Examination of EV-Grid Integration Using Real Driving and Transformer Loading Data

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Abstract

The growing environmental concerns and the increase in oil prices will lead to the proliferation of electric vehicles (EVs) in the near future. The increase in the number of EVs, while providing green and inexpensive solutions to transportation needs, may cause constraints on the operation of the utility grid that should be investigated. In this paper, the real user driving information is collected from individual data tracking devices of passenger vehicle owners instead of assuming randomly distributed trip characteristics. The collected trip data are first analyzed to generate a statistical model of the trip characteristics in terms of home arrival times and state of charge (SOC) levels. The resulting model is then used to simulate and analyze the impact of EV integration in a real grid with different EV penetration levels. For this, real distribution transformer data provided by Başkent Electric Distribution Co. is used. The proposed method produces more realistic results in comparison to the studies assuming random scenarios.

1. Introduction

The growing environmental concerns and the increase in oil prices will lead to a significant replacement of traditional vehicles with the electric vehicles (EVs) in the near future. Worldwide annual sales of EVs are expected to increase from 2.7 million in 2014 to 6.4 million in 2023 [1]. The ratio of the EV penetration to that of traditional vehicles is also expected to be more in the developed countries. In [2], it is estimated that 25% of all automobile sales in the U.S. will be EVs in 2030. In Canada, more than 500.000 EVs are expected to be on the road by 2018 [3]. In this paper, the term EV is used to include battery electric vehicles and plug-in hybrid electric vehicles. It stands for all electric-drive vehicles that can be connected to the utility grid. So, the term EV is used instead of plug-in electric vehicle (PEV) for brevity.

While providing green and inexpensive solutions to transportation needs, increasing number of EVs may cause constraints on the operation of the grid. Since a large amount of electrical energy is consumed during the charging of EVs, this demand can lead to extra and undesirable peaks in the electric energy consumption. It is claimed in [4] that the electrical energy consumed to charge the EVs will be 5% of the total consumption in Belgium by 2030. With increasing EV adoption and new policies result in grid integration issues in countries such as Malaysia and Thailand [5, 6]. Thus, it is important to investigate the effects of integrating a large number of EVs into the grid. In order to ensure supply reliability in Turkey also, distribution companies (DisCos) are continuously revising their investment plans depending on population growth, general trends in the electricity consumption, and new emerging markets. EV-grid integration directly impacts distribution grid management and new infrastructure investment planning.

In order to analyze the impact of the EV integration into the utility grid, one should determine a) the user driving patterns specific to the location analyzed, b) the EV types that are being used, and c) the electrical vehicle supply equipment (EVSE) ratings used for charging vehicles, and d) the start of daily vehicle battery charging times (home arrival time of each user). User driving patterns help to understand the daily traveled distance by the average vehicle owner. The EV types that are analyzed present the information regarding the size of the traction battery (kWh), the rating of the on-board charger (kW), and the energy consumed per km for each analyzed vehicle (kWh) to estimate the state of charge (SOC) during vehicle re-connection to the utility grid.

In the literature, papers investigate the EV-grid integration and analyze the problems and opportunities resulting from modeling the EV user data [7-13]. Alam *et al.* suggests that the grid can be supported during peak load periods by discharging the EVs depending on their SOC values and the traveling range requirements [7]. They assume a single type of EV (Nissan Leaf) for the case studies. The EVs are assumed to arrive home according to a Gaussian distribution with a mean arrival time of 19:00 with SOC levels selected randomly between 60% and 80% according to a uniform distribution. Clement *et al.* introduces a coordinated EV charging technique to minimize the power losses and voltage deviations in a grid [8]. Each EV is assumed to have a battery capacity of 11 kWh and the charger has a rated power of 4 kW. A 24-hour distribution transformer loading profile is randomly selected. Depending on the EV penetration level, four different scenarios are considered; (i) no EVs, (ii) 10%, (iii) 20%, and (iv) 30% EV penetration. The EVs are randomly located throughout the grid. Each vehicle starts charging at a random time step within predefined time intervals, i.e., 10:00-16:00, 18:00-21:00, 21:00-06:00. It is also assumed that there is only one vehicle per household or office. In [9], the impact of EVs on the distribution network is investigated by considering the driving patterns, charging characteristics, charge timing, and vehicle penetration level. It is assumed that the average mileage made by an EV is roughly 26 miles per day and the EVs arrive home within different and specific time intervals. Charging characteristics and charge timing is determined due to two types of approaches: uncontrolled charging and smart charging. They use different vehicle penetration levels based on the studies carried out in different countries. More similar approaches can be found in [10-13].

