Investigating the charging and discharging impacts of Electric Vehicles on power grid

A PROJECT REPORT

Submitted in partial fulfillment of the
requirements for the award of the degrees

Of
BACHELOR OF TECHNOLOGY
in
ELECTRICAL ENGINEERING

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Guided by:
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CANDIDATE'S DECLARATION

I hereby declare that the project entitled **" Investigating the charging and discharging impacts of Electric Vehicles on power grid"** submitted in partial fulfillment for the award of the degree of Bachelor of Technology in 'Electrical Engineering' completed under the supervision of **Dr. Trapti Jain, Assistant Professor,** IIT Indore is an authentic work.

Further, I declare that I have not submitted this work for the award of any other degree elsewhere.

Signature and name of the student(s) with date

CERTIFICATE by BTP Guide(s)

It is certified that the above statement made by the students is correct to the best of my knowledge.

Signature of BTP Guide(s) with dates and their designation

Preface

This report on "Investigating the charging and discharging impacts of Electric Vehicles on power grid" is prepared under the guidance of Dr. Trapti Jain.

Preface write-up may be decided by the students. An example of the same is given below:

Through this report I have tried to give a detailed algorithm for calculating the load profile for charging and discharging of large number of Electric vehicles based on their mobility traits. The developed load profile is be used to estimate vehicle to grid potentials for regulation service commitment.

The second objective was to develop an intelligent charging scheme for Aggregator to achieve load-leveling/valley filling based on conventional load profile.

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Abstract

Global Warming due to increase green-house-gas emissions, limited supply of fossils fuels are the major concerns of the present generation. The advent of energy -efficient electricity-powered vehicles, battery electric vehicles (BEVs) and/ plug-in hybrid EVs (PHEVs), have the potential to reduce fossil fuel consumption and GHG emissions. Electrifying the transportation sector raise concerns about their negative impacts on power generation, transmission, and distribution installations. Positive and negative impacts of PHEVs on the power grid can be estimated from extensive data on the utilization of each individual PHEV are available. In order to estimate the aggregated impact of PHEVs on the electricity demand profile, one needs to know 1) when each PHEV would begin its charging process, 2) how much electrical energy it would require, and 3) how much power would be needed. This project extracts and analyzes the data that are available through national household travel surveys (NHTS) to estimate the load profile. The EVs are also researched to provide short-term energy security in the interest of power system energy supply-demand balance when plugged into the grid via grid-to-vehicle (G2V) and vehicle-to-grid (V2G) modes. Hence, a cluster of EVs could serve as a kind of fast power ramping mobile energy resource - a load or even a generation source in the range of MWs. Most of the studies followed a stochastic approach to realize G2V/V2G system considering homogenous transportation traits. However, a practical approach is further needed to create a robust model of these modes inspecting heterogeneous mobility attributes. Characterized by this, in this project I attempted to create an empirical model for the G2V/V2G modes to precisely predict the fleet level effects of an EV dominated transportation system on the grid. After studying the impact charging of EV on conventional load profile a smart charging strategy is suggested to use EVs as controllable load.

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C 1: INTRODUCTON

Global warming, Air Pollution and limited supply of fossils fuels are the major concerns for sustainable development. There are numerous factors which are coming together to change the way we think about energy. There are growing concerns over energy security, and our dependence on foreign oil/petroleum. The worldwide use of energy is growing, creating greater demand, but as we know supply is limited. The oil that is available is becoming harder and more dangerous to extract as evidenced by the catastrophic Deepwater Horizon oil spill. The result is that nations around the world have come to realize that action must be taken to reduce our use of oil and to reduce our greenhouse gas (GHG) emissions. The mounting effects of climate change have become even more apparent, prompting action locally and globally. On national and international levels, efforts have begun in order for the countries to achieve the commitments it made to reduce green-house emissions, significant steps must be taken to reduce our use of energy from fossil fuels. One of the most promising ways to do this is the electrification of transportation. Up until now, the energy to power the transportation sector has come almost exclusively from oil. With the electrification of transportation, carbon emissions can be reduced to null if source of electricity is renewable. This marks the largest disruption in the automotive industry since its choice of the internal combustion engine. Now, we can choose to use renewable sources of energy, to fuel our vehicles. This will have profound and lasting effects not only our nation's power industry, but also beyond the transportation sector, affecting our overall use of the world's resources. In order to realize the cost/benefit tradeoffs of grid enabled vehicles, it is important to take a systems perspective. The analysis in this project identifies certain areas which must be addressed in order to achieve widespread adoption. While PHEVs rely on electricity from the power grid, they raise concerns about their negative impacts on power generation, transmission and distribution installations. On the other hand, they have the potential to be used as a distributed energy storage system and controllable load for the grid. Therefore, they can pave the way for a more sustainable power grid in which renewable resources are widely employed.

The objective of this report is to present an algorithm to determine the daily load profile due to charging and discharging of a large number of electric vehicles (EV) based upon their mobility behavior. The estimated load profile can be used to predict MW capacity that can be contracted in ancillary services market on a long-term basis to provide the regulation up (RU) and down (RD) to the grid. The algorithm uses a scheme which delivers the schedule of power supplied to or drawn from the grid by treating the mobility attributes dependent electrical parameters. Two operational places, the workplace, and the home were identified as per driving pattern of customers for the provision of regulation services. An illustrative model considering a fleet of representative battery electric vehicle (BEV) is presented based on the mechanism, to obtain the minute-wise MW contract capacity. Results demonstrate that two major mobility traits namely, driven distance and arrival pattern, as well as the charging and discharging power standards directly influences the regulation schedule. Further, the load developed from algorithm was used to analyze impact on conventional load profile and it was realized that peak load due charging of EVs occurs along with peak load of conventional load profile which results in increase peak load demand .So next part of project was dedicated on developing a smart charging profile to use EV as controllable load.

C2: Modelling the charging (G2V) and discharging (V2G) load profiles of EVs based on mobility behavior to estimate regulation services commitment

I. Introduction

This work presents a model followed by an algorithm to determine the daily load profile due to charging and discharging of electrical vehicles. Specifically, per minute power scheduling during the charging and discharging mode is executed to determine the minute wise MWs capacity over a complete day for a large deployment of EVs. The model features two operational places, the workplace, and home, for G2V and V2G mode of operation, assuming predefined work purpose trips in which vehicles commute between the workplace and home. The arrival and departure times, travel and parking durations are incorporated for varied driven mileages. Non-linear charging characteristics of Li-ion battery (LIB) is replicated in the charge-discharge scheduling. [2] Here, the mobility attributes and arrival pattern data forms the input side of the model to calculate the G2V and V2G load profile and the associated charging and discharging parameters. The algorithm treats these parameters and gives the schedule of net power drawn or supplied to the grid at different times of the day, thereby forming the basis for regulation down and up (RD/RU) capacity determination. In an example computation considering BEVs, the commercial DC fast charging (DCFC) and the domestic AC charging standards power levels are chosen, respectively for the above two operational places. The arrival pattern is extrapolated and simplified from the National Household Travel Survey (NHTS) [18] real transportation data. Also, the driven mileage and proportions determine the aggregated state-of-charge (SOC) at a particular moment. For the analysis, we selected a complete range of driven distances that could be possible with the available battery capacity while combining it with the number of vehicles arriving at different times. The developed load profile was compared with conventional load profile of Ontario ISO. It also helps on determining power side activity of the entity called aggregator responsible for integrating of EVs into the grid to provide load as well as generation services Even though various mobility traits affect the possible regulation capacity contracts, these contracts represent significant revenue opportunities when tested on a long-term commitment basis.

II. Model Features

We developed a model to simulate the following four cases in order to determine load profile and the provision of regulation up and down capacity contract through EVs:

1) Home charging (G2V) - regulation down
2) Workplace charging (G2V) - regulation down
3) Workplace discharging (V2G) - regulation up and home charging (G2V) – regulation down
4) Home discharging (V2G) - regulation up and workplace charging (G2V) - regulation down

A. The Power Levels

To simulate the model for an example BEV, we utilize the following power levels at the two places:

(a) 6.6 kW for home charging and discharging patterns. This falls under the ambit of Level 2 of SAEJ1772 [19] and EPRINEC [20] electric vehicle charging standards. This suits the typical single-phase residential applications with the voltage rating of 208-240 V and amperage 16-40A.

(b) 50 kW for the workplace charging and discharging patterns. This ranges into middle rate DC fast charging (DCFC) standards namely, CHAdeMO and SAE Combo/CCS which are supported by several automakers [21]. These rapid charging stations are located at many strategic locations for commercial applications with voltage ratings up to 300-500 V DC at 100-300 A.

The relatively moderate size batteries (25 kWh) of modern subcompacts like Nissan LEAF, Fiat 500e, Volkswagen e-Golf, Kia Soul EV etc., require only _ 50 kW to charge in about 30 minute (up to 80% capacity) as assured by the manufacturers. Most of the EVs now come equipped with charger ports to support both, SAE J1772 AC level 2 domestic charging and CHAdeMO or Combo/CCS DCFC. For a sample calculation in this formulation, we consider only the case of fully electric vehicles, i.e. the BEVs supporting both the AC slow as well as DC fast charging.

B. Regulation Up and Down Timings

When we consider the trips made for work purpose, the daily commute routes are supposed to be well-defined. The arrival times along with parking and travel durations are needed to determine the charging and discharging patterns. The travel duration, in turn, depends on the travel distance and speed of the vehicle. As an example, the home arrival times simplified into (24 intervals) arrivals throughout a day are shown in Fig. 1 against percentage of vehicles arriving. The simplification represents the arrival times averaged into the hourly basis for example if 600 vehicles arrive in hours between 00:00 to 00:01 then 600/60 = 10 vehicles arrive every minute, the source being the National Highway Travel Survey (NHTS) [18] transportation data as adopted in [22]. The greater number of vehicles arrive in the evening period as can be seen from the peaking bars in the evening and late evening hours. This validates the general working timings of morning and afternoon with a few sparsely distributed also into odd hours. This home arrival scenario is treated as the base case upon which the workplace arrival pattern is built by employing workplace parking and travel durations to it. In the sample computation shown in this work, the most common 7 h workplace parking duration [23] is applied. Home-workplace and workplace-home travel durations are formulated considering highway and city component travel proportions (distance and speed) as per Environmental Protection Agency (EPA) Federal Test Procedure (FTP-75) [24]. The FTP specifies speed and travel proportions for each of the two city and highway driving cycles. This travel duration varies with trip distance. The, thus developed workplace arrival pattern against numbers of vehicles is shown for a typical trip distance of 27.5 km in Fig. 1 , with one way travel duration determined as 20 min. Here, the peaking bars shifts toward morning hours. The vehicles start charging (G2V or RD) or discharging (V2G or RU) soon after the arrival.

