SECTORAL HARMONIZATION OF ELECTRIC VEHICLE TRANSPORT AND POWER APPROACHING DEMAND SIDE ENERGY MANAGEMENT-A CASE STUDY IN WEST BENGAL

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Abstract

Targeting a solution for mitigating fossil fuel crisis along with diminishing environmental pollution, rapid development of electric vehicles (EV) are taking place. Not only light EVs , but heavy EVs also, like Electric Bus penetrations are increasing day by day. Consequently charging strategy of those vehicles coming up with great concern. As stochastic charging activities of EVs can greatly stress the distribution system causing performance degradations, peak load increases significantly and the grid may be overloaded, a scheduling of charging is needed immensely. On the other side, power system load curve smoothening is a very important topic for Load Following, Frequency Regulation, and Voltage Regulation. Till date many researches has been done on load curve smoothening and EV charging strategy separately but there is still a deficiency in proper planning of a transport industy and power industry conjunction where these two complement each other considerably. The integration of rooftop photovoltaic (PV) generation has also been taken into acount. A Demand side management is presented in this article with consideration of transport industry's demands and maximum local consumption of PV power and EV charging infrastructure following the load curve flactuations which can effectively improve the performance, minimizing the load factor, alleviate overloading and underloading of the distribution system, ensure proper utilization of clean energy utilization and load ripple reduction. After going through a detailed survey, multi aggregator based on online fuzzy coordination algorithm (OL-FCA) for charging plug-in electric vehicles (PEVs) in smart grid networks with maximum efficient usage of rooftop PV generation is presented here which is applicable on the real ground of city Kolkata, India.

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Chapter 1

INTRODUCTION

1.1 Overview

Climate change, carbon emission reduction, and independence from fossil-fuels have been important issues on the international agenda during the past few decades. The numerous efforts aimed at dealing with and realizing these topics have begun to show positive effects and the share of energy generated from renewable sources has significantly increased. At the same time, there has been an increased tendency towards electrification of products, services, and technology. Whereas electrification of transportation being perhaps the most representative example. Transportation electrification offers two important advantages. First, it reduces local carbon emissions and fossil-fuel dependency. Second, it shifts energy needs towards a power system that is increasingly able to leverage energy produced from renewable sources . Electric vehicles (EV), in particular, allow for emission reduction in urban areas and, due to their use-patterns in urban environments, can potentially operate as flexible electric loads to support the operation of power systems and the integration of renewable energy.

The wide adoption of EVs, however, faces a number of challenges. First, the limitations on energy density of batteries and their effects on cost restrict the range or autonomy of EVs to way below that of their fuel-based siblings. Second, the requirements in terms of a new charging infrastructure, particularly if extended beyond places of residence or work, involve significant investments. For example,according to a recent study, investment in fast-charging infrastructure is unlikely to be profitable at low EV adoption rates, unless investment cost can be lowered.Last, the time required for charging an EV is substantial, with the additional disadvantage that, in general, increasing the charging power negatively influences the battery's lifetime. A higher EV adoption rate can only be reached if sufficient infrastructure is made available.

These major challenges, particularly related to the use of EVs in urban environments, have been the subject of intense research in the last years. Although advances in chemistry, battery, and charging technology play a role in addressing these challenges, we believe that information and communication technologies (ICT) can make a major contribution in efficiently managing the available resources, reducing the required amount of infrastructure for a given service level, and assist in planning and dimensioning fast-charging infrastructure. Technologies used to update utility electricity systems with computer-based automation and control through two-way communications structures constitute the core of the "smart grid" concept. Enabling the transition to plug-in hybrid electrical vehicles (PHEVs) and plug-in electrical vehicles (PEVs) is one of the anticipated benefits of the smart grid. These vehicles provide many incentives for the transportation industry and the environment. Large-scale integration of these vehicles has potential impacts and benefits for the grid.

One of the apparent impacts is the increase of the peak demand, which can destabilize the grid if not managed properly. If EV owners decide when and where their EV is charged (uncontrolled charging), the load during peak hours increase as these times coincide with the time at which the owner either arrives at work/home. The larger the number of EVs that are charged, the greater is the increase in the peak load of the grid. On the other hand, the PHEV/PEVs can benefit the grid by being treated as a flexible load through charge/discharge scheduling to shapethe load profile. Moreover, on the customer side, the increased satisfaction from the charging process in terms of time and cost of charging as well as the state-of-charge (SoC) of the vehicle, when leaving the charging station, can improve the adoption rate of the electric vehicles (EVs). Therefore, employing efficient energy-management policies to control and optimize the charging process for EVs is becoming a critical need for the future grid.

EV charge scheduling(EVCS) results in an efficient management of charging requests, which contributes towards one or more of the stakeholder benefits given in Fig. 1. The key stakeholders involved in charge scheduling include the grid operator, the service provider (aggregator), and the consumer (EV owner). The charge scheduling problem is addressed as an complex optimization problem.

