Intra-city EV charging optimization based on vehicle usage pattern and traffic congestion analysis

Ameya Ulhas Ghodke
ICF Consulting India Pvt Ltd
New Delhi, India
Email: ameyaulhas.ghodke@icf.com

Pramod Singh
ICF Consulting India Pvt Ltd
New Delhi, India
Email: pramod.singh@icf.com

Agrim Rattan
ICF Consulting India Pvt Ltd
New Delhi, India
Email: agrim.rattan@icf.com

Rakesh Maurya
ICF Consulting India Pvt Ltd
Bangalore, India
Email: rakesh.maurya@icf.com

***Abstract*— India's mobility sector is undergoing a transition towards a cleaner future. Fuel consumption by India's light-duty vehicles grows by 7.7%/year during the period 2012-2040 as per a study by EIA, accounting for 51% of the total increase in transportation energy use [1]. Making India's passenger mobility shared, electric and connected can cut its energy demand by 64% and carbon emissions by 37% by 2030 as compared to 2015 levels [2]. Electric vehicles are also touted as a solution for higher renewable integration since they can be used as flexible demand and supply resources which will help manage the variable and uncertain renewable generation. With the announcement of FAME – 2 by Government of India and EV policies by several states, recent years have witnessed a major policy push, both at the central and state level. This paper focuses on charging part of the EVs ecosystem, providing solutions for effective trip planning and charging scheduling for EV fleets. This study also emphasizes on a need to have a telematics platform which can provide real time updates on charger availability and traffic congestion.**

Keywords- Electric Vehicles; trip planning; charging scheduling; telematics platform

I. INTRODUCTION

Increasing focus on climate change related issues such as reduction in greenhouse gas emissions, rising sea levels and expectation of depletion of oil reserves is leading to fuel price increase. EVs would be the suitable solution for emission reduction and fossil fuel exhaustion. As the NITI Aayog is setting targets to phase out the sale of diesel and petrol vehicles by 2030 and promote adoption of electric vehicles, the implementation of intelligent EV charging scheduling and power system load management has become very critical for both the vehicle fleet owners and the electric utilities [3].

The ability to control or schedule charging (grid to vehicle) and discharging (vehicle to grid) brings more flexibility into the energy system. So EVs can be complementary to the power system from the flexible load management and grid balancing perspective.

To attain an efficient transport system operation, it is very important to plan for a system which has minimal impact on the typical customer behavior towards vehicle usage. General EV adoption trend across the world starts from public and commercial use vehicles like state run bus fleets and commercial car fleets and then moves towards private vehicles. This trend has been majorly driven by government initiatives to promote clean mobility.

Deployment of large number of EVs in government and commercial fleets emanate the need for smart fleet management which includes, trip planning, charging scheduling, charging station location planning, type of battery charging models to use (battery swapping/ plug-in charging) to make commercial sense for fleet operators.

This paper analyzes the existing driving patterns of Electric four wheelers operating in New Delhi, India and depicts the energy consumption patterns over the entire day. Based on this data analysis, a model is created to forecast the distance that can be travelled by an EV in order for the driver or the EV fleet manager to make a decision whether to go for charging first or pursue the next trip. The paper analyzes both fixed route and flexible route fleet operations.