C. Battery Characteristics

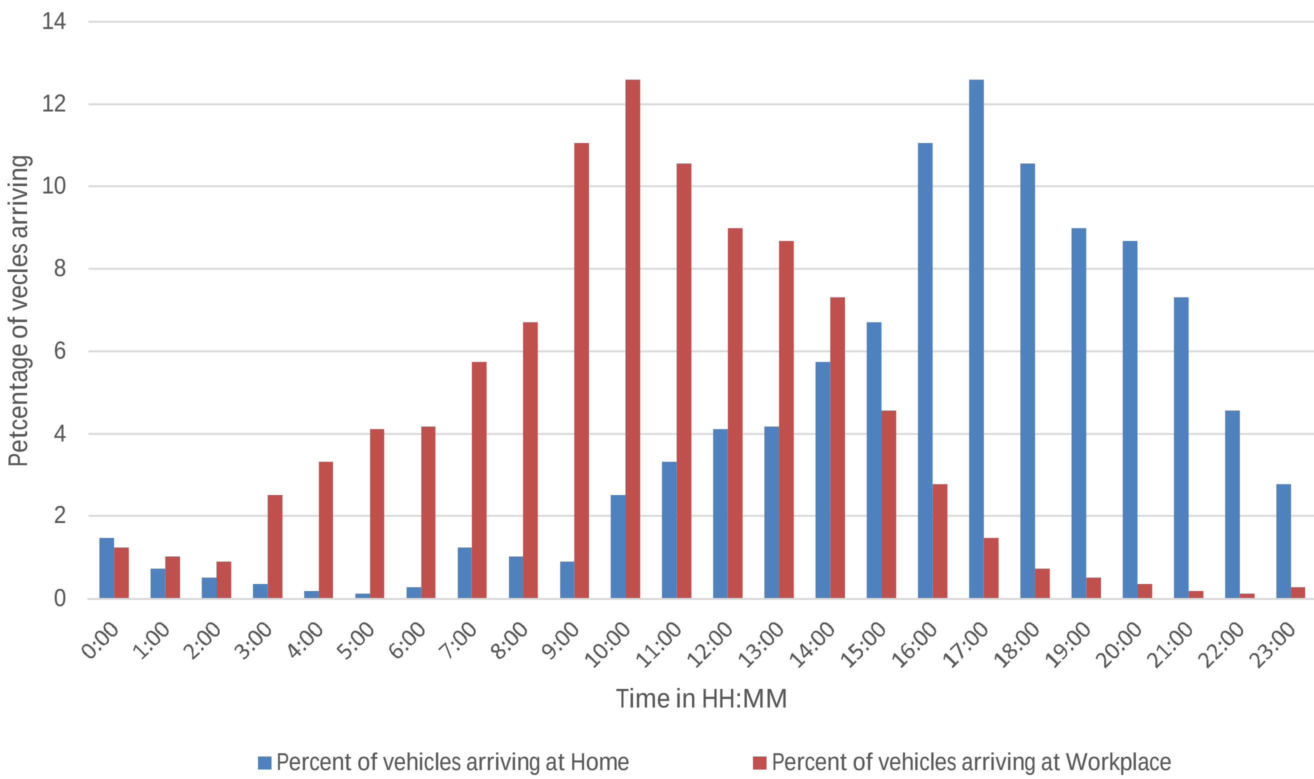
Non-linear characteristics of LIB involves two phases in charging.

1) Constant current (CC) - In CC phase, the charging current is held steady so that constant power is injected into the battery, as the voltage rises to the reference limit. So, depending on the SOC, the charging time varies. This phase sustains till SOC reaches 70% (65-75% depending upon the cell chemistry) of capacity [22] defines it as constant power (CP) scheme.

2) Constant Voltage (CV) scheme [25], [26] - In CV phase, the charging current varies, actually decaying exponentially, till the battery is fully charged at the constant reference limit voltage [27]. The decaying current results in almost 1.5 times the CC phase time to deliver the remaining 30% energy. This is referred as constant time (CT) scheme in [22].

   For example, suppose a depleted 50 kWh EV battery, carrying a SOC of 10 kWh have a charging power standard of 10 kW. So, out of 40 kWh needed, the 35 kWh (0.7_50) is delivered in CP phase in 3.5 h with 10 kW level (power fixed). The remaining 5 kW is supplied in CT phase in 5 hours (50/10) (time fixed) with the power level at each hour being 1 kW. The above phenomenon is modelled in vehicle charging process in the algorithm.

Fig 1 Vehicle arrival da



III. The Model

A. Electric Vehicle and Mobility Attributes

1) *Battery capacity* B - it represents the weighted mean value of the various battery capacities of EVs present in the system.
2) Vehicle Mileage city(K_{100c}) and highway(K_{100h})-The estimated fuel consumption rate, specified in the EPA fuel economy and environment label of EV, reveals the amount of electricity used, and thus relates directly to cost. This is given in kWh/100 miles and is different for city and highway driving. Even if it deviates from what is quoted on the label, based on the driving experience and vehicle type, the revised one can be made available by the owners. The averaged value for V vehicles is: kWh/100 miles in city and highway.

   $K_{100c} = \frac{1}{V}\sum_{i=1}^{V} K100ci$

   $K_{100h} = \frac{1}{V}\sum_{i=1}^{V} K100hi$

3) *Depth of Discharge (DOD)*-Li-ion batteries are now invariably used in EVs because it offers high energy density, lifetime and number of cycles. Also, shallow discharge cycles instead of deep discharges further promise high lifetime and cycle count. Based on the utility, the EV owners decides the limit of (DOD) for their vehicles with a motive of increasing battery's life. Let the mean allowed DOD for V vehicles is:

   $x= \frac{1}{V}\sum_{i=1}^{V} Xi$

4) City(C %) and Highway (H %) driving component t- The mean value of battery capacity after accounting for x% DOD = x*B. The percentage of city and highway driving will differ among the EV owners. Let with V vehicles, weighted average percent's of city and highway driving are,

   $C\% = \frac{1}{V}\sum_{i=1}^{V} Ci$ H% $\frac{1}{V}\sum_{i=1}^{V} Hi$

5) *Preserved Range (Rp)-EV* owners would not like to completely drain the battery while participating in V2G, instead keep a certain amount of range secured for sudden or emergency trip. Let the mean value of preserved ranges in km for V vehicles is,

   $Rp = \frac{1}{V}\sum_{i=1}^{V} Rpi$

B. Arrival Pattern

Commuters arrives at home and the workplace all through the day. Let there are n arrival times of home and hence the workplace as following:

A_{H1}, A_{H2}, $A_{H3\ldots}$, A_{Hn} and A_{H1}, A_{W1}, A_{W2}, $A_{W3\ldots}$ A_{Wn}

We define the arrival times here in more generic form and subscript H and W can be used respectively for home and workplace, whichever the case referred to. So, the arrival times are:

A_1, A_2, $A_{3\ldots\ldots}$ A_n

As per the statistics available (Fig. 1) the home arrival times are treated as the base, thereafter the workplace arrival times are built upon them as following:

$$A_W = A_H - \left(Tp + \frac{Td}{2}\right)$$

Tp - workplace parking duration,

Td - the total travel time for d^{th} mileage (described later) which is the sum of city (Tcd) and highway (Thd) travel times.

With n being 24, the arrival times at workplace are shown in Fig. 1. In order to determine the aggregate EV capacity available at a particular time, the information of numbers of vehicles arriving at the two locations is required. Vehicles arriving per hour are further subdivided into per minutes. For example if 600 vehicles arrive in hours between 00:00:00 to 01:00:00, then 600/60 = 10 vehicles arrive every minute. Let the number of vehicles arriving at home and the workplace at times 1 to k (k = n x 60 = 1440) are:

N_{H1}, N_{H2}, N_{H3} ……. N_{1k}, and N_{W1}, N_{W2}, $N_{W3\ldots}$ N_{Wk}

More generally,

$N_K = n(k) * N$

n(k) – Percentage of vehicles arriving at that minute at . For k = 1 to 1440

N – Total number of vehicle arriving in a day.

C. Available Battery Capacity and Electric Range

The difference of total and preserved capacity gives the net electric capacity, and thus the electric range available for driving as well as V2G. Their computations are as follows: City and highway km possible with preserved range,

Rpc = C% .Rp and Rph = H%. Rp (8)

Battery energy (capacity) required for city and highway km of preserved range (* 100 miles = 160.934 km),

$$B^{R_{pc}} = \frac{R_{pc}}{(160.934/\mathbf{K_{100c}})} \qquad B^{R_{ph}} = \frac{R_{ph}}{(160.934/\mathbf{K_{100h}})}$$

Total battery energy (capacity) required for preserved range,

$$B^{R_p} = B^{R_{pc}} + B^{R_{ph}}$$

Net available battery capacity for driving and V2G

$$B^{Net} = \mathbf{x} \cdot \mathbf{B} - B^{R_p}$$

City component of net available battery capacity,

$$B_c^{Net} = c_{\%} \cdot B^{Net}$$

Highway component of net available battery capacity,

$$B_h^{Net} = h_{\%} \times B^{Net}$$

City distance (in km) and Highway distance (in km) possible with net available battery capacity,

$$d_c = \left(\frac{160.934}{\mathbf{K_{100c}}}\right) \cdot B_c^{Net} \qquad d_h = \left(\frac{160.934}{\mathbf{K_{100h}}}\right) \cdot B_h^{Net}$$

Total combined distance (in km) possible with net available battery capacity,

$$d = d_c + d_h$$

D. Driving consumption and V2G energy under various mileage

Within the limit of “d”, we classify 1 to “m” mileage groups (M) representing various trip distances travelled by the vehicle owners. For each of the mileages, the driving consumption and the energy available for V2G support are the complement to each other. The two can be obtained as below.