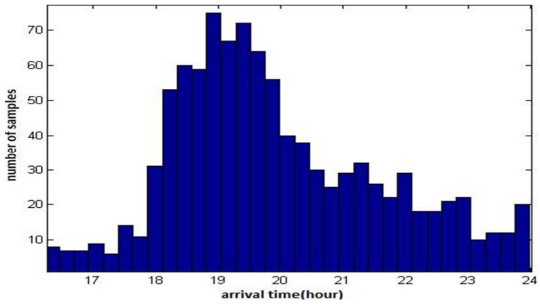

Fig. 1. Histogram of the collected home arrival time data

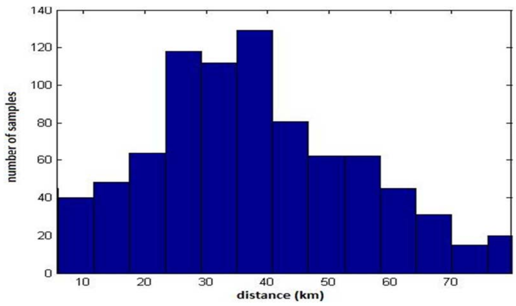

Fig. 2. Histogram of the collected daily trip distance data

In this paper, instead of assuming randomly distributed trip characteristics, the real user driving information is collected from individual data tracking devices of passenger vehicle owners. The collected trip data are first analyzed to generate a statistical model of the trip characteristics in terms of home arrival times and SOC levels. The SOC level of each vehicle before being connected to the grid is calculated based on the total daily distance covered by that vehicle. The resulting model is then used to simulate and analyze different EV-grid integration scenarios. In addition to real trip data, real field information of the utility grid is used in the analyses to assess the impact of the EV integration on distribution transformer loading. Thus, the proposed method produces more realistic results in comparison to the studies assuming random scenarios. To the best of our knowledge, this study is the first one examining real distribution transformer loading integrated with real EV user profiles in Turkey.

In Section 2 of this paper, the real EV usage data modeling is discussed. Section 3 is concerned with explaining how the on-board charging takes place for different EV types and the connection hardware used for this study. Section 4 focuses on the distribution transformer data modeling. Section 5 presents the results and discussions of the study.

2. Modeling of EV Usage Data

To the best of our knowledge, there is no available data on the driving patterns of vehicle owners in Turkey provided by Turkish Statistical Institute or other organizations at the time of this publication. Thus, the daily trip data (home arrival time and trip distance) of 10 personal vehicle owners are first collected for 365 days to form a more realistic scenario. These data belong to daily personal usage of management staff at Başkent DisCo, and it is collected using data tracking devices connected at each vehicle. The sample set consists of data belonging to people with over middle-income profiles since the possibility to buy an EV, at least in the near future, is higher for those people.

In this study, the impact of EVs on a real distribution grid, which serves about 1000 mostly residential customers, is investigated. To analyze this impact in a realistic way, hundreds of trip data is needed in case of penetration levels above 10% which is very difficult to collect. Therefore, a model should be generated such that the trip characteristics can be estimated. The procedure in this paper is as follows. In each data set, the extraordinary cases are ignored, i.e., only the daily trip distances between ranges 10 km – 80 km and home arrival times after 16:00 are considered. The corresponding histograms of the filtered home arrival times and trip distances are shown in Figs. 1 and 2, respectively. As it is clear from the figures, both of the constructed histograms are quite similar to a Gaussian distribution. The mean and standard deviations of the so-called Gaussian distributions are (19h55, 1h40) and (39.5 km, 15.8 km), for home arrival time and trip distance distributions, respectively. It is also observed that both of the histograms mostly satisfy the well-known 68-95-99.7 rule. As a result of these observations, the EVs will be assumed to arrive home according to a Gaussian distribution with a mean of 19h55 and a standard deviation of 1h40 while analyzing the EV-grid integration. It will also be assumed that each EV in the scenario will make a trip distance according to a Gaussian distribution with a mean of 39.5 km and a standard deviation of 15.8 km. At the time of grid connection, the SOC levels of EVs are calculated accordingly as explained in the next section.

