conclude the V2G and G2V service contracts.

The second part includes the expected operating costs of the independent system operators for the actual energy payments sent for regulatory services. The next part of the production costs of conventional generators is the costs of the current load and decreased costs of renewable energies. In addition, the energy outage costs are considered in the model because when the surplus energy is generated by renewable sources, ISO should be allocated to others to receive the additional energy [23].

$$\begin{aligned} \sum^{T} \quad & \sum_{t=1}^{} \sum_{a=1}^{A}\left(C_a^{+Agr} X_{a,t}^{V2G} + C_a^{-Agr} X_{a,t}^{G2V}\right) + \sum_{s=1}^{S} P_s\left[\sum_{t=1}^{T}\sum_{a=1}^{A}\left(C_t^{Dis} b_{a,t,s} + C_t^{Dis} d_{a,t,s}^{-}\right)\right] \\ & + \sum_{s=1}^{S} P_s\left[\sum_{t=1}^{T}\sum_{a=1}^{A}\left(C_g^{Gen} P_{g,t,s} + C_k^{ul} Z_{k,t,s} + C_k^{cur} C_{k,t,s}\right)\right] \end{aligned} \tag{6}$$

Equation 7 is similar to Equation 2 in terms of showing the power balance per bus.

The overall energy flux to the bus (generating electricity) through conventional generators, renewable energy sources, and energy discharge from the aggregators is equal to the total overall energy output from the bus (base demand, charged energy of the aggregators, reduction of renewable energies).

$$\sum_{l=1}^{L} H_{l,k} F_{l,t,s} + P_{g,t,s} + Z_{k,t,s} + d_{a,t,s}^{-} + \varphi_{j,t,s} + \psi_{n,t,s} = \lambda_{k,t,s} + d_{a,t,s}^{+} + C_{k,t,s} \forall_{k,t,s} \tag{7}$$

The SOC of each aggregator is presented in Equation 8, which changes based on the charge/discharge status and battery efficiency. Initially, the aggregators must supply the charge of the vehicles that immediately leave the place and need charge. The SOC of the input and output vehicles often affects the overall charge of the aggregators. Equation 9 shows the charge of the remaining battery capacity of the aggregators. The improvement of the charge/discharge pattern affects the remaining battery capacity (RBC) of an EV after arriving at the parking lot. Moreover, the RBC is affected by the SOC of the input and output vehicles.

$$SOC_{a,t,s}^{Agr} = SOC_{a,t-1,s}^{Agr} + \eta_a^{+Agr} d_{a,t,s}^{+} - \frac{1}{\eta_a^{-Agr}} d_{a,t,s}^{-} - SOC_a^{-}\pi_{a,t,s}^{-} + SOC_a^{+}\pi_{a,t,s}^{+} \forall_{a,t,s} \quad (8)$$

$$\begin{aligned} RBC_{a,t,s}^{Agr} &= RBC_{a,t-1,s}^{Agr} - \eta_a^{+Agr} d_{a,t,s}^{+} + \frac{1}{\eta_a^{-Agr}} d_{a,t,s}^{-} \\ &+ (1 - SOC_a^{+})\pi_{a,t,s}^{+} - (1 - SOC_a^{-})\pi_{a,t,s}^{-} \forall_{a,t,s} \end{aligned} \quad (9)$$

The equations 10-12 show a method similar to the equations 3-5. However, the flux constraint was not presented for lines with error ($\delta_{l,t,s} = 1$).

$$-M\delta_{l,t,s} \le F_{l,t,s} - B_l\left(\theta_{\alpha(l),t,s} - \theta_{\beta(l),t,s}\right) \le M\delta_{l,t,s} \forall_{g,t,s} \quad (10)$$

$$-F_l^{max} \le F_{l,t,s} \le F_l^{max} \forall_{l,t,s} \quad (11)$$

$$P_g^{min} \le P_{g,t,s} \le P_g^{max} \forall_{g,t,s} \quad (12)$$

$$R_g^{dn} \le P_{g,t,s} - P_{g,t-1,s} \le R_g^{up} \forall_{g,t,s} \quad (13)$$

Equations 10-12 show a method similar to Equations 3-5. However, the flux constraint was not presented for the lines with error ($\delta_{l,t,s} = 1$).

In addition, Equation 13 guarantees the use of the generator in the allowed range. On the other hand, Equation 14 indicates the risk coefficient required for the operator. Accordingly, the probability of any mismatch between the power source and demand would be less than or equal to the specified error limit (γ). In addition, Equations 15 and 16 guarantee the operation of the aggregator only in one of the V2G or G2V states at any moment.

$$r\left(\sum_{k-1}^{k} Z_{k,t,s} + \sum_{k-1}^{k} C_{k,t,s} \ge 0\right) \le \gamma \qquad \forall_{s,t} \quad (14)$$

$$0 \le d_{a,t,s}^{+} \le Mq_{a,t,s} \qquad \forall_{a,t,s} \quad (15)$$

$$0 \le d_{a,t,s}^{-} \le M\left(1 - q_{a,t,s}\right) \qquad \forall_{a,t,s} \quad (16)$$