II. MODEL DESCRIPTION

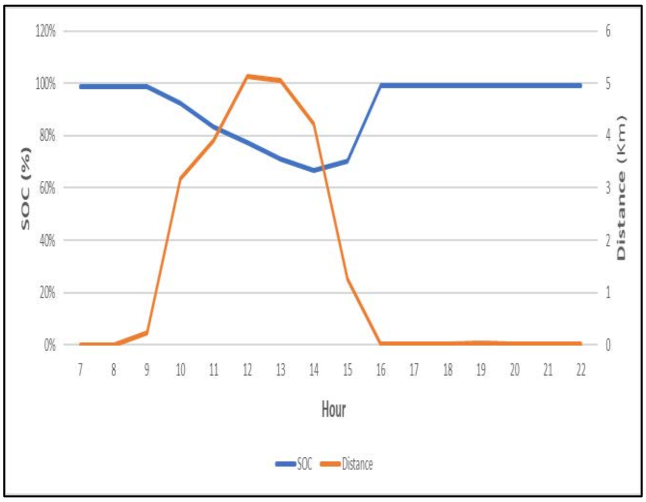
Telematics data is collected for the month of June 2019 from two electric four wheelers operating in the North Delhi region. The major parameters for data collection are battery State of Charge (SoC), distance travelled and vehicle speed. This data is gathered using a proprietary data collection server from Embedded Design Services India Private Limited. Table 1 shows the battery specifications of the vehicle which is used for data collection.

TABLE I. BATTERY SPECIFICATIONS USED IN VEHICLE

Battery Capacity	280 Ah
Technology	Lithium-ion
Battery on-board power	15.4 kWh
Driving Range	140 Km

A driving and energy consumption pattern for a typical day in the month of June is shown in the Figure 1.

Figure- 1 SOC & Distance Travelled on a typical day of June



Above graph depicts a typical EV usage pattern where the driver starts the day with 90% SoC and drives the vehicle over the day and then plugs the vehicle in for charging at 3 PM. As the battery has not been fully depleted when the vehicle is plugged in for charging, there is a need to set a minimum State of Charge level (SoC_{min}). It has also been observed, from a monthly vehicle usage pattern, that the EV is being charged during the evening electricity demand peak period (17 – 21 hours). With increase in penetration of EVs, a similar charging pattern can result in a drastic increase in the peak load for electric utilities. Thus, peak time charging needs to be shifted to off-peak periods through intelligent charging scheduling. Collected telematics data for the month of June'19 is used to evaluate the actual energy consumption of the electric vehicle across the day given varying traffic and road conditions.

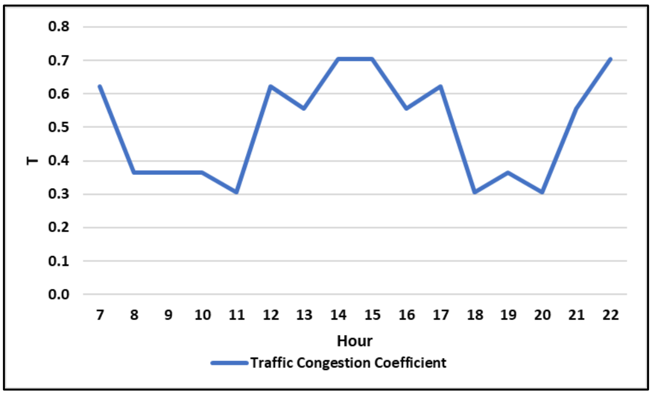
Traffic congestion across different hours of the day plays an important part in the energy consumption by an EV. The author has defined a Traffic Congestion Coefficient to analyze the interlink between traffic and energy consumption. This coefficient is calculated as the ratio of actual energy consumed by an EV to cover a certain distance during particular hour of the day, to the energy consumed by it during the same period to cover the same distance on an empty road under ideal conditions. The coefficient varies between 0 to 1, with 1 reflecting an empty road condition and 0 being standstill traffic. This traffic congestion coefficient might vary from place to place. This coefficient takes into consideration the energy loss due to frequent breaking and accelerating and extra energy consumed during vehicle ignition. All other minor inefficiencies are included in this coefficient.