Table 1. Charging limits according to IEC 61851 Standard [14]

Charging Level	Grid Maximum Limits
Mode 1	230 V 1- ϕ, 16 A, 3.7 kW 400 V 3- ϕ, 16 A, 11 kW
Mode 2	230 V 1- ϕ, 32 A, 7.4 kW 400 V 3- ϕ, 32 A, 22 kW
Mode 3	230 V 1- ϕ, 63 A, 14.5 kW 400 V 3- ϕ, 63 A, 43.5 kW
Mode 4	400 V DC, 125 A, 50 kW

3. Residential On-board EV Charging

On-board chargers convert the utility ac voltage into dc to charge the vehicle battery and they are physically located on the vehicle. The power rating of the on-board chargers differ at each vehicle depending on the topology used and directly impact the charging time. IEC 61851 is currently employed in Europe as the EV-grid conductive connection standard [14]. Table 1 lists the charging limits imposed by the IEC 61851. The maximum charging power of the EV is set by the minimum of the following components: power rating of the EVSE and the power rating of the on-board charger. For this study, the calculation of the arrival SOC for each vehicle is found as follows:

$$SOC = \left(1 - \frac{x}{R}\right) \cdot 100 \qquad (1)$$

where *SOC* is the state of charge of the battery (%), and *x* is the daily traveling distance of the EV (km). Moreover, the charging time is found as:

$$T_c = \frac{0.8 \times C_B(1 - SOC)}{P \cdot \eta} \quad (2)$$

where T_c is the total charging time (h), C_B is the vehicle nominal battery capacity (kWh), P is the charging power (kW), and η is the on-board charger efficiency. Each of the on-board chargers used in this study is assumed to have a constant 90% operating efficiency and 1.0 power factor. The constant 0.8 stands for the derating used for the nominal battery capacity to limit the battery charging and discharging window and to increase battery lifetime.

Several EV brands are selected in this study. Those are either currently sold in Turkey or have the potential to be introduced into the market in the near future. Table 2 lists the EVs used in this study. The vehicles that are already available in the market as of mid-2015 are BMW i3 and Renault Zoe – Twizy.

Table 2. Type of EVs and their specifications

Vehicle Make and Model	Battery Capacity (kWh)	EV Range (km)	Charger Power (kW)
Opel Ampera	15	56	3.3
Mitsubishi MiEV	16	100	3.3
Toyota Prius PHEV	4,4	24	2.0
BMW i3	22	160	7.4
Renault Zoe	22	100	43
Renault Twizy	7	80	2.2
Tesla Model S	42	250	20

Table 3. Case studies for two different EV charging cases: normal on-board charging (case 1) and higher power on-board charging (case 2)

Vehicle Make and Model	EV Market Share (%)	
	Case 1	Case 2
Opel Ampera	14	8
Mitsubishi MiEV	14	8
Toyota Prius PHEV	14	8
BMW i3	14	8
Renault Zoe	14	30
Renault Twizy	14	8
Tesla Model S	14	30

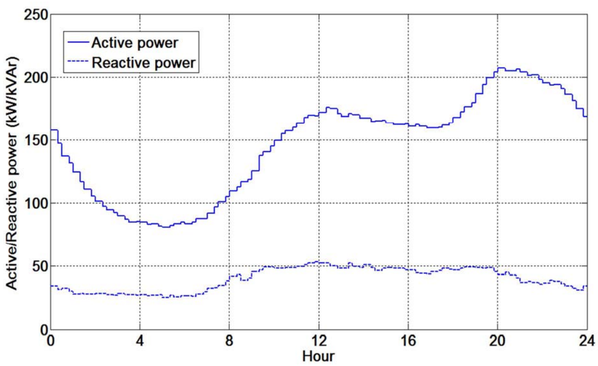

Fig. 3. Active and reactive power data of TR#2789 averaged over the month September 2014

The study here investigates the impact of charging the EVs listed in Table 2 utilizing Modes 1 – 3 charging. The availability of different charging modes depends on the available wiring and the EVSE infrastructure. For this study, only 22 kVA EVSEs are used (Mode 2 charging). Those EVSE models are currently available in Turkey, i.e., Esarj [15] and VoltRun [16].

This study investigates 10%, 20%, and 30% EV penetration levels into the vehicle market in Turkey. It is assumed that EV customers are uniformly distributed across the distribution grid fed by the distribution transformer. For the first case study, the types of EVs are selected uniformly among vehicles listed in Table 1. However, in the future, the charging time of the EVs are expected to decrease as new vehicles enter into the market with more powerful on-board chargers. Therefore, a second case study is assumed with an increased share of higher power on-board chargers, i.e., Model S and Zoe. Off-board fast charging is not considered in this study. The vehicle energy consumption (kWh/km) is calculated based on the manufacturers' expected EV range utilizing the available battery capacity.