Moreover, Equation 17 demonstrates that discharge is limited by the available energy, while Equation 18 guarantees that the level of charge does not exceed the empty capacity available to the accumulators.

$$\frac{1}{\eta_a^{-Agr}} d_{a,t,s}^{-} \le SOC_{a,t-1,s}^{Agr} - SOC_a^{Des}\pi_{a,t,s}^{-} + SOC_a^{+}\pi_{a,t,s}^{+} \qquad \forall_{a,t,s} \quad (17)$$

$$\eta_a^{+Agr} d_{a,t,s}^{+} \le RBC_{a,t-1,s}^{Agr} + (1 - SOC_a^{+})\pi_{a,t,s}^{+} - (1 - SOC_a^{-})\pi_{a,t,s}^{-} \qquad \forall_{a,t,s} \quad (18)$$

Nonetheless, Equations 19 and 22 are boundary constraints. The non-provided load and decreased energy are limited by the actual load and renewable energy available in Equations 19 and 20. The required storage was determined in the aggregators' contract and limited to their capacities to support the V2G and G2V services, while constraint 21 shows the limit of this capacity in the G2V state. Similarly, the discharge energy of the aggregators is limited by the maximum storage defined for the V2G state in their contracts.

$$0 \leq Z_{k,t,s} \leq \lambda_{k,t,s} \quad \forall_{k,t,s} \tag{19}$$

$$0 \leq C_{k,t,s} \leq \varphi_{j,t,s} + \psi_{n,t,s} \quad \forall_{k,t,s} \tag{20}$$

$$0 \leq b_{a,t,s} \leq X_{a,t}^{G2V} \quad \forall_{a,t,s} \tag{21}$$

$$0 \leq d_{a,t,s}^{-} \leq X_{a,t}^{V2G} \quad \forall_{a,t,s} \tag{22}$$

Equation 23 shows the G2V reservation storage. Moreover, the maximum period guarantees the level of G2V reservation required when the generated energy is higher than the system's demand. In such case, EVs are charged, and the G2V reservation level is estimated based on their participation in the use of the surplus energy. Equation 24 shows that the G2V service provided by each aggregator cannot exceed its charge amount, and the range of changes in the variables is shown in Equation 25.

$$\sum_{a=1}^{A} b_{a,t,s} = min\left(\sum_{a=l}^{A} d_{a,t,s}^{+}, max\left(0, \sum_{j=1}^{J} \varphi_{j,t,s} + \sum_{n=1}^{N} \psi_{n,t,s} - \sum_{k=1}^{K} \lambda_{k,t,s}\right)\right) \quad \forall_{a,t,s} \tag{23}$$

$$b_{a,t,s} \leq d_{a,t,s}^{+} \quad \forall_{t,s,a} \tag{24}$$

$$X_{a,t}^{G2V} \geq 0\,,\; X_{a,t}^{V2G} \geq 0 \quad \forall_{a,t} \tag{25}$$

The aforementioned model is a nonlinear complex number programming problem, which could be converted into a linear complex number programming problem. To establish linearity, Equation 14 is replaced by Equations 26 and 27. Moreover, the $W_{s,t}$ binary variable is equal to one if there is incompatibility between the energy sources and existing demand; otherwise, it would be zero. In order to make Equation 23 linear, we used Equation 28 through Equation 31 to cover all the possible cases.

$$\textstyle\sum_{k=1}^{K} Z_{k,t,s} + \sum_{k=1}^{K} C_{k,t,s} \leq MW_{t,s} \quad \forall_{t,s} \tag{26}$$

$$\textstyle\sum_{s=1}^{S} P_s W_{t,s} \leq r \quad \forall_{t,s} \tag{27}$$

$$-M\left(W'_{t,s}\right) \leq \sum_{j=1}^{J} \varphi_{j,t,s} + \sum_{n=1}^{N} \psi_{n,t,s} - \sum_{k=1}^{K} \lambda_{k,t,s} \leq M\left(1 - W'_{t,s}\right) \quad \forall_{a,t} \tag{28}$$

$$\sum_{j=1}^{J} \varphi_{j,t,s} + \sum_{n=1}^{N} \psi_{n,t,s} - \sum_{k=1}^{K} \lambda_{k,t,s} - \sum_{a=l}^{A} d_{a,t,s}^{+} \leq M\left(1 - W''_{t,s}\right) \qquad \forall_{a,t} \tag{29}$$

$$\sum_{a=1}^{A} b_{a,t,s} \geq \left(\sum_{j=1}^{J} \varphi_{j,t,s} + \sum_{n=1}^{N} \psi_{n,t,s} - \sum_{k=1}^{K} \lambda_{k,t,s} \right) - M\left(1 - W''_{t,s}\right) - MW'_{t,s} \quad \forall_{t,s} \tag{30}$$

$$\sum_{a=1}^{A} b_{a,t,s} \geq \sum_{a=1}^{A} d_{a,t,s}^{+} - MW''_{t,s} - MW'_{t,s} \qquad \forall_{t,s} \tag{31}$$

4. Model Implementation and Simulation

In order to evaluate the proposed models, we applied a one-day program on the standard 33 bus grid as the case study, the characteristics of which are presented in Table 1, along with the base load. The maximum generating capacity was 700 kw, and the minimum production value for the conventional generators was not set. The transmission capacity of each 2 MW line with equal susceptance risk was estimated at 10 p.u. The charging of EVs imposes an additional load to the system, which does not include the base load.