A few terms used for determining the type of charge scheduling, are briefly described as:

- Centralized/ Decentralized Scheduling - The aggregator manages the scheduling based on EV inputs and slot availability at a charging station in centralized scheduling and the EV owner's charging station preference is not included. Whereas, the EV owner makes the final selection based on aggregator's information in decentralized scheduling.
- Online/Offline Scheduling - Online and Offline scheduling refer to the real-time and day-ahead management of scheduling requests, respectively.
- Mobility Aware/ Static Scheduling - The scheduling includes mobility parameters (location, EV's route, distance to charging station) and their impact on SOC in mobility aware scheduling. Static scheduling considers the EV as a stationary body .

Different techniques for charge scheduling, such as first available scheduling (FAS), random and first available scheduling (RFAS), greedy local search, Simulated Annealing, and heuristic algorithms have been used to optimize the charging cost and off-peak charging activity.

1.2 Literature Review

Pump storage plant(PSP) is a century old technoogy and most used accross the countries for power system load curve smoothing. But as decades passed, many problems arose with PSP. Efficiency of PSP is as low as 60 percent cited in [19], which is due to high response time,leakage losses, high transition losses due to mechanical operation. This control is also very centraized. Therefore, a faster, smart and decentralized technology was in need for load curve smoothing. [1] cited that

European PSP is confronted with economic challenges which are not harvesting a good result whereas new distributed energy sources(DES) like solar PV, wind generation are already enabled with potential of peak shaving and load curve smoothing.
To fill that void, Battery energy storage systems(BESS) came up as a feasible solution instead of PSP, overcoming challenges like slow charging/discharging rate, low power density, efficiency. Lithium ion cells made an major advancement in this era with 80-90 percent efficiency, 300-2000 w/kg power density and nearly flat discharge curve.

An algorithm was succesfully run with test bench set up using smart meter for BESS with the same objective of load curve smoothing[7]. Whereas a feedforward artificial neural network(ANN) forecasting was used to forecast the load pattern which is pattern recognition procedure enabled[2]. Using this forecasting they used it to develop an algorithm to achieve custom optimal flow scheduling for a microgrid consisting PV farm, Disel generators, BESS and load. In [17], an unified state model is described to minimize line to line power fluctuations and smooth load curve iencluding demand side resources i.e. Distributed generators(DGs), EVs(electrical Vehicles), thermo-statically controlled loads which has been used as a storage system. Till now, no one explored EV‘s potential for load curve smoothing and didn‘t focus on maximum efficient usage of DGs. Another side for indiscriminately increasing pollution rate and decrease in the storage of conventioanl fuel, it has become inevitable to accept EVs into grid system. If a fossil fuel driven transport Bus in Kolkata city has been compared with same capacity electric bus, the EV saves 18 percetage energy w.r.t. the conventional if the EV is supported fully from solar PV installation and Ev can save as much as 49 percentage energy w.r.t. conventional if the EV is supported by Grid power [14]. In [16] by adding rooftop PV generation to smart home and by considering its generation's uncertainty, charging discharging scheduling of existing electric vehicles, by paying attention to the constraints of homes consumption and vehicle's batteries, has been carried out. Here, some kinds of reserve has been used that can compensate the renewable energy resources' uncertainties like energy storage, load curtailment or using demand response programs.

However, the requirements in terms of a new charging infrastructure for EVs, particularly if extended beyond places of residence or work, involve significant investments. For example,according to a recent study [23], investment in fast-charging infrastructure is unlikely to be profitable at low EV adoption rates, unless investment cost can be lowered. Last, the time required for charging an EV is substantial, with the additional disadvantage that, in general, increasing the charging power negatively influences the battery's lifetime[20]. A higher EV adoption rate can only be reached if sufficient infrastructure is made available.

Coordinated EV charging can be broadly classified into two types, i.e., time coordinated charging (TCC) and power coordinated charging (PCC). In TCC, the number of EVs allowed to charge at a given time is controlled to ensure that the total EV load demand is within the total power available for EV charging, whereas, in PCC, the power consumed by each EV is controlled to ensure that the total EV load demand is within the total power available for EV charging.