Figure-2 shows the variations in the traffic congestion coefficient (T) over the day.

$$T = \frac{Actual\ Distance\ Travelled\ by\ an\ EV}{Distance\ Travelled\ by\ an\ EV\ under\ ideal\ condition}$$

Where,
T = Traffic congestion coefficient

Figure-2 Traffic Congestion Coefficient Variation



Before scheduling the next trip for EV, its state of charge has to be assessed to evaluate whether the remaining battery level is sufficient enough to take the next trip or to travel to the nearest charging station [4]. A general equation for the distance that an EV can travel during a certain hour of the day can be derived as:

$$D = \sum_{i}^{i+1} (I_{SoCi} - SoC_{min}) * (r * Ti)$$

Where,
D = Distance travelled over the operating period per day, (Km)
I_{SoC} = Initial State of Charge of the Battery at the start of an hour, (%)
SoC_{min} = Minimum State of Charge of the battery, (%)
r = Range of an electric vehicle under ideal conditions, with low traffic and no obstacles, in a single charge, (Km)
T = Traffic Congestion Coefficient

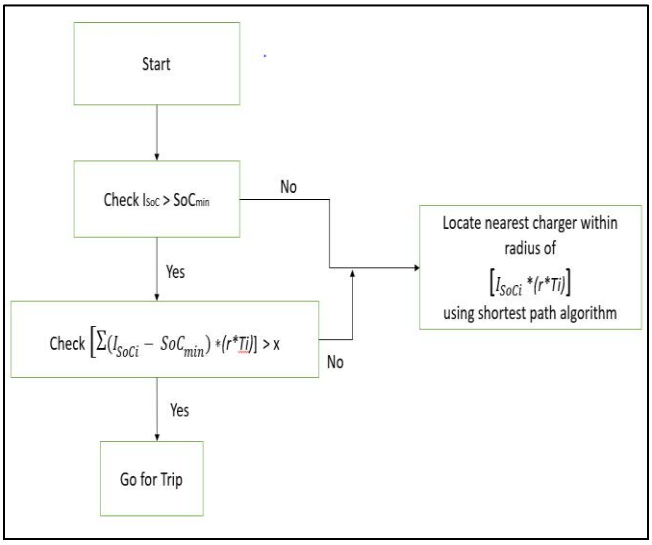
For a better charging scheduling, a proper process has to be followed. Figure-3 shows a flowchart for making a decision, whether to go for charging first or accept the next trip. These decisions can either be made by vehicle drivers or by fleet operators while scheduling the trips for the vehicles in the fleet.

In the following flowchart, 'x' can either be distance in Km for the next trip or distance to be travelled during next hour. Most likely for fixed route fleets, the trips are scheduled during certain periods of time but for the fleets with flexible routes the distances are not fixed.

This decision-making tree also shows that the SoC_{min} level should be planned such that nearest charging station locations fall under [SoC_{min} *(r*Ti)] distance radius from the pick-up or drop-off locations of EVs.

These observations are used in MS excel based simulation modelling for EV fleets operating on fixed and flexible routes.