The Parking pattern in Figure 2 was considered for the evaluation of the number of the EV inputs and outputs each day. Each parking region had the maximum capacity of 200 vehicles and was managed by an aggregator. Therefore, it was assumed that each EV has a battery with a 24 kwh capacity and 99% charge/discharge efficiency. In addition, it is expected that 35% of the parked vehicles are EVs. In general, EVs enter the parking with 30% charge and prefer to leave the parking with 90% battery charge. Figure 3 shows the generated energy by the wind and solar power plants as selected based on the data of California ISO wind and solar power plants [24].

The cost related to renewable energy decreased, and the reduced load was assumed as 1.5 and 5$/kw, respectively as shown in Equation 23. Furthermore, the cost related to the generation of emergency electricity by a conventional generator was presented as 0.20 $/kwh. The aggregators cost 0.02 $/kwh for the available capacity to provide the V2G and G2V services. The aggregators could benefit from 100% discount if they charge when there is the need for energy reduction. In addition, the independent system operator deals with the aggregators, high costs of regulation services, and other services. However, the different services had various costs, which mostly depend on the electricity market cost. For instance, 0.01 $/kwh was considered as the base cost of electricity.

Table 1 Characteristics of a standard 33 bus grid

Br.No	Rc.Nd	Sn.Nd	r(ohm)	x(ohm)	PL(KW)
1	0	1	0.0922	0.47	100
2	1	2	0.493	0.2511	90
3	2	3	0.366	0.1864	120
4	3	4	0.3811	0.1941	60
5	4	5	0.819	0.707	60
6	5	6	0.1872	0.6188	200
7	6	7	0.7114	0.2351	200
8	7	8	1.03	0.74	60
9	8	9	1.044	0.74	60
10	9	10	0.1966	0.065	45
11	10	11	0.3744	0.1238	60
12	11	12	1.468	1.155	60
13	12	13	0.5416	0.7129	120
14	13	14	0.591	0.526	60
15	14	15	0.7463	0.545	60
16	15	16	1.289	1.721	60
17	16	17	0.732	0.574	90
18	1	18	0.164	0.1565	90
19	18	19	1.5042	1.3554	90
20	19	20	0.4095	0.4784	90
21	20	21	0.7089	0.9373	90
22	2	22	0.4512	0.3083	90
23	22	23	0.898	0.7091	420
24	23	24	0.896	0.7011	420
25	5	25	0.203	0.1034	60
26	25	26	0.2842	0.1447	60
27	26	27	1.059	0.9337	60
28	27	28	0.8042	0.7006	120
29	28	29	0.5075	0.2585	200
30	29	30	0.9744	0.963	150
31	30	31	0.3105	0.3619	210
32	31	32	0.341	0.5302	60