4. Distribution Transformer Data

In 2004, High Planning Council of Turkey has finalized the privatization of the distribution network with 21 different regions across Turkey. Başkent DisCo (which operates since 2008) serves 3.8 million customers at seven provinces, and distributes 14.3 TWh of annual energy to its customers.

Distribution transformer loading data used in this study were collected between 1 – 30 September 2014 in Ankara using Schneider ION 7650 power quality meter. The meter is installed at the secondary side of 34.5 kV/0.4 kV, 1000 kVA distribution transformer (TR#2789). The total 985 customers that TR#2789 feeds are comprised of 90% residential apartment houses and 10% small-scale commercial shops.

The measurements have been taken according to the IEC 61000-4-30 [17] and the collected data are transmitted to the Başkent DisCo servers via 3G communication. The power measurements are recorded with 10 min averages. Fig. 3 shows the collected active power data in kW and reactive power data in kVAr averaged over the month of September 2014. This data is used as the base loading data for TR#2789 with no EV integration. The loading on TR#2789 has two peaks, one is around noon and the other is between 19:00 –21:00 approximately. This correlates with the home arrival data described in Section 2. The maximum active power drawn from the transformer is around 200 kW and 50 kVAr which corresponds to a maximum kVA loading of ~20% levels. Therefore, TR#2789 is a lightly loaded transformer with a significant capacity margin, especially in the fall season. It is important to note that the most common air heating method in the apartment houses in Turkey is through burning natural gas (NG). As of 2015, most of the cities in Turkey have NG distribution systems for residential houses.

In this study, each residential apartment house is assumed to possess one passenger vehicle. Three EV penetration cases are examined among those vehicles, which are 10%, 20%, and 30%. The following section describes the analysis and results of the performed study.

5. Analysis and Results

In this section, the developed EV user model is translated into charging power model and then integrated with the distribution transformer data. Each of the two cases is simulated with 10%, 20%, and 30% penetration levels. Simulation results are illustrated in Figs. 4 – 9. It is important to note that the data starts at noon and continues until 4 am in the morning to focus only on the charging events. The non-charging time frame is not included to present a better understanding of the charging time frame. Moreover, this charging power is only valid for one EV charging simulation, and the data is different for each simulation run as this is a random process. However, the overall impact will be similar as the vehicle usage characteristics follow the Gaussian distribution.

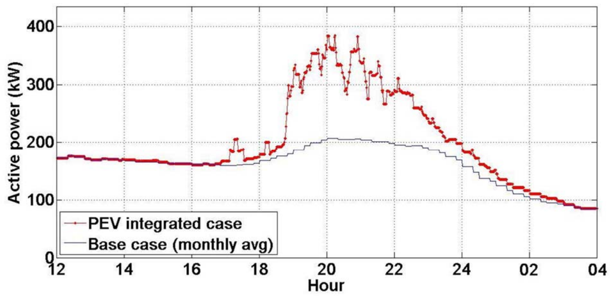

Fig. 4. Result of transformer loading for 10% EV penetration (case 1)

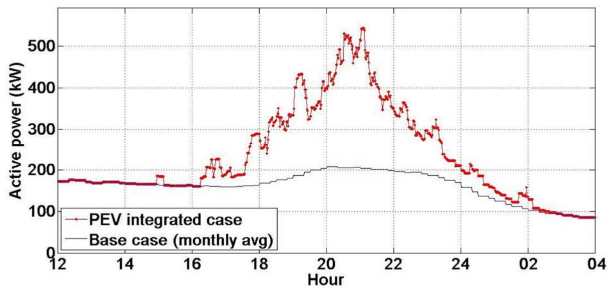

Fig. 5. Result of transformer loading for 20% EV penetration (case 1)

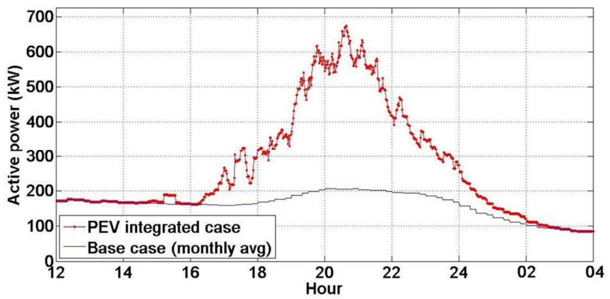

Fig. 6. Result of transformer loading for 30% EV penetration (case 1)

According to the results presented in Figs. 4 – 9, the power consumption at peak hours will increase considerably depending on the EV market penetration. Two important conclusions can be drawn from the results:

- as the ratio of EV penetration increases, TR#2789 has to supply higher peak power to its customers.
- higher on-board charging power translates into higher peaks as shown in Figs. 7 – 9. Although the total average travel distance is the same for the two cases (case 1&2 in Table 3), case 2 results in a higher peak power demand from TR#2789.