City km per trip for various mileages,

$$c_{km} = \mathbf{c_{\%}} \cdot (M_1,\ M_2, M_3,\ ...., M_m)$$

Highway km per trip for various mileages,

$$h_{km} = \mathbf{h_{\%}} \cdot (M_1,\ M_2, M_3,\ ...., M_m)$$

Energy consumed in city and highway km per trip,

$$E_c = \left(\frac{\mathbf{K_{100c}}}{160.934}\right) \cdot c_{km} \qquad E_h = \left(\frac{\mathbf{K_{100h}}}{160.934}\right) \cdot h_{km}$$

Total energy consumed per trip for a particular mileage group “M”, i.e. the driving consumption,

$$E^M = E_c + E_h$$

The counterpart of E^M is the capacity (energy) available for V2G support,

$$E^M_{V2G} = B^{Net} - E^M$$

At a particular arrival time “n”, with a view to vehicles arriving at home (H) and workplace (M), the available energy for V2G,

$$E^{H_n}_{V2G} = N_{H_n} \cdot E_{V2G} \qquad \forall\ M \in M_1, M_2, M_3, ..., M_m$$

$$E^{W_n}_{V2G} = N_{W_n} \cdot E_{V2G} \qquad \forall\ M \in M_1, M_2, M_3, ..., M_m$$

In general,

$$E^n_{V2G} = N_n \cdot E_{V2G} \qquad \forall\ M \in M_1, M_2, M_3, ..., M_m$$

Similarly, the counterpart of above is the driving consumption,

$$E_{G2V}^{H_n} = (B^{Net} \cdot N_{H_n}) - E_{V2G}^{H_n} \qquad \forall \ M \in M_1, M_2, M_3, ..., M_m$$

$$E_{G2V}^{W_n} = (B^{Net} \cdot N_{W_n}) - E_{V2G}^{W_n} \qquad \forall \ M \in M_1, M_2, M_3, ..., M_m$$

In general,

$$E_{G2V}^{n} = (B^{Net} \cdot N_n) - E_{V2G}^{n} \qquad \forall \ M \in M_1, M_2, M_3, ..., M_m$$

E. Charge (G2V) and discharge (V2G) modelling

(a) Energy required from the grid

When EVs participate in V2G, the charging (G2V) energy required from the grid is the summation of driving consumption as well as energy used up due power injected into the grid. However, only the driving consumption is required from the grid when EVs do not engage in V2G. Thus, the energy required by the EVs arriving at "n^{th}" time from the grid for the two cases are:

With EVs participating in V2G:

$$E_{Grid}^{n} = E_{G2V}^{n} + E_{V2G}^{n}$$

With driving consumption alone

$$E_{Grid}^{n} = E_{G2V}^{n}$$

A part of the charging energy drawn from the grid is in CP mode,

$$E_{CP}^{ch} = \left\{ \left[0.7 \cdot (B \cdot N_n) \right] - \left[(x \cdot B) - \left(\frac{E_{Grid}^{n}}{\eta_c} \right) \right] \right\}$$

Where, $\left[0.7 \cdot (B \cdot N_n) \right]$ represents the 70% of aggregated battery capacity of vehicles arriving at n^{th} time, $(x \cdot B)$ is the battery capacity allowed after accounting for x% DOD, and $\left(\frac{E_{Grid}^{n}}{\eta_c} \right)$ is the total energy required from the grid with converter efficiency of η_c.

Balance energy is drawn in CT mode,

$$E_{CT}^{ch} = \left(\frac{E_{Grid}^{n}}{\eta_c}\right) - E_{CP}^{ch}$$

(b) Charging power level and charging time

Let, P_L be the power level for charging/discharging of EVs. Then, the aggregate CP mode and CT mode charging power level of vehicles arriving at kth time,

$$P_{CP}^{ch} = P_L \cdot N_n \qquad \text{and} \qquad P_{CT}^{ch} = P_L \cdot \left(\frac{E_{CT}^{ch}}{B \cdot N_n}\right) \cdot N_n$$

where, $\left(\frac{E_{CT}^{ch}}{B \cdot N_n}\right)$ describe the percentage of energy drawn through CT mode as of aggregate battery capacity. The CP and CT mode charging times are:

$$T_{CP}^{ch} = \frac{E_{CP}^{ch}}{P_{CP}^{ch}} \qquad \text{and} \qquad T_{CT}^{ch} = \frac{E_{CT}^{ch}}{P_{CT}^{ch}}$$

The total charging time,

$$T^{ch} = T_{CP}^{ch} + T_{CT}^{ch}$$

(c) Discharging power level and discharging time

The energy that can be injected into the grid by the vehicles arriving at nth time with converter efficiency of η_c, $\frac{E_{V2G}^{n}}{\eta}$. The aggregate CP mode discharging power level, $P_{CP}^{dis} = P_L \cdot N_n$ and, the total discharging time, $T_{CP}^{dis} = \left(\frac{E_{V2G}^{n}/\eta}{P_{CP}^{dis}}\right)$

F. Algorithm for per minute power scheduling and regulation contract capacity

We consider here "k" variables parallel to "k" arrival times for each of the two CP and CT mode charging/discharging approaches.

Let the "k" variables associated with CP mode charging/discharging approach are:

$I_{CP}(1, t)$, $I_{CP}(2, t)$, $I_{CP}(3, t)$, $I_{CP}(4, t)$…… $I_{CP}(k, t)$

And with CT mode charging approach,

$I_{CT}(1, t)$, $I_{CT}(2, t)$, $I_{CT}(3, t)$, $I_{CT}(4, t)$…… $I_{CT}(k, t)$

A complete day's timeline (t) in terms of number of minutes (t = 1440) is:

t = 1 to 1440 or t = 00:00 to 23:59

In line with the charging and discharging modelling constructed above, we define the variables $I_{CP}(k, t)$ and $I_{CT}(k, t)$ as following:

$$I_{CP}(k, t) = \begin{Bmatrix} 1 \ \ for\ Ak \leq t \leq Ak + Tcp \\ 0\ otherwise \end{Bmatrix}$$

$$I_{CT}(k, t) = \begin{Bmatrix} 1 \ \ for\ Ak + Tcp \leq t \leq Ak + Tcp + Tct \\ 0\ otherwise \end{Bmatrix}$$

For k = 1 to 1440 and t = 1 to 1440

The power required from the grid at any minute of the day (G2V),

$$P_{req}(t) = N\sum_{K=1}^{1440}\{P(k)[Icp(k,t) * Pcp + Ict(k,t) * Pct]\}$$

And, power delivered into the grid (V2G),

$$P_{del}(t) = N\sum_{T=1}^{1440} P(k)[Icp(k,t) * Pcp]$$

for k = 1 to 1440 and t = 1 to 1440

The net power drawn or delivered to the grid at any minute of the day is the difference of the above two powers,

$P_{net} = P_{req}(T) - P_{del}(T)$

However, with regard to the cases where EVs do not participate in V2G, the $P_{del}(T) = 0$

Finally, the "k" minutes regulation down (RD) and regulation up (RU) capacity contract for any "t" minutes time interval during the day can be obtained as,

Pnet(t) for t = 1 to 1440

where, P_{net} represents the average value power required or delivered to the grid for a defined "t" minutes. For instance, the RD and RU time intervals may take the following forms:

IV. Sample Case: Load Profile and Regulation capacities through BEVs

For a sample computation of load profile and regulation down/up capacities through G2V/V2G modes at different times around the day, we use a fleet of 42500 Nissan LEAF EV as a representative BEV in the modelling. The relevant modelling parameters are detailed in Table 1.1.:

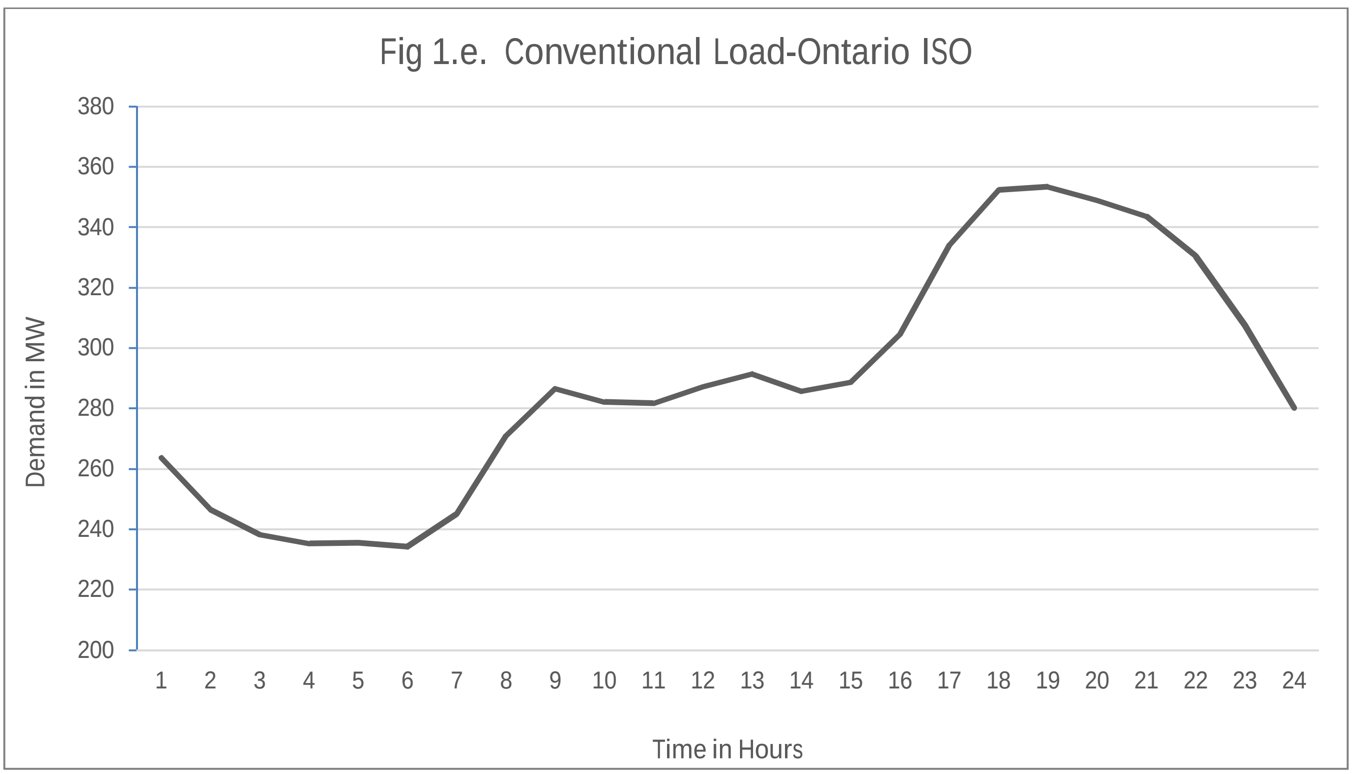
1) Home charging (G2V) - regulation down

2) Workplace charging (G2V) - regulation down

3) Workplace discharging (V2G) - regulation up and home charging (G2V) – regulation down

4) Home discharging (V2G) - regulation up and workplace charging (G2V) - regulation down

A. **Load Profile due to charging of BEVS.** Load profile due to charging of EVs for all the four cases and all possible trip distances is calculated by algorithm, shown in Fig1. (a to d).Fig. 1.e shows daily conventional load profile obtained from Ontario ISO (normalized to 290MW peak load,) to compare the impact of additional 42500 EVs to the system.