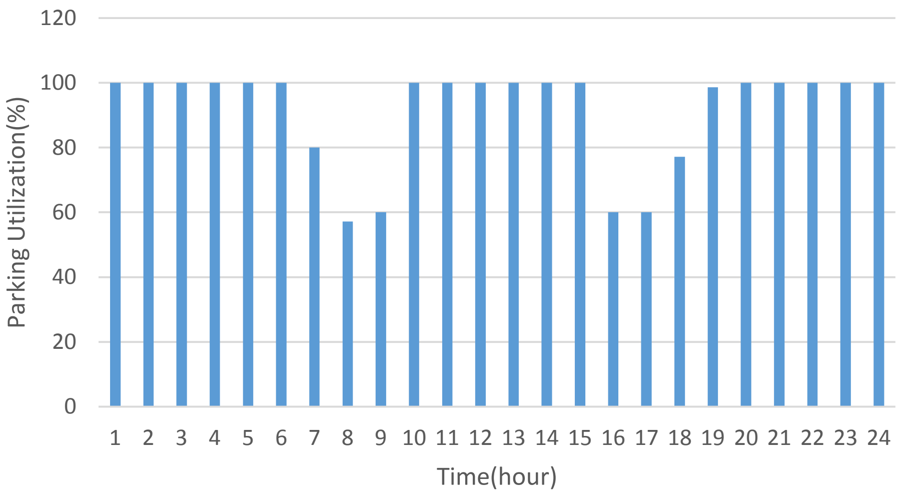

Fig. 2 Parking pattern

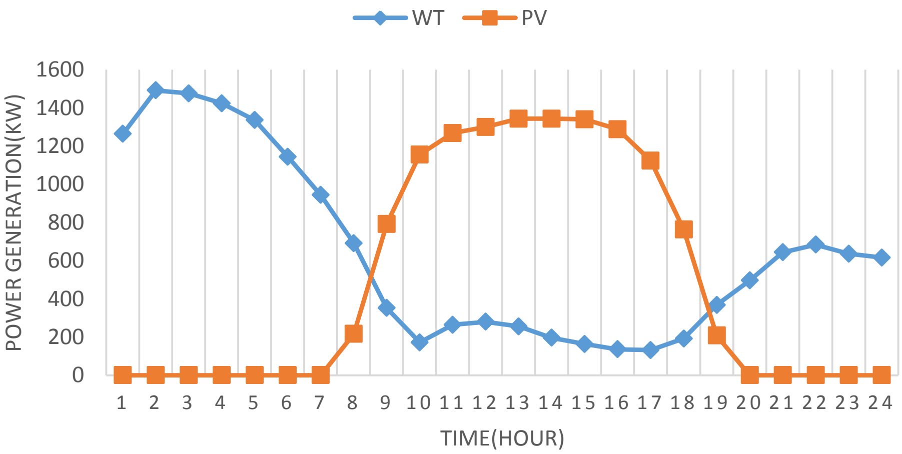

Fig. 3 Pattern of electricity generation by wind and solar sources

This model was developed in MATLAB software and solved by the CPLEX solver in the definitive and randomized forms. It is notable that the definitive cases were considered as the base case, and no risk range was considered for the definitive cases. The model was solved after adjusting the random parameters for their expected values. The results regarding the load levels in the definitive cases are shown in Figure 4, where the collaboration of EVs was observed to be effective in correcting the available load and using renewable energies, while transferring the load charge to off-peak periods. Figure 5 illustrates the results on the G2V and V2G services in the definitive cases. In this regard, EVs provided the G2V reserve at hours by generating more renewable energy and insufficient base load. In addition, the EVs were discharged to provide V2G services at the load peak. Conventional generators are applied to generate the necessary electricity in periods when the sum of renewable energies and emitted energy by EVs is insufficient to reach the base load.

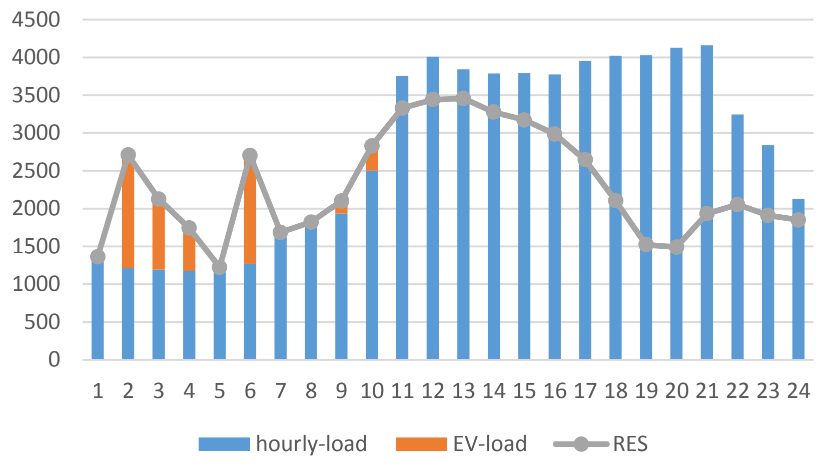

Fig. 4 Results of EV participation in base state

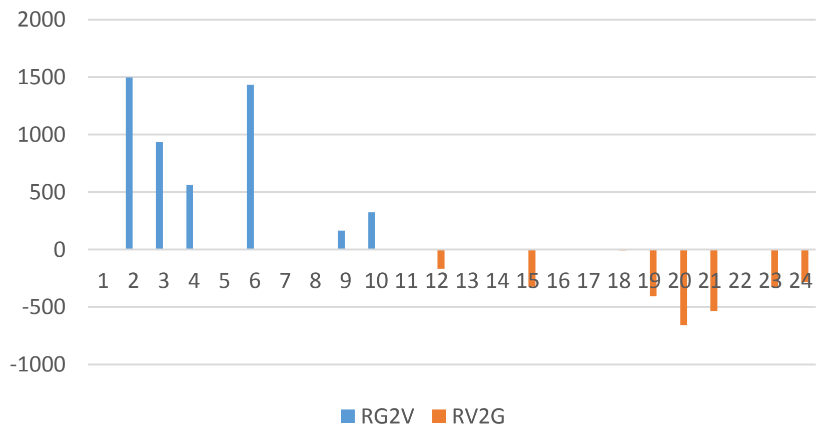

Fig. 5 Results of EV participation to provide reservation services in base state

The capacity of the lines also reduced to observe the effect of transmission line congestion on the cost function in the definitive form. The maximum capacity of transmission lines was 2 MW, and decreased congestion constraint to 1 MW led to the congestion of the lines. As a result, the cost of system operation increased. Figure 6 illustrates the results of decreased transmission line congestion and the effects on the V2G and G2V states. As is observed, the reservation amount decreased in the G2V state with the transmission line congestion. In contrast, the reservation amount increased in the V2G state.