Figure-3 Flowchart for Charging Decision Making



III. Possible Solutions

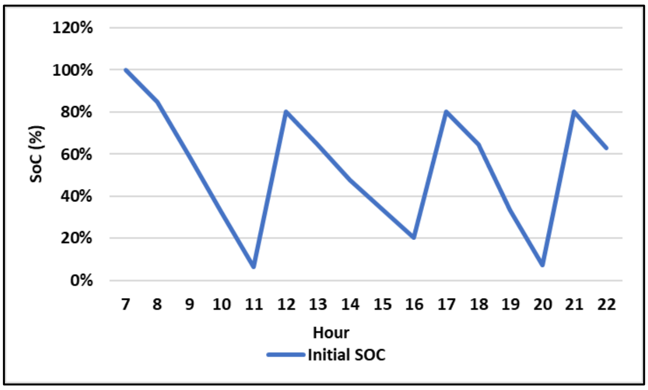
A. *Assumptions for Simulation*

- For fixed route electric vehicle, it is assumed that the daily travel will be 200 Km between the period of 7:00 and 22:00 hours of the day.
- The model is simulated for different scenarios of initial state of charge at the start of day at 7 AM. A minimum State of Charge level of 5% and SoC_{max} is assumed to be 80%. The rate of battery charging depends on the SoC. When the SoC is between 80%-100%, charging takes place at a slower rate compared to the charging rate when the SoC is between 0%-80% [5].
- The SoC_{min} level might vary depending upon the number of charging stations available in the fleet operating region. This gives the charging and discharging pattern for the EV over the operating hours. On-peak electric load hours in New Delhi are 6 AM to 10 AM and 6 PM to 10 PM.
- A 15kW DC charger with 87% efficiency which will charge the vehicle battery from 0% to 80% SoC in one hour is assumed [6].

B. *Results and Discussion*

Figure- 4 shows that the EV has to be charged twice in a day, if the driver starts the day with 100% fully charged battery. The battery has to undergo two charging events per day during the 11^{th} and 17^{th} hour of the day, out of which the 17^{th} hour coincides with the peak demand of electric utility, also with the peak requirement for transport service. There is an opportunity loss for EV driver or fleet on account of customer unserved during the peak requirement. For electric utility, there may be an additional cost impact to manage additional EV load at the peak demand time. These factors can discourage EV adoption.

Figure- 4 Charging & Discharging cycles with 100% starting SoC



In a situation where the number of vehicles in a fleet is greater than the available charging points, there would be a waiting queue at the charging stations resulting in loss of business opportunity. Because if all the vehicles in a fleet start their day of operation at the same State of Charge, then they are most likely to end up getting fully discharged at around the same time. A solution to reduce the waiting time at charging stations is to have a set of vehicles start their day with different initial SoC levels so that they will follow a non-coinciding charging and discharging pattern over the day.

Figure-5 Charging & Discharging cycles with 70% starting SoC

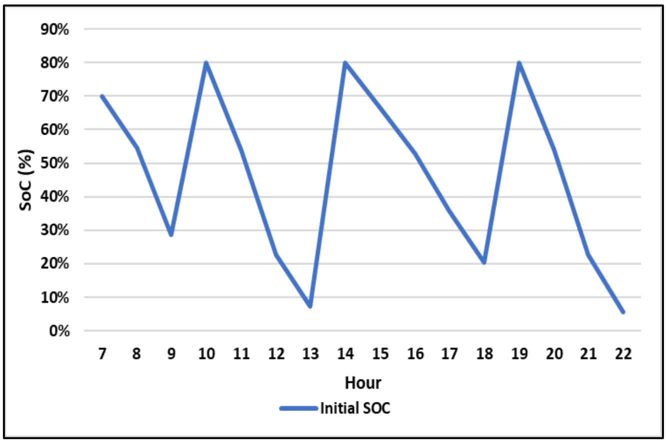


Figure-5 shows the charging and discharging pattern with 70% SoC starting point. It depicts that, a limited number of vehicles in a fleet can start their day of operation at 70% SoC which will lead to non-coincident charging patterns for vehicles. This type of charging pattern adds one more charging cycle during the operating period. There is a trade-off for the EV drivers or fleet managers whether to start with 100% SoC level and wait in line at the charging station or start with lower SoC and spend more time for additional charging cycle. This decision-making process might be easier if its evaluated on the basis of the opportunity cost or revenue lost during the time spent either waiting or charging at the charging station.

For the fixed route vehicles, the travel demand and thereby the revenue generated per hour is almost constant throughout the day. Hence for fixed route vehicle fleets, shifting the charging periods would be a better suitable solution. The decision-making timeframe for these fleets will be hourly based.

For flexible route vehicle fleets, charging scheduling depends upon a lot of factors like availability of nearest charging station in the drop off location of the last trip, private or public ownership of that charging station etc. as the traffic congestion would be different in different locations. A suitable solution for flexible route vehicles would be to have a telematics platform that will provide real time updates to the vehicle driver about charger availability, waiting time, traffic congestion, possible distance to travel, charging rates and pricing etc. Drivers operating in these fleets will be making charging decisions based on next incremental trip details.