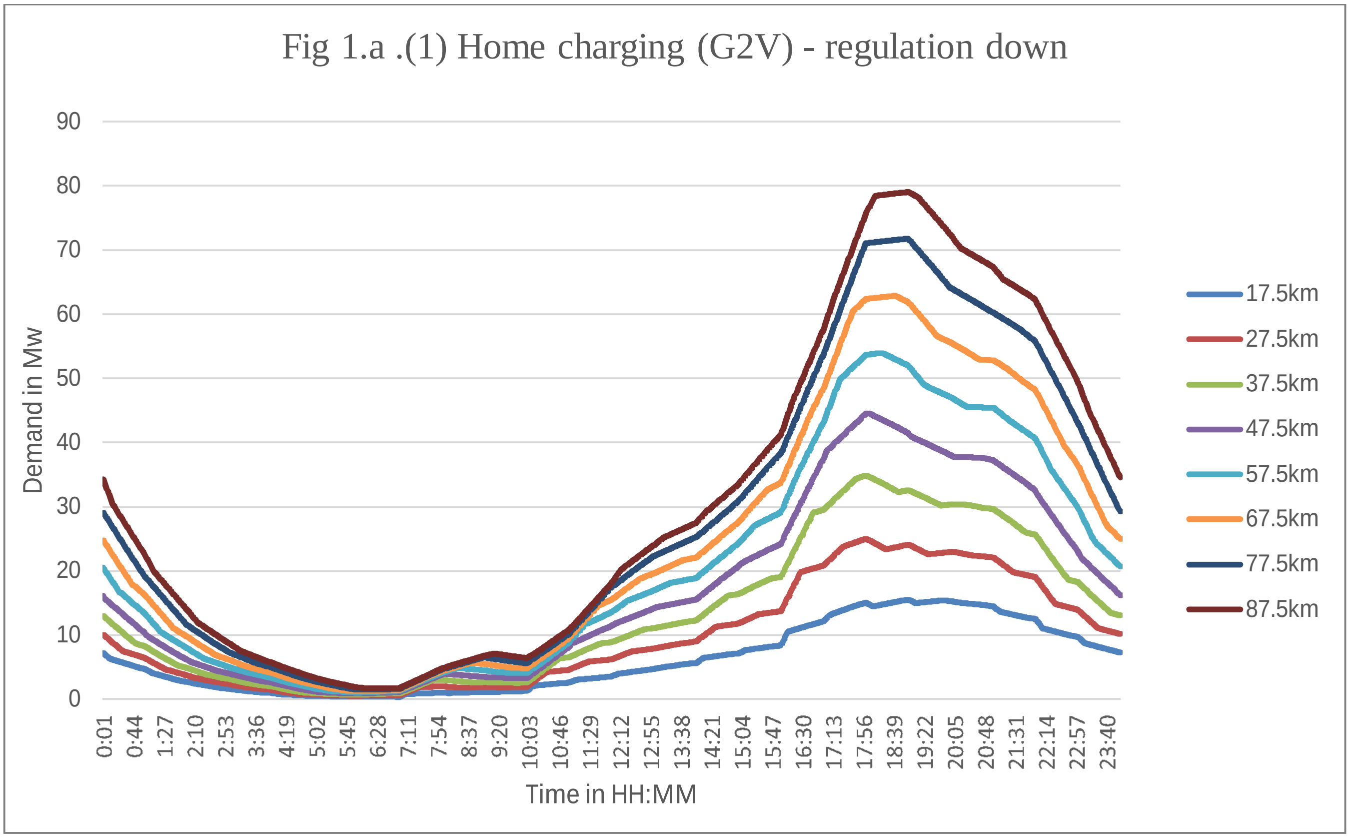


Fig 1.a .(1) Home charging (G2V) - regulation down
Demand in Mw
0
10
20
30
40
50
60
70
80
90
0:01
0:44
1:27
2:10
2:53
3:36
4:19
5:02
5:45
6:28
7:11
7:54
8:37
9:20
10:03
10:46
11:29
12:12
12:55
13:38
14:21
15:04
15:47
16:30
17:13
17:56
18:39
19:22
20:05
20:48
21:31
22:14
22:57
23:40
Time in HH:MM
17.5km
27.5km
37.5km
47.5km
57.5km
67.5km
77.5km
87.5km

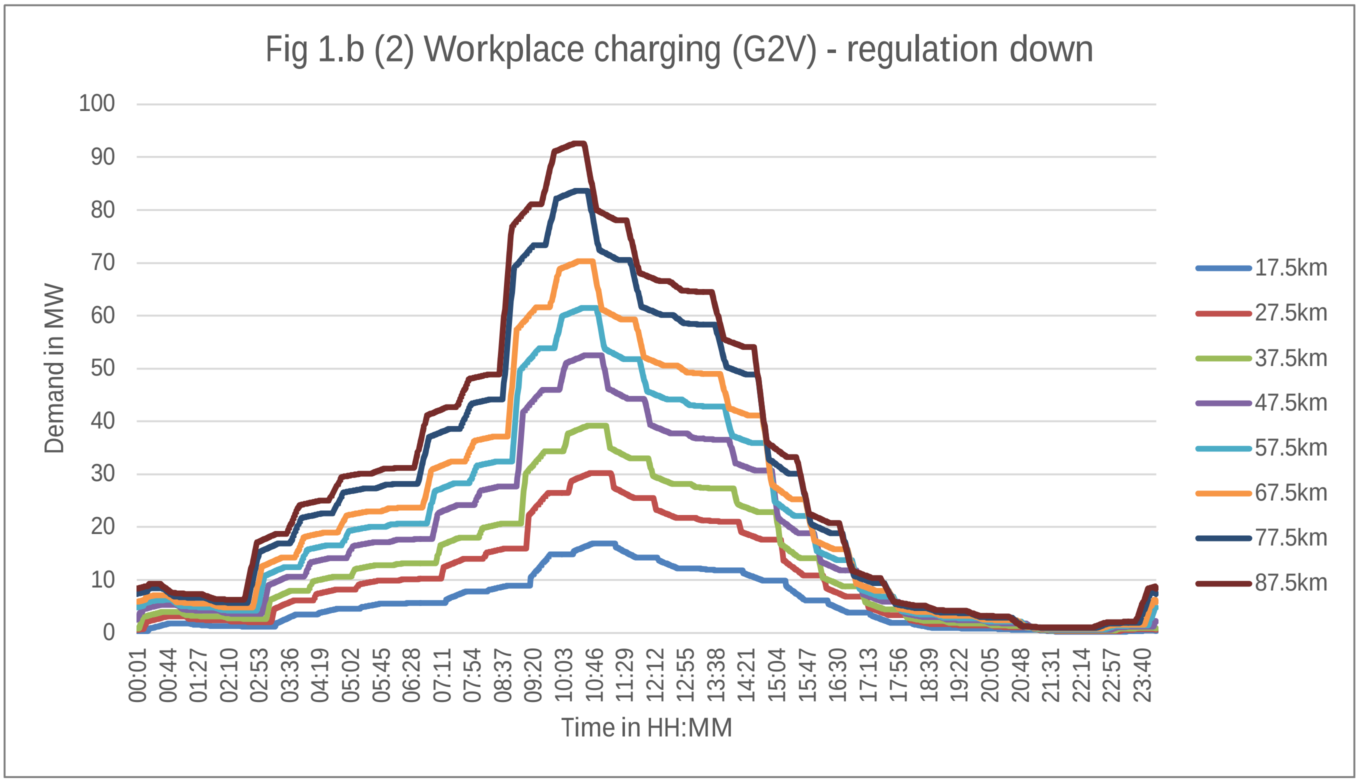


Fig 1.b (2) Workplace charging (G2V) - regulation down
Demand in MW
0
10
20
30
40
50
60
70
80
90
100
00:01
00:44
01:27
02:10
02:53
03:36
04:19
05:02
05:45
06:28
07:11
07:54
08:37
09:20
10:03
10:46
11:29
12:12
12:55
13:38
14:21
15:04
15:47
16:30
17:13
17:56
18:39
19:22
20:05
20:48
21:31
22:14
22:57
23:40
Time in HH:MM
17.5km
27.5km
37.5km
47.5km
57.5km
67.5km
77.5km
87.5km