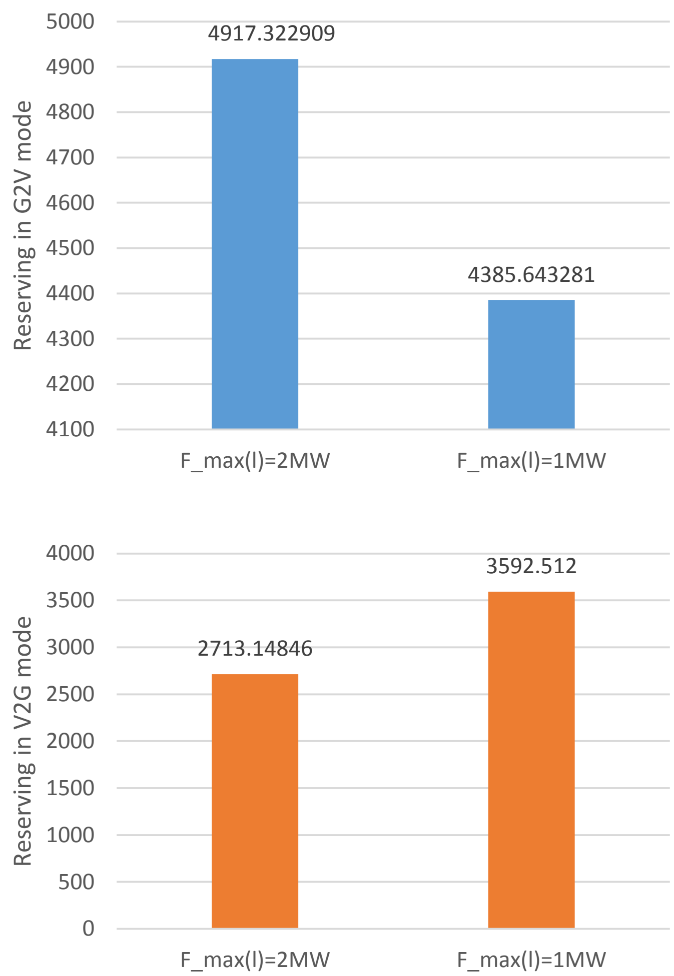

Fig. 6 Effect of transmission line congestion on reservation plans in base state

In general, the reservation level in the G2V and V2G states increased, which in turn led to the increased system operating costs.

4.1. Charging method

This section illustrates the effects of charging the EVs on the operating costs of the power systems. The definitive base model was run with three different charging models and policies. In the first policy, it was assumed that the EVs do not participate in recharge programs and are charged once when they arrive in the parking lot. The second policy showed that the EVs participated in the time-based program of the demand response, which led to the planning of EV charging by the aggregators to reduce the electricity costs and eliminate the load peak. When the aggregators attended the time-based programs of the demand response, the independent system operator only responded to the charging patterns by minimizing its operational costs. Table 2 shows the time spent to manage consumer recharge. The total charging cost of the aggregators participating in the time of use program was calculated using the $\sum_{t=1}^{T}\sum_{a=1}^{A} C_t^{ch} d_{a,t,s}^{+}$ equation.

Table 2 Hourly electricity cost

Hour	Price($)	Hour	Price($)2
1	0.05	13	0.19
2	0.05	14	0.19
3	0.05	15	0.19
4	0.05	16	0.12
5	0.05	17	0.12
6	0.05	18	0.12
7	0.05	19	0.19
8	0.12	20	0.19
9	0.12	21	0.19
10	0.12	22	0.12
11	0.19	23	0.12
12	0.19	24	0.05

In the third policy, the participation of the EVs in the motivation-based program of the demand response was assumed, and the vehicles were motivated to participate in the G2V and V2G states. The overall energy cost of the aggregators in this policy was estimated using the equation below:

$$\sum_{t=1}^{T}\sum_{a=1}^{A}\left(C_t^{ch} d_{a,t,s}^{+} - C_t^{Reg} b_{a,t,s} - C_t^{Dch} d_{a,t,s}^{-} - C_a^{+Agr} x_{a,t}^{V2G} - C_a^{-Agr} x_{a,t}^{G2V}\right) \tag{32}$$

In the equation above, the negative values indicated that not only the aggregators did not pay the costs, but they also inspire revenue generation in most cases. The results of the charging strategy are presented in Table 3.

Table 3 Results of three charging policies of EVs

DR charging policy	ISO reserve cost ($)	ISO operation cost ($)	Aggregator's energy payment ($)	Generation (KWh)
No participation	0	44500.572	261.791	15812
time-based	0	37312.752	116.64	14756
incentive-based	417.89	25804.761	-179.741	13590

The conventional power generation and charging patterns of the three policies are shown in figures 7 and 8. Participation in the demand response programs decreased the costs of the aggregators and independent system operator. Compared to the time-based program, the motivation-based program provided more saving in the costs of the independent system operator, which was mainly due to the fact that the use of EVs for the management of the V2G and G2V states could reduce the costs related to the lost load and energy reduction. Participation in the motivation-based programs is often associated with positive income generation for the aggregators.

As is depicted in Figure 7, unplanned charging forced the conventional power systems to generate more power during the peak times when the system experienced higher load. Motivational programs often cover the need for routine energy generation by entirely using renewable sources. The main goal of demand response programs is to decrease the load peak. According to the obtained results, participation in the time-based and motivation-based programs led to 48% and 51% decrease in the load peak, respectively. As is shown in Figure 8, the participation of the aggregators in the demand response programs created the motivation for the lack of charging at the peak hours, thereby increasing the desire to charge at the non-peak hours.