In a scenario where vehicle stops for a top up charging in the off-peak hours even though I_{SoC} is greater than SoC_{min}, still there is a good chance of a need to charge the vehicle during on-peak electric load hour. From the power system perspective, time of use (TOU) pricing can be applied for EV charging to shift the EV charging load to the off-peak hours of the day.

IV. CONCLUSION

As India is just starting its electric mobility adoption, the availability of data on vehicle usage and customer behavior is very scarce. Based on the limited amount of data, this paper studies the energy consumption of an EV to come up with following conclusions:

1. For a fixed route EV fleet, it is desirable to start a day with different SoC levels rather than starting with 100% SoC by all vehicles to avoid waiting time at charging stations.
2. A fleet manager needs to decide depending upon the lost opportunity cost in terms of revenue, whether to reduce the waiting time at charging station or have more number of charging cycles throughout the day.
3. For a flexible route EV fleet, there is a need to have a common telematics platform which can integrate both transport and power system constraints to provide real time updates on vehicle energy consumption, traffic congestion, charger availability and TOU pricing.
4. As the number of EVs increase over the years, the large EV fleet owners need to make a decision whether to use public charging infrastructure or invest in a privately-owned charging infrastructure to avoid losing revenue due to waiting time, vehicles charging during peak travel demand periods dropping off of drivers from the fleet due to lack of motivation to use EVs.

REFERENCES

[1] https://www.eia.gov/outlooks/ieo/pdf/transportation.pdf

[2] India Leaps Ahead: Transformative Mobility Solutions for all- NITI Aayog, India, May 2017

[3] https://www.firstpost.com/news%20&%20analysis/only-electric-vehicles-to-be-sold-after-2030-says-niti-aayog-in-its-latest-proposal-6835331.html

[4] Yugong Luo, Tao Zhu, Shuang Wan, "Optimal Charging Scheduling for large-scale EV deployment based on the integration of the smart grid and intelligent transport system,"

[5] P. Papadopoulos, L. Cipcigan, N. Jenkins, I. Grau, "Distribution networks with electric vehicles", 44th Universities Power Engineering Conf., Glasgow, UK, 2009

[6] R. Pratt, M. Kintner-Meyer, K. Schneider, M. Scott, D. Elliott, and M. Warwick, "Potential impacts of high penetration of plug-in hybrid vehicles on the U.S. power grid, 2007, [Online], Available at: http://www1.eere.energy.gov/ vehiclesandfuels/avta/pdfs/phev/pratt_phev_workshop.pdf, [Accessed: Dec. 2012]

BIOGRAPHICAL INFORMATION

Ameya Ulhas Ghodke, born in Pune, Maharashtra on 1st of June 1993, holds a master's degree in Energy Systems from Northeastern University, Boston USA and has done a Bachelor's in Production Engineering from College of Engineering Pune. He has been working at ICF for last one and half years focusing on power generation and renewables based projects.

Mr. Pramod Singh has over 12 years of experience in energy efficiency, power, renewable, climate change and Electric Vehicles projects.

He has managed several consulting assignments for international donor agencies (ADB, USAID, US-EPA, UNDP, GIZ, IFC, BHC, DFID, World Bank and Climateworks Foundation), state governments (Assam, Punjab, Haryana, Gujarat, Maharashtra, Tamil Nadu, Andhra Pradesh, Karnataka and others) and central government organizations (BEE, CEA, SECI and others). He has the experience of working in developed and developing countries in Australia, Bangladesh, Europe, Nepal, India, Philippines, Thailand, Solomon Islands, and the US.

He holds a Master's degree in Energy Policy and Technology from California State University, Humboldt and a Bachelor's degree in Electrical Engineering from Indian Institute of Technology, Roorkee.