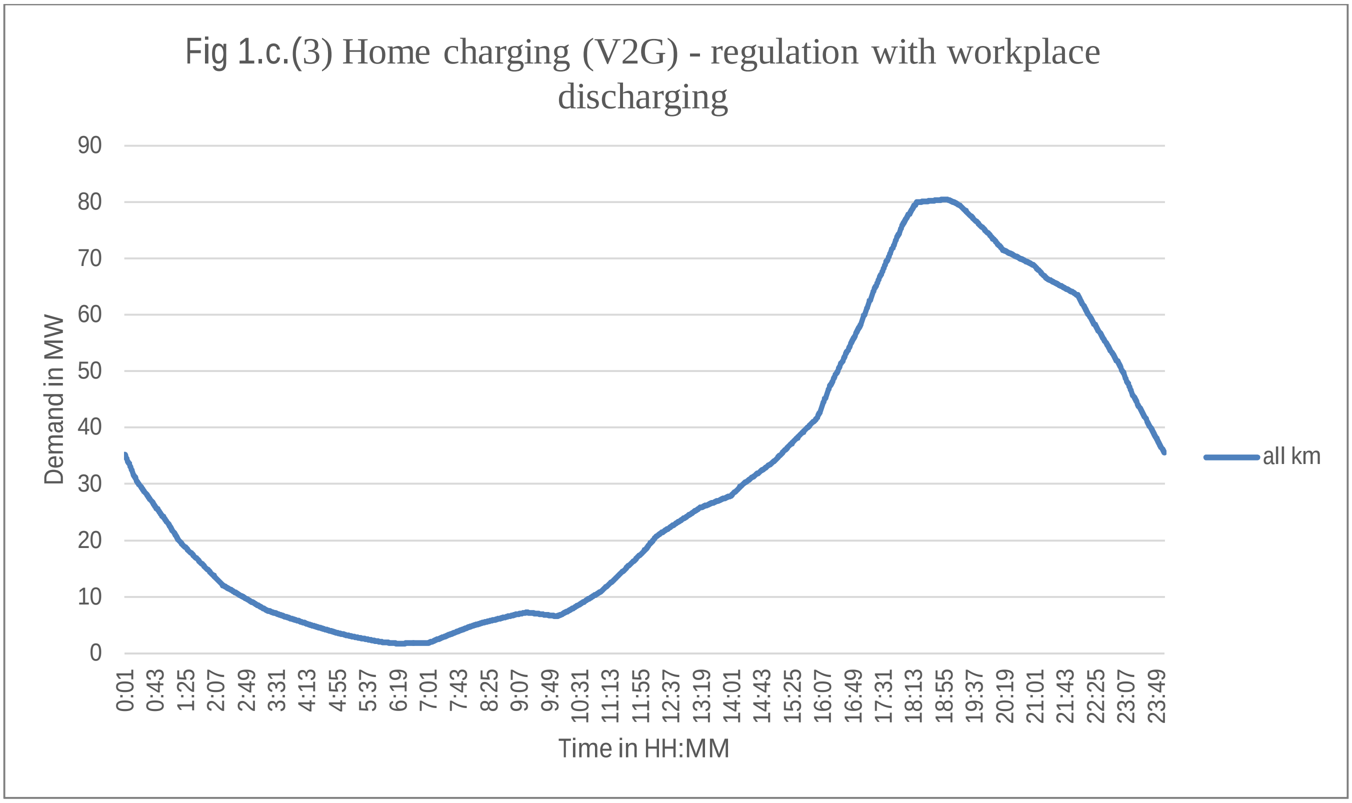


Fig 1.c.(3) Home charging (V2G) - regulation with workplace discharging
Demand in MW
90
80
70
60
50
40
30
20
10
0
0:01
0:43
1:25
2:07
2:49
3:31
4:13
4:55
5:37
6:19
7:01
7:43
8:25
9:07
9:49
10:31
11:13
11:55
12:37
13:19
14:01
14:43
15:25
16:07
16:49
17:31
18:13
18:55
19:37
20:19
21:01
21:43
22:25
23:07
23:49
Time in HH:MM
all km

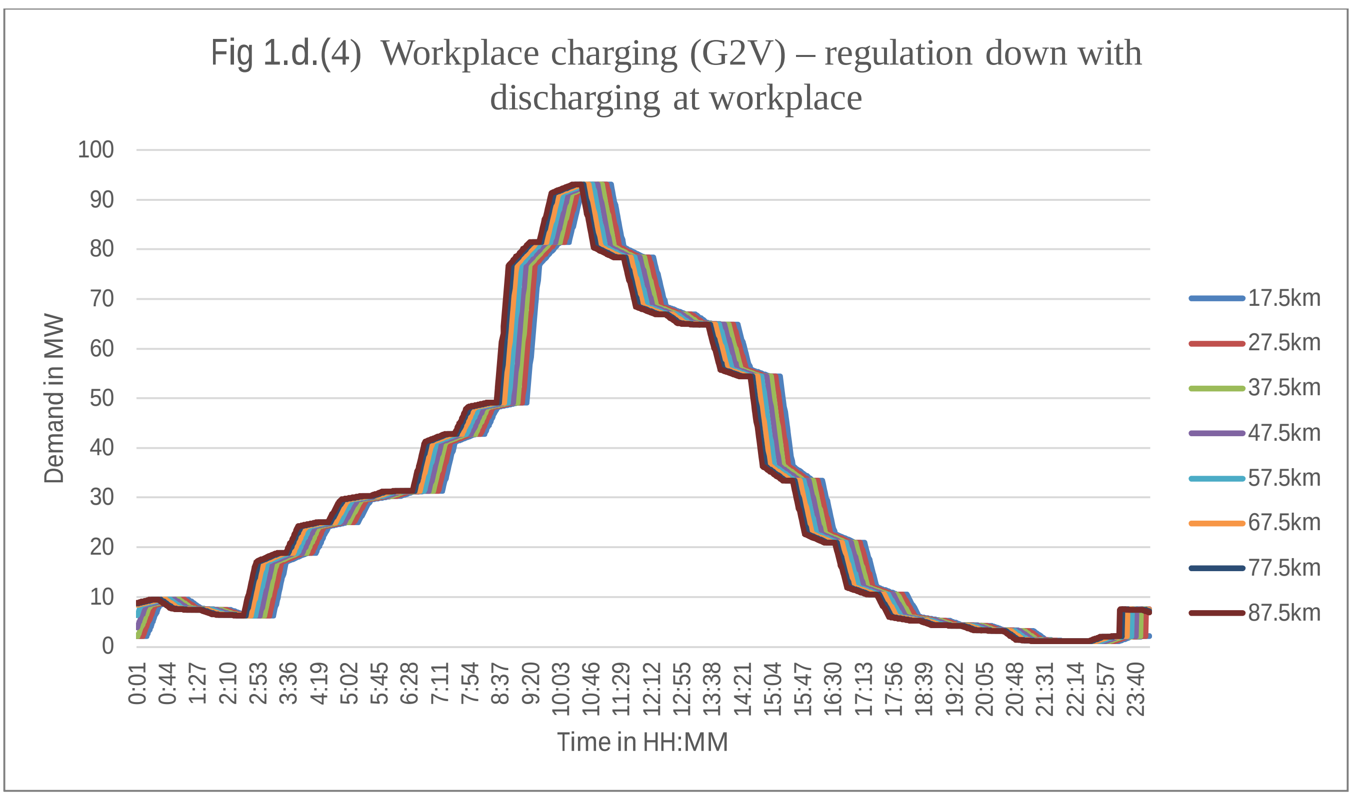


Fig 1.d.(4) Workplace charging (G2V) – regulation down with discharging at workplace
Demand in MW
100
90
80
70
60
50
40
30
20
10
0
0:01
0:44
1:27
2:10
2:53
3:36
4:19
5:02
5:45
6:28
7:11
7:54
8:37
9:20
10:03
10:46
11:29
12:12
12:55
13:38
14:21
15:04
15:47
16:30
17:13
17:56
18:39
19:22
20:05
20:48
21:31
22:14
22:57
23:40
Time in HH:MM
17.5km
27.5km
37.5km
47.5km
57.5km
67.5km
77.5km
87.5km

Conclusion:-

Following conclusions can be derived from the load profile for all the four cases.

1) Home charging (G2V) – As seen from the load profile(Fig 1.a) the peak load due to G2V coincides with the peak load of conventional at around 18:00:00 it will lead to increase in overall peak demand by 80 MW max 15 MW min depending on SOC(which is dependent on trip distance) of EV.

2) Workplace charging (G2V) - regulation down - As seen from the load profile (Fig 1.b) the peak load due to G2V occurs 10:00:00 around and i.e. 95 MW max and 10 MW min but it will lead to overall increase in peak demand by at max 35 MW because it does not coincides with the peak demand of conventional load.

3) Workplace discharging (V2G) - regulation up and home charging (G2V)) - regulation down - In this case charging load profile(Fig 1.c) is same for all trip distance because remaining battery energy is utilized in G2V and hence DOD is same for all trip distances.

4) Home discharging (V2G) - regulation up and workplace charging (G2V)– regulation down – In this case charging load profile (Fig 1.d)is same for all trip distance because remaining battery energy is utilized in G2V and hence DOD is same for all trip distances but time lag in load profile for different trip distances is due difference in travel time for different distances as arrival time at workplace is dependent on trip distances.