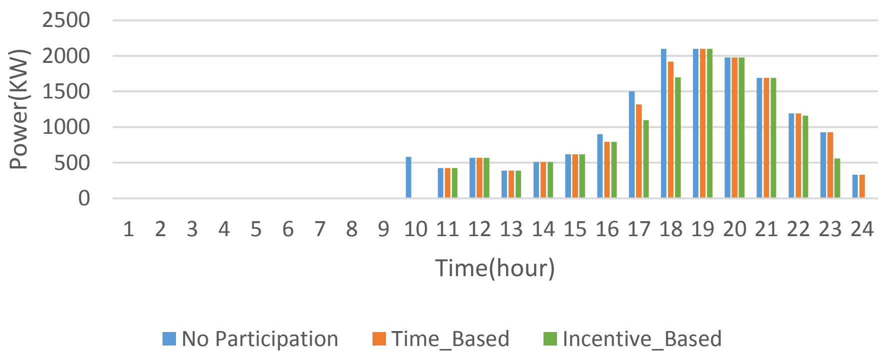

Fig. 7 Conventional power plant production rates in three different charging policies

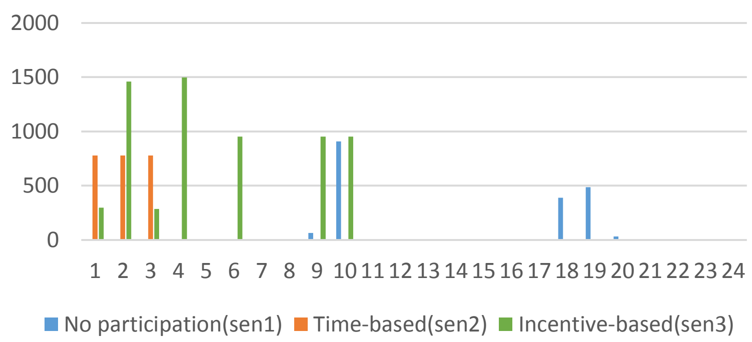

Fig. 8 Charging activity of EVs in three different charging policies

Figure 9 shows the effect of transmission line congestion on the production of conventional power plants in the three charging policies. According to the results, the energy produced by conventional power plants significantly reduced in case of congestion in the transmission lines. Considering that conventional power plants are used to supply part of the system load that is not responsive to renewable energies and electric vehicles, the network cannot supply that part of the system load.

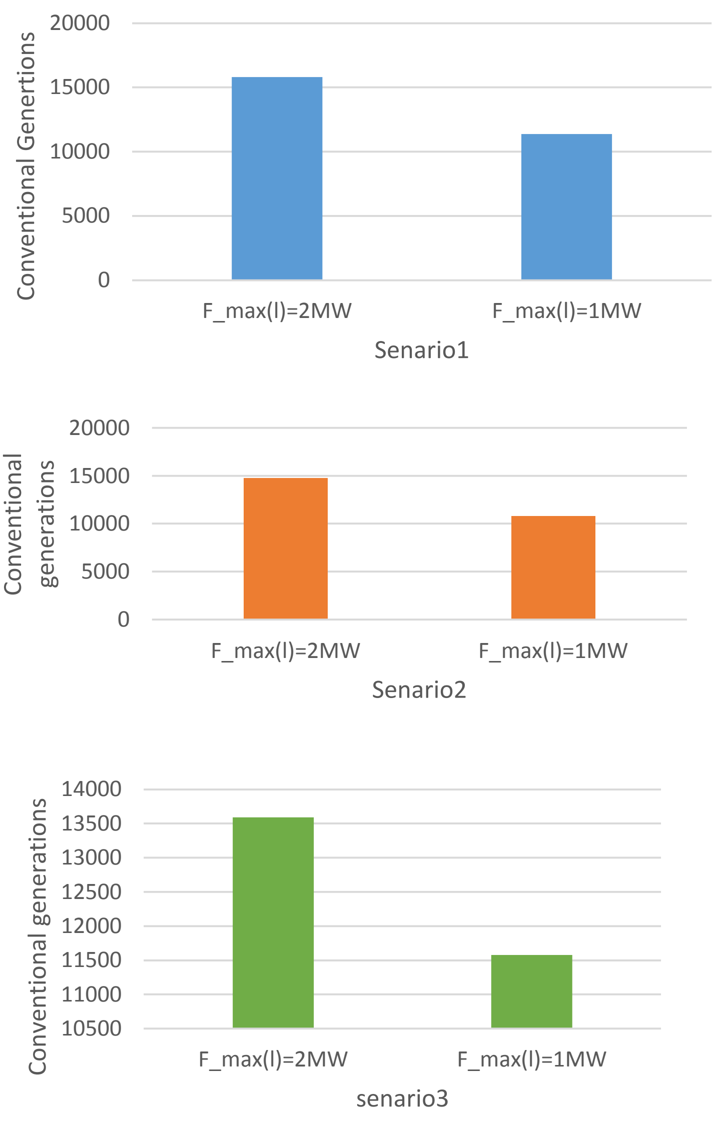

Fig. 9 Effect of transmission line congestion on production of conventional power plants

According to the simulation results, the costs of the independent system operator increased with the decreased transmission line congestion. Figure 10 depicts the results in the three charging policies.