Results show that the installation of EVSEs should be tightly regulated by the DisCos to manage the increasing charging power demand by the on-board chargers. Another solution is to manage the charging events depending on the loading of the transformer. Applications such as smart charging or vehicle-to-grid power transfer can be utilized to provide a more sustainable solution for the operation of the utility grid with increased ratio of EV penetration.

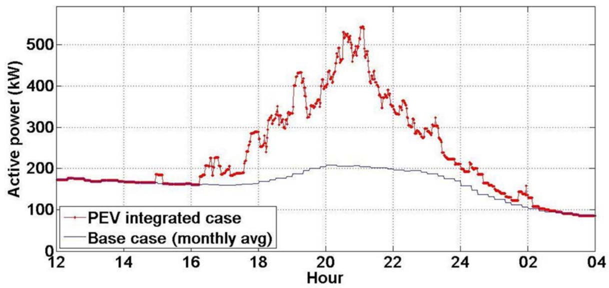

Fig. 7. Result of transformer loading for 10% EV penetration (case 2)

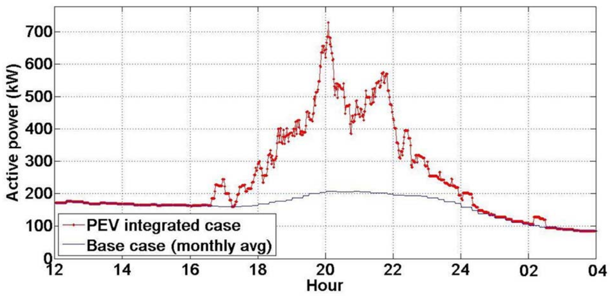

Fig. 8. Result of transformer loading for 20% EV penetration (case 2)

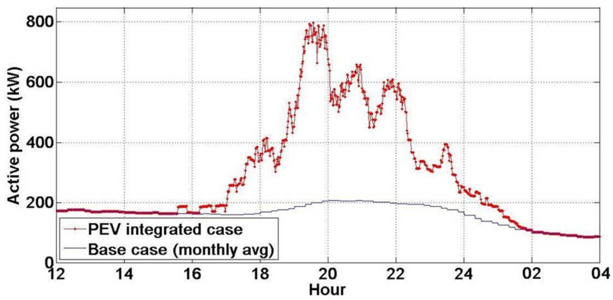

Fig. 9. Result of transformer loading for 30% EV penetration (case 2)

Although TR#2789 is a lightly loaded transformer, it is in general less loaded than an average transformer located in the city of Ankara. Therefore, considering older infrastructure and more heavily loaded transformers, the impact shown in the figures might worsen. What is more, the distribution components (i.e. conductors, switches, fuses, LV circuit breakers, and other protection/control devices) might also need upgrades depending on their loading level. Specific to transformers, according to the duration and severity of the overload, decrease in the lifecycle can be calculated based on the model described in IEEE Std. C57.91 [18]. Looking at the results, it is expected that TR#2789 will age faster depending on its hot-spot temperature [19].

In addition to the above discussions, on-board charging power rates are increasing with newer EV models. As illustrated by the Figs. 7 – 9, this will worsen the impact of EVs on the grid compared to lower power on-board chargers. However, if the work place charging gets more widespread, the impact of EV-grid integration at the time of home arrival will be reduced. Also, increasing employment of swappable batteries instead of fixed battery packs will reduce the required energy demand from the grid using on-board chargers at the end of the day. The most imminent result from this analysis is the need to develop a more advanced charging strategy to cope with all the problems that will arise as the penetration levels increase. This study only considers, the transformer loading but a future study will include a more complete impact on the utility grid.

6. Conclusion

Increasing penetration of EVs has to be carefully examined to assess the negative impacts of their integration into the distribution grid. This study presents one of the first analyses in Turkey that translates the real user behavior into demanded active power from the distribution transformer. The study concludes that while the user profiles are stochastic, they can be modeled as a Gaussian distribution that helps estimating the power demand. Increasing on-board charger power ratings of new EVs will worsen the situation for the utility grid and require increased infrastructure component ratings. It is of utmost importance for the DisCo to understand those impacts and take necessary actions that will direct users towards smart and controlled charging. What is more, DisCos in Turkey should carefully examine and regulate the ratings and numbers of the installed EVSEs in the residential neighborhoods.

Acknowledgement

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