B. **Regulation capacities though BEVs**

Load profile for all the four cases is calculated by algorithm and is used **estimate t**he variation in RD/RU capacities as a function of trip distance considering the example BEV for the four cases are shown in Fig. 2 to 5. The following ramifications can be derived

The relevant modelling parameters are detailed in Table 1.1.:

1) **Effect of trip distance**: RD capacity increases as the trip distance increases, as more charging energy is required from the grid for the batteries depleted in driving. The rise is steep in the cases of home and the workplace G2V alone (Figs. 2 and 3), but the slope decreases when EVs participate in V2G also (Figs.4 and 5). This is because during the RD periods of the two cases (Figs. 4 and 5), although sparsely, V2G participations always there by the vehicles causing RU and hence resulting in lower net RD. The RU capacity reduces with increase in trip distance, as more energy is being consumed in driving leaving little to be discharged into the grid in V2G mode. Further, at a certain stage the charging (RD) becomes predominant resulting in shifting from RU to RD mode at different times in higher mileages (Figs. 4 and 5).
2) **Effect of arrival times versus number of vehicles arriving**: We classified the possible RD/RU capacities into high, medium and low categories. The timings of high, medium and low RD/RU capacities are dependent on arrival times at the two places versus number of vehicles arriving at these times. Since the vehicles start charging or discharging soon after arrival, the number of vehicles arriving have a direct bearing on RD/RU capacities at a particular time. As indicated in Figs. 2 and 3, it can be observed that the high RD capacities are closely associated with times of peaking bars of Fig. 1 Home arrival and 1 Workplace arrival respectively, whereas, the medium around them and the low capacities away from the peaking bars. The time intervals for the three categories of the cases in Fig. 4 and 5 are listed in Table 1.2. It can be seen that in home G2V workplace V2G case, the high RD and RU capacities are closely linked with home and workplace arrival peaking bars respectively, while medium around and low away from them. Likewise, vice-versa in the case of workplace G2V home V2G.
3) **Effect of G2V and V2G power levels**: For a given amount of energy to be supplied or released, high charge/discharge power level causes a limited boost in RD and RU capacities near arrival times, respectively during the charging (G2V) and discharging (V2G) process. This is due to fast charging and discharging. The effects can be observed in RD/RU capacities in Figs. 2 to 5. As workplace charging power level is 50kW, the highest point of RD and RU capacities at workplace G2V and V2G respectively, is greater than that of the highest point of RD and RU capacities, respectively at home G2V and V2G with the power level of 6.6 kW. Here, we insist upon to consider the upper ranges, corresponding to last trip distance of high RD capacity and first trip distance of high RU capacity, for the comparison as the remaining ranges are suitably selected to normalize the scenarios. So, comparing Fig. 2 with Fig. 3 (and also Fig. 4 with Fig.

5), this highest point RD capacity is 90.5 MW with workplace G2V (as can be seen in Figs. 3 and 5) against the 78.6 MW of home G2V (Figs. 2 and 4). Similarly, amidst Figs. 4 and 5, this highest point RU capacity being 65 MW (Fig. 4) with workplace V2G when compared with 62 MW of home V2G (Fig. 5). The farthest range of high RD capacities of 90.5 MW and 78.6 MW linked to the G2V scheme as mentioned above are same for all the four cases because the last trip distance of 86.8 km leaves zero margins for V2G (and hence RU) owing to fully depleted batteries in driving.

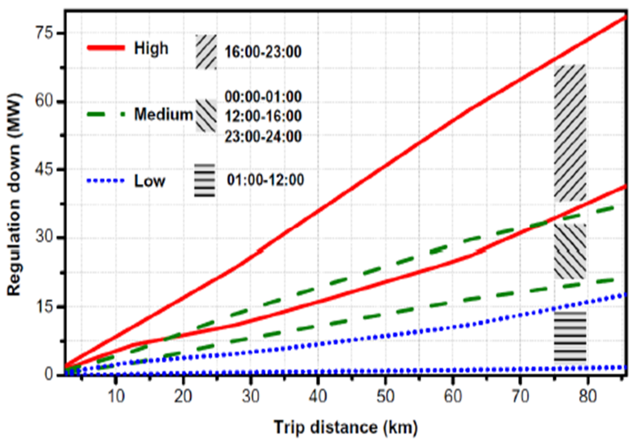


Fig. 2. RD capacity versus mileage with home G2V

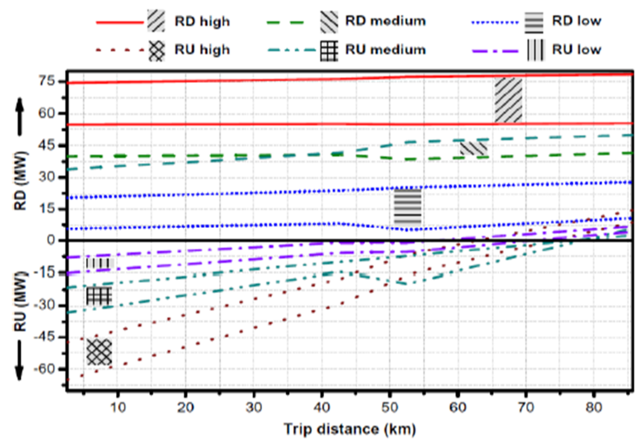


Fig. 4. RD/RU capacity versus mileage with home G2V workplace V2G

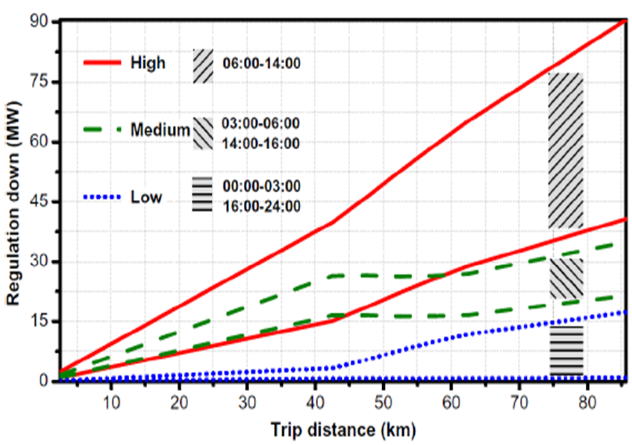


Fig. 3. RD capacity versus mileage with workplace G2V

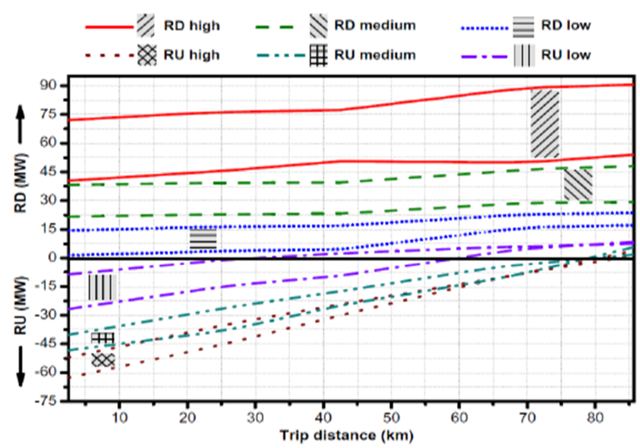


Fig. 5. RD/RU capacity versus mileage with workplace G2V home V2G

V. Implementation

In order to utilize the resource (both load and generation) of EVs to facilitate services to the grid, an aggregator entity is needed as a mean to group and control EVs in the range of MWs [8], [9]. The aggregator will provide an interface of willing customers to the system operator for participating in competitive power markets by offering the grid services. The aggregator will receive mobility data from individual EV owners as input and process them to evaluate the model parameters for aggregation. The algorithm delivers the final regulation (both up and down) schedule over a complete day as output by treating the model parameters. The thus obtained schedule could be offered in ancillary service market by the aggregator to exploit the power trading opportunities. We demonstrate the possible revenue that could be earned through the participation of EVs in the regulation power market. Let us consider an example of trip distance 27.5 km. Our computation shows the following average aggregated RD and RU capacities (in MW/h) against the number of hours for a typical weekday. For RD, 9.71 for 24 h in case 1 and 2, 41.36 for 13 h in case 3, and 36.93 for 15 h in case 4. For RU these values are 19.92 for 11 h in case 3, and 26.25 for 9 h in case 4. Since the primary function of the vehicles is transportation and remaining energy in the battery is used for V2G, the RD capacity is invariably higher than RU capacity. Suppose the vehicles contract to provide regulation for 250 days a year (excluding weekends and holidays). The annual capacity price of NY-ISO (averaged over a period of 2006-13) in $/kW-year [28] and average retail price of electricity in NY region [29] are summarized in Table 1.3. Conservatively, we extrapolated the capacity price for D days, where D is the net number of days of regulation contract. For example, as in case 3, the net RD and RU contracts are of 135 (13_250/24) and 114 (11_250/24) days. The regulation service payment comprises of capacity payment and an energy payment. Based on the above pricing, the estimated annual revenues per vehicle for these two parts are listed in Table 1.4. It can be seen that the energy payment costs are negligible in comparison to capacity payment costs. Thus, even if no energy is being supplied during regulation service a guaranteed capacity commitment to the service would yield considerable revenue. This is indeed after separating the charging energy cost during RD provision. However, the regulation capacity pricing in the ancillary services market is highly volatile which will influence the revenue. For example, between 2006-2012 the prices even varied from 3 $/kW-year to 115 $/kW-year [28] depending upon independent system operator (ISO) / regional transmission operator (RTO) regions.

TABLE 1.1

Parametres for RD and RU capacity evaluation from a fleet of Nisaan Leaf (BEV)

Parameters	Value	Parameter description / Comments
Electric vehicle and mobility attributes maintained / furnished by EV owners		
B (kWh)	24	Weighted mean battery capacity
K_{100c} and K_{100h} (kWh/100 miles)	26.12 and 33.04	Fuel consumption rate from EPA label
x (%)	80	Battery DoD limit for longevity
$x.B$ (kWh)	19.2	Available capacity after DoD limit
$c_{\%}$ and $h_{\%}$ (%)	55 and 45	Weightage of city and highway values in combined fuel economy [24]
R_p (km)	20	Assumed preserved range for an unanticipated trip or emergency purpose
$A_{H1}, A_{H2}, A_{H3}, \ldots\ldots\ldots\ldots, A_{Hn}$ (hh:mm)	00:00, 00:30, 01:00, ……, 23:00	Representative of home arrival times with n being 24. Averaged hourly from [18], [22]
$A_{W1}, A_{W2}, A_{W3}, \ldots\ldots\ldots\ldots, A_{Wn}$ (hh:mm)	7 hours + one-way travel time ahead of home arrival times	Representative of workplace arrival times with n being 24. Obtained from 6.
Arrival pattern		
$N_{H1}, N_{H2}, N_{H3}, \ldots\ldots\ldots\ldots, N_{Hn}$	As per trend in Fig.	Number of vehicles arriving at home at different times with n being 24 (X1,Y1)
$N_{W1}, N_{W2}, N_{W3}, \ldots\ldots\ldots\ldots, N_{Wn}$	As per Fig.	Number of vehicles arriving at the workplace at different times with n being 24 (X2,Y2)
Available battery capacity and electric range		
R_{pc} and R_{ph} (km)	11 and 9	City and highway km possible with preserved range
$B^{R_{pc}}$, $B^{R_{ph}}$ and B^{R_p} (kWh)	1.785, 1.847 and 3.632	Battery energy required for city km, highway km and combined total km of preserved Range
B^{Net}, B_c^{Net} and B_h^{Net} (kWh)	15.568, 8.562 and 7.005	Net available battery capacity with its city and highway components
d_c, d_h and d (km)	52.75, 34.12, 86.87	City, highway and combined total distance possible with net available battery capacity
Driving consumption and V2G energy For illustration we considered only one mileage group/trip distance (M) and one arrival time pattern for home (A_H) and the workplace(A_W)		
d (km)	27.5	Trip distance
A_H and A_W (hh:mm)	17:30 and 10:10	Home and workplace arrival times, respectively. Number of vehicles arriving at these times is 5354
c_{km} and h_{km} (km)	15.125 and 12.375	City and highway driven km per trip
E_c and E_h (kWh)	2.45 and 2.54	Energy consumed in city and highway driven km per trip per vehicle