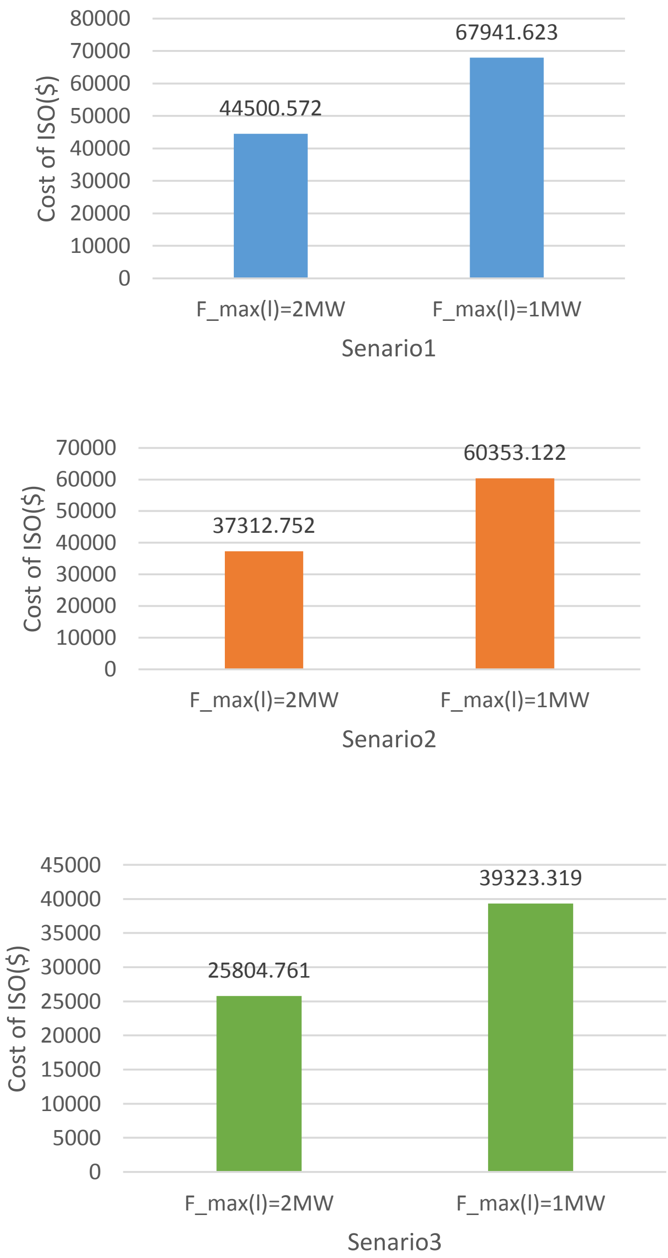

Fig. 10 Effect of transmission line congestion on costs of independent system operator

4.2. Risk Perspective and Random Solutions

In this section, the model is solved in the random form by the predefined risk level of 0.01, which indicated that the possibility of mismatch between the load and source must be less than 1%. Therefore, it was assumed that the load, renewable energy production, behavior of the EV owners, SOC input and output of the aggregators, and line errors were uncertain. To reduce the computational time of the random model, the reduction scenario presented in was used to construct a tree scenario with 10 scenarios [25-26]. In the random model, a higher reserve level was required compared to the definitive status due to the uncertainty and risk level parameters. The random model was also solved for various risk thresholds, including 0.01, 0.1, and 1. As can be seen in Figure 11, the higher risk threshold tolerated the higher probability of mismatch between the source and load, thereby requiring less storage.

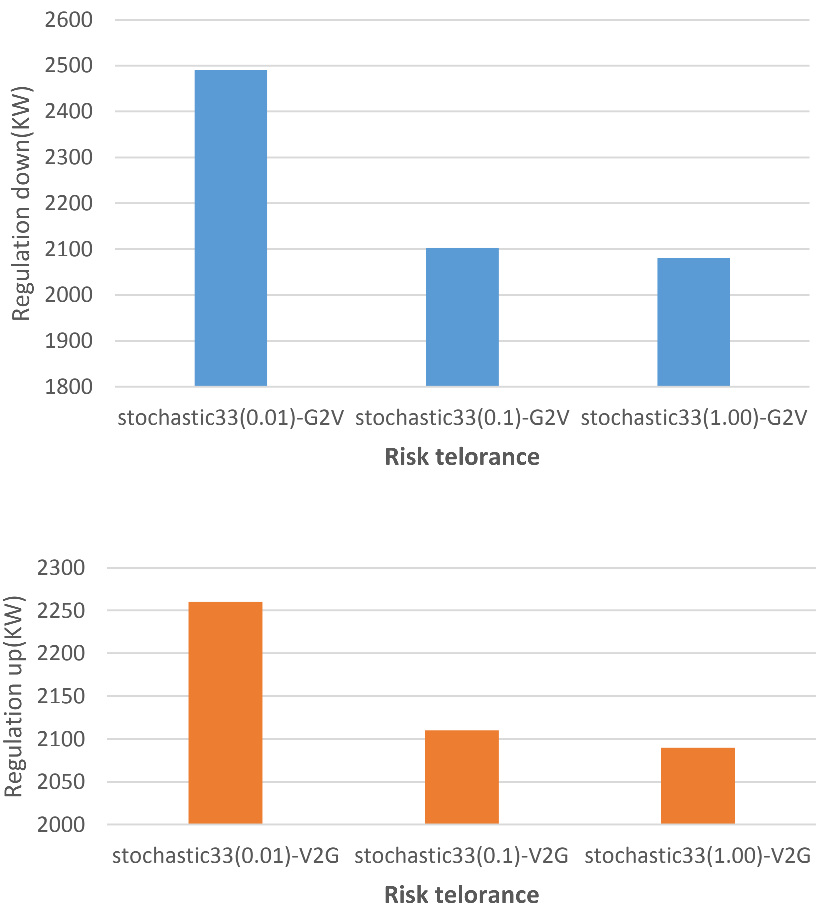

Fig. 11 Effect of imbalance between energy source and demand on reservation programs with various risk factors

Similar to the definitive form, the reservation level increased in the V2G and G2V states by applying line congestion in the random form, which led to the increased cost of system operation. However, the amount was lower compared to the definitive form, which was due to the presence of a risk coefficient and possible disproportion between the load and energy source. The results for 1% risk coefficient are shown in Figure 12.

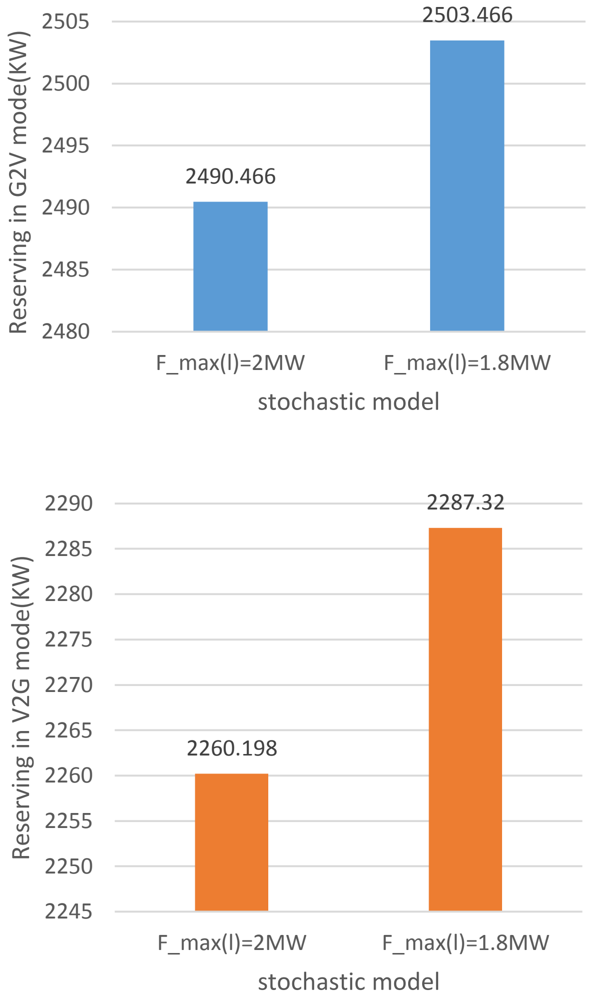

Fig. 12 Effect of transmission line congestion on reservation level of demand respond programs in random form

5. CONCLUSION

In the present study, we applied a new EV participation plan in demand response programs and their timing in a smart grid. In addition, we evaluated the effects of transmission line congestion on the cost of system operation and level of reservation in the definitive and random forms. The applied system was a standard 33-bus system exposed to the possible risk of various load levels due to the uncertainty of EVs, production of renewable energies, transmission line congestion, and behavior of the EV owners in a group manner. We also assessed the participation of EVs in demand response programs in time-based and motivation-based areas, observing that the participation could be extensively effective in the response to the load of the smart grid, thereby providing considerable load and reducing the load peak, which led to the reduction of the operational costs of the system, aggregators, and EV owners, as well as monetization in some cases. The random model enables users to determine the level of risk and costs and their profits considering the available factors. The model evaluated in this thesis could be used to improve the storage levels required by an independent system operator by considering the profits of the aggregators. The independent system operator could reduce operational costs by improving the conventional production schedule and renewable energies, as well as the participation of EVs. Moreover, the aggregators attempted to reduce the electricity costs by optimizing the charge/discharge schedule of EVs in order to receive the maximum discount and revenue from participation in the demand response. The definitive and random cases were assessed to demonstrate the effects of parameters such as charging policy, level of risk, penetration of renewable energies, and residential load pattern. According to the results, services such as time-based programs affected the reduction of electricity costs for the independent system operator and aggregators. In addition, the participation of EVs in the motivation-based programs by the park model had a significant impact in this regard.

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