E^{M} and E^{M}_{V2G} (kWh)	5 and 10.57	Per trip per vehicle driving energy consumption and that available for V2G support
$E^{H_n}_{V2G}$ and $E^{W_n}_{V2G}$ (MWh)	56.60	Available energy for V2G from the vehicles arriving at home and the workplace
$E^{H_n}_{G2V}$ and $E^{W_n}_{G2V}$ (MWh)	26.74	Driving consumption of the vehicles arriving at home and the workplace
Charge (G2V) and discharge (V2G) modelling		
Energy required from the grid		
E^{n}_{Grid} (MWh)	83.34	Considering EVs engage in V2G
E^{ch}_{CP} (MWh) and E^{ch}_{CT} (MWh)	78.74 and 12.85	Energy drawn from the grid in CP and CT charging mode
P(k) average MW	23.46	Home G2V at 6.6 kW
Tcp and Tct and T^{ch} (min)	134, 218 and 352	
P^{dis}_{CP} (MW)	47.63	Workplace V2G at 50 kW
T^{dis}_{CP} (min)	11.54	

TABLE. 1.2

RD and RU time intervals for Fig. 4 AND Fig. 5

RD	Time Interval	RU	Time Interval
Fig. 4			
High	17:00-23:00	High	05:00-09:00
Medium	16:00-17:00	Medium	05:00-09:00
	23:00-00:00		12:00-14:00
Low	00:00-03:00	Low	03:00-05:00
	15:00-16:00		14:00-15:00
Fig. 5			
High	08:00-14:00	High	18:00-21:00
Medium	04:00-08:00	Medium	17:00-18:00
	14:00-15:00		21:00-23:00
Low	15:00-16:00	Low	16:00-17:00
	02:00-04:00		23:00-02:00

TABLE. 1.3

Details	Value
NYISO capacity payment price (Mean of average annual price over a period of 2006-13) [28]	22.28 $/Kw-year
Capacity payment price for D number of days	(22:28 D)=365$/kW-D days
New York average electricity price to customers (June 2015, residential) [29]	0.1897 $/kWh

TABLE. 1.4					
Case	Capacity Payment ($)	Energy payment ($)	Total Payment ($)	Charging Energy Cost ($)	Net revenue ($)
1 and 2: Home G2V and Workplace G2V	20924.49	260.04	21184.54	260.04	20924.49
3: Home G2V Workplace V2G	35041.7	844.5	35886.2	599.99	35286.21
4: Workplace G2V Home V2G	38928.12	881.77	39809.89	618.14	39191.75

VI. Conclusion

The power markets can provide significant business opportunities for an extensive deployment of electric vehicles. The developed algorithm in this work models the mobility attributes to determine the time, duration and amount of electric energy that can be made available as a regulation contract, thus creating an avenue for revenue stream taking advantage of price excitability in the ancillary services market. This is apart from the primary function of transportation. For ascertained G2V and V2G locations, the mobility features like mileages, charge/discharge power levels, vehicles' arrival pattern influence the regulation up and down capacity in different ways. The capacity payment alone for the regulation commitment can generate compelling revenue, even though customers keep paying for charging of the vehicles as per the retail tariffs. This will serve as an incentive for greater acceptance of these energy efficient vehicles. However, a comprehensive framework is required to be developed to facilitate services market operation with grid-integrated electric vehicles, including the communication link between customer-aggregator-ISO/RTO, as highlighted in. The present analysis seconds this notion.

C:3 Developing a Smart charging(SC) scheme of EVs for Aggregator to achieve load-leveling/valley filling.

I. Aggregator

Battery storage capacity of a single EV is too small to have significant impact on power grid due to its charging or discharging. However, aggregation of EVs together can act as a resource (both load and a generation/storage device) of significant size, representing total capacities of batteries i.e., an amount in range of MWs, that can impact the power grid in order to take advantage of economic competence in power markets. The aggregator functions as a mean of grouping EVs, according to owner's consent to exploit the business opportunities in these markets by providing interface between ISO or RTO and ESP. It is the aggregator that determines the optimal deployment of this aggregation in which individual aggregation can serve as both – a controllable load and a resource. EV aggregation can be utilized as a distributed energy resource (DER) that can act either as a generation/storage device capable of providing capacity and energy services needed by the grid or a controllable load to energy service provider (ESP) to be charged in way which is beneficial to grid. The ISO/RTO now has to deal with aggregator who behaves as a single decision maker, rather than individual owners. The ISO/RTO operates and controls the power system while ESP provides supply to customers through distribution grid. Aggregators can provide physical commodity or information (communication/control) signals like: an automobile manufacturer, a battery manufacturer, a cell phone network provider, or a distribution generation manager. One of the many possible objectives of aggregation is load levelling .For every load there is a typical daily shape characterized by peak and off-peak periods and these shapes are highly dependent on seasonal factors. The hourly load price follows these load shapes closely. Since EV loads are highly controllable, aggregators can control their charging to reduce the load fluctuations during off-peak periods. This requires proper consideration of state of charge of each battery. In opposition, if charging periods are not managed properly (that will be the case of no aggregation and centrally managed control) the increase in load demand by EVs will increase the requirement of regulation service. With load leveling the load profile becomes flat which can be easily forecasted and does not require expensive down regulation service from generators. Additionally it eases out the ISO/RTOs operations, as they can dispatch flat load with far less complexity than a fluctuating load. So the next part of project is dedicated to developing a smart charging scheme of EV for Aggregator to achieve load-leveling/valley filling.

II. Overview

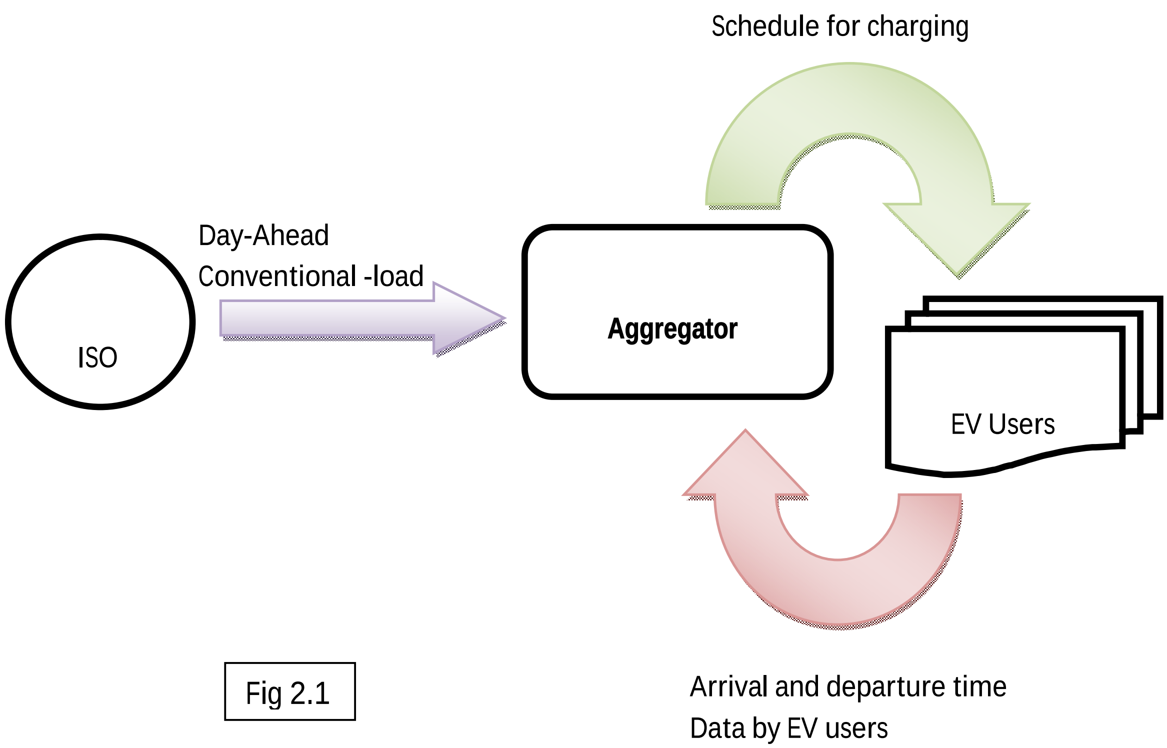


Fig 2.1

The objective of this work was to develop an algorithm for the management of charging schedule of EV user, based on day-ahead conventional load predicted by ISO, to achieve load levelling. The algorithm considers the parked duration of vehicles so that no vehicle is left un-charged. This work shows how large pool of EVs can be used as controllable load to reduce the load fluctuations during off-peak period.

Overview

The information flow is explained by a flow chart (fig 2.1) above.

1. The System operator communicates the day-ahead conventional load to the aggregator. This data is in form of hourly scheduling.

   $P(k)$ for $1 \leq k \leq 24$

   e.g. $P(2) = 233$, $P(5) = 245$ i.e. from 00:01 to 00:02 load is 233 MW every second and from 00:04 to 00:05 load is 245 Mw.

2. The EV Users provide their arrival and departure data for the next day. It is then summed up in form total of number of vehicles arriving in an hour. This can be denoted as NA (k) for$1 \le t \le 24$. e.g. NA (2) = 2330, NA (5) =275 i.e. from 00:01 to 00:02, 2330 vehicles will arrive and from 00:04 to 00:05, 275 vehicles will arrive. The EV user also provide the time for which vehicle is parked.
3. The aggregator after receiving this data calculates the charging schedule for EV user and communicates back to EV users. To calculate the charging schedule the algorithm is developed which is explained next.

III. The Algorithm

1) NP (t, k) for $2 \le t \le Tp$ – It is the maximum number of vehicles that can charged in k^{th} hour in t^{th} iteration.

- NP (1, k) = $\frac{Pmax - P(k)}{Pc}$ for $1 \le k \le 24$.
- Tp – it is time period for which vehicles is unused or parked.
- P_{max} – It is the load at which energy price is minimum.
- Pc – EV charger rating .

e.g. NP (2, 4) denotes number of vehicles that are charged in interval 00:04 to 00:05 in 2nd iteration

2) NA (t, k) for $2 \le t \le Tp$ – It is the number of vehicles available for charging in k^{th} hour from $(k\text{-}t)^{th}$ hour.

- NA (1, k) - It is the number of vehicles available for charging in k^{th} hour in 1^{st} iteration. This data is provided by EV users.

3) NC (t, k) for $2 \le t \le Tp$ – It is the number of vehicles that will be charged in k^{th} hour in t^{th} iteration

- NC (t) = $\left\{ \begin{matrix} NA(t,k) \quad if \ NP(t,k) > NA(t,k) \\ NP(t,k) \quad if \ NA(t,k) > NP(t,k) \end{matrix} \right\}$

4) NL (t, k) – It is the number of vehicles that will not be charged in k^{th} hour but will be available for charge in $(K+1)^{th}$ hour in $(t+1)^{th}$ iteration.

- NL (t, k) = $\begin{cases} 0 \;\; if \;\; NP(t,k) > NA(t,k) \\ NA(t) - \; NP(t,k) \;\; if \; NA(t,k) > NP(t,k) \end{cases}$

5) NA (t+1,k+1) = NL (t, k)
6) NP (t+1, k) = NP (t, k) – NC (t, k)
7) At the end of Tp iteration if NA (Tp, k) = 0 for k = 1 TO 24 i.e. none of the vehicles is left uncharged then final charging pattern is printed else if not the N is reduced proportionately i.e. some vehicles at different hours will be rejected from participation by aggregator.
8) The final charging schedule is given.
   - NC (k) = $\sum_{t=1}^{Tp} NC(k,t)$ for k = 1 to 24

IV. Sample System

1. P (k) - Conventional hourly load from Ontario ISO [30]. The data is normalized to peak of 300MW. As shown in table 2.1.
2. NA (k) - Vehicles arrival data from NHTS [18]. As shown in table 2.1.

Vehicles Attributes

a) All the vehicles have same SOC (Td=27.5 Km).
b) Charge time is 1 Hour and charge voltage is 6.6 KW (SAEJ1772).
c) Each vehicle is parked for 11 hours therefore Tp =11.

TABLE. 2.1

k	Home arrival time		NA (1, k)	conventional load (MW)	NP (1, k)	NC(k)
	From	To				
1	00:30	01:30	897	255.673269	6716	6716
2	01:30	02:30	443	242.668509	8687	8687
3	02:30	03:30	310	235.528942	9768	9723
4	03:30	04:30	216	233.333333	10101	216
5	04:30	05:30	116	234.530938	9920	116
6	05:30	06:30	72	233.532934	10071	72
7	06:30	07:30	166	243.605097	8545	166
8	07:30	08:30	758	264.056502	5446	758
9	08:30	09:30	625	281.083986	2866	625
10	09:30	010:30	548	277.36834	3429	548
11	10:30	15:30	1528	268.063872	4839	1528
12	11:30	16:30	2015	269.261477	4657	2015
13	12:30	17:30	2491	269.230769	4662	2491
14	13:30	18:30	2535	263.119914	5588	2535
15	14:30	19:30	3482	257.454322	6446	3482
16	15:30	20:30	4063	268.202057	4818	4063
17	16:30	21:30	6699	274.021188	3936	3936
18	17:30	22:30	7634	283.755566	2461	2461
19	18:30	23:30	6400	296.038692	600	600
20	19:30	00:30	5447	300	0	0
21	20:30	05:30	5264	296.315062	558	558
22	21:30	06:30	4434	290.634116	1419	1419
23	22:30	07:30	2768	282.78827	2608	2608
24	23:30	08:30	1688	265.177338	5276	5276

V. Results and Conclusion

Load profile for EV charging based on Smart charging schedule is shown in Fig.2.2. The individual vehicle owners are given schedule for charging from the output as shown Table 2.2 below. The complete schedule is 24x33 Excel sheet which is not possible to attach in this report hence it is only shown for two cases.

Table 2.2

Charging schedule Schedule for EV Owners

For Vehicles arriving at 1:00:00					**For Vehicles arriving at 21:00:00**			
Time	NP	NA	NC		Time	NP	NA	NC
13:30:00	2461	7634	2461		21:30:00	558	5264	558
14:30:00	0	5173	0		22:30:00	0	4706	0
15:30:00	0	5173	0		23:30:00	0	4706	0
16:30:00	0	5173	0		00:30:00	413	4706	413
17:30:00	0	5173	0		01:30:00	5819	4293	4293
18:30:00	0	5173	0					
19:30:00	0	5173	0					
20:30:00	0	5173	0					
21:30:00	0	5173	0					
22:30:00	7981	5173	5173					

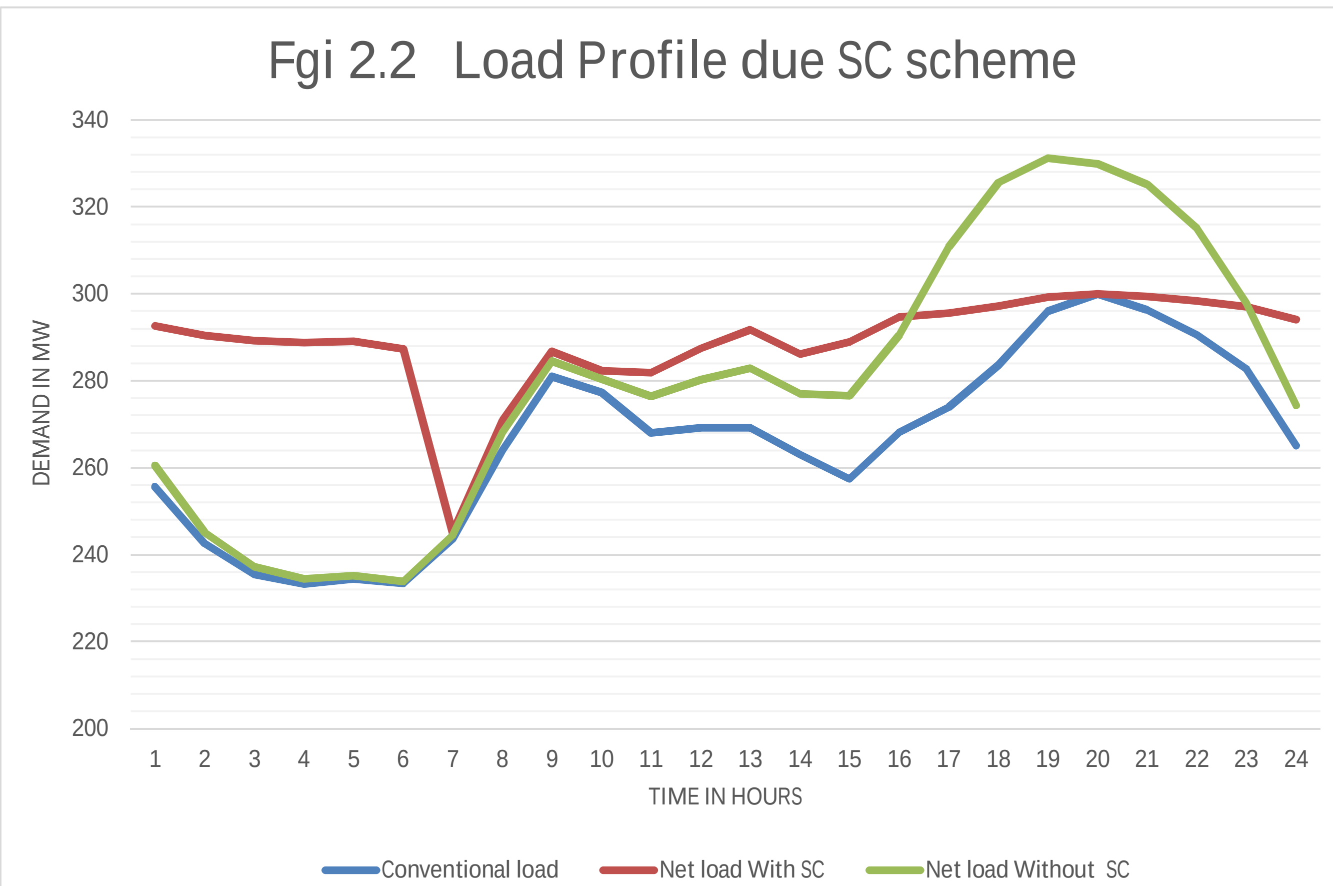
1. Out of 7643 vehicles arriving at 13:00:00, 2461 are scheduled to charge from 13:30:00, rest 5173 will be scheduled to charge from 20:30:00.
2. Out of 5246 vehicles arriving at 21:00:00, 558 will be scheduled to charge at 21:30:00, 413 vehicles from 00:30:00 and remaining 5819 vehicles from 01:30:00.
3. And likewise each group of vehicle will be schedules to charge from particular hour. The final charging schedule shown in Table 2.1 in NC column
4. Net Load profile = V2G load + conventional load is shown in fig.2.2

Conclusion

Following conclusions can be made from the load profile.

1. Charging vehicles without Smart charging scheme i.e. charging vehicles as soon as they arrive to destination, will result in additional demand from power grid up to 30MW for this particular case. The increase in load demand by EVs will increase the requirement of regulation service.

2. If EV owners participate in Aggregation then the additional peak demand can be avoided and EVs can be used as controllable load for load leveling, with load leveling the load profile becomes flat which can be easily forecasted and does not require expensive down regulation service from generators. Additionally it eases out the ISO/RTOs operations, as they can dispatch flat load with far less complexity than a fluctuating load.



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