A PCC is proposed in [13] for minimizing power losses and improving voltage profile during EV charging. A novel PCC method for mitigating the complications in power system operation due to different levels of penetration of EV load is proposed in [4]. In [22], a PCC method which focuses on minimizing the variance in SOC is developed for achieving fair aggregation of EVs for V2G application. Research work in [25] proposes a PCC method that maximizes the total amount of energy which can be delivered to all EVs over a charging period while ensuring that network limits are not exceeded. Both the TCC and PCC methods aim to control the overall EV load demand within the recommended limits in order to circumvent the impacts of EV charging on the power system operation. Scheduling of EV charging forms the vital component in both types of coordinated EV charging methods. A novel PCC algorithm to intelligently allocate electrical energy to EVs connected to the grid based on priority criteria such as energy prices, battery capacity, and charging time is proposed in [25]. Another PCC method proposed in [8] uses EV charging profiles and energy prices as priority criteria for scheduling EV charging. Based on the idea, in [12] they have developed a data-driven simulation which is used for evaluating and comparing the performance of different charging strategies of EVs with different combinations of priority criteria. The impact of all possible combinations is studied of three priority criteria i) SOC ii) Slack time iii) time/energy already allocated for the EV.

In all of these models an E-trading is going on always , a trade-off exists between aggregator and customer for optimizing benefits from each one's perspective. However,[24] - [10] attempt to address both stakeholders benefits in a multi-objective approach to maximize aggregator profit and minimize charging cost, where they achieve an optimal trade-off. A coordinated charging framework in a multi-aggregator situation [28] and a work place based charging station [27] optimizes the benefits of all three stakeholder. Furthermore, a coordination between aggregators for scheduling has been explored for profit maximization.
A multi-agent approach [29], a cooperative distributed algorithm and Monte Carlo [21] simulations have been used for a scalable scheduling solution. Whereas, a multi aggregator based charge scheduling scheme has been presesnted in [9] with the objective of maximizing total profit and the number of scheduled EVs. This incorporates collaborative charging and realistic situations with variable energy purchase (VEP) and cancellation charges. VEP reflects a practical situation where the aggregator purchases energy based on average scheduling requests per day and customers are penalized for not arriving at the scheduled slot.

A heuristic search algorithm is presented in [3] to allocate suitable charging rate sensing EV user's demand taking real time(PV) generation Power. Charging characteristics of power battery and characteristics of PVCS is used as constraints. Improving the maximum sensitivity (MSS) optimization, an online fuzzy coordination algorithm is cited [15] with objective of minimizing the cost of charging PEVs, keeping constraints of maximum voltage deviation, maximum demand level, total system loss. By using Starklberg game model, a pricing strategy and charging strategy for PVCS is presented keeping aim of minimizing the operating cost(OC) & maximum utilization of PV generation [26].In [11], they presented a mixed-linear integer programming (MILP) targetting minimizing OC for one day operation in terms of net power used from grid, solar surplus sold to grid, the price for purchasing and profit earning. It showed the implementation of cancellation charges on the customer further resulted in an increase in the profits. But in case of vehicle under ownership as they travel for various reasons always can not be predicted day ahead, rigid scheduling for those vehicles may not run properly. Therefore in case of [11], it may seem disadvantageous from consumer's point of view. Storage capacity has been calculated from the charging/discharging scheduling. Whereas on the real ground of Ankara city, USA [5] has developed a EV charging model. It showed it's not impossible to run solar PV assisted EV charging station (PVCS) without grid connection and according to availability of irradiance and temparature variation battery back pack be used for back up. In [6], they presented a real time information dependent driving, charging and scheduling model for long distance Evs(>150 km) by an intelligent choice of charging station stops to minimize overall distance. This was mobile communication enabled system.

In [16] - [11], they have presented EV's charging schdule taking priority vehicle's characteristics like SOC, slack time but didn't take load curve profile as priority. So all those plans may not avoid charging at the time of peak load occurance in grid. Moreover, in [3] [15], they are capable of peak shaving to some great extent but in those models the charging rates are to be controlled[3] and too many sensors are required as many real time parameters are needed [15] to run the scheduling which is cost effective and complex.

In our work, we have presented a multi aggregator based an online fuzzy coordination algorithm (OL-FCA) for charging plug-in electric vehicles (PEVs) in smart grid networks with maximum efficient usage of rooftop PV generation applicable on the real ground of city Kolkata, India. We didn't go for real time scheduling because in that case the aggregator should be enabled with ANN pattern recognition technique to forecast the load pattern[2] and to forecast the PV generation output based on weather conditions (not only weather conditions , dust precipitation is a major factor for diminishihng solar panel efficiency), which is very costly and complex. Instead we have taken total generation data from a rooftop 1 kwp solar PV installation(equador facing poly-crystaline sillicon) in Kolkata's condition for more than single year and calculated solar panel efficiency using monthly average irradiance data from the "Surface Meteorology and Solar Energy NASA open data portal". In this way without any sudden weather fluctuation, a proper asuumption of solar generation potential can be achieved averaging out all the factors which can influence the generation. A daily solar power generation profile has been constructed using "JRC European Commission Photovoltaic Geographical Information System - Interactive Maps" with the help of calculated solar panel efficiency. Now coming to point that co-ordinated EV charging schedule depends on variables like i) availability of CSs (where we have proposed 341 CSs all over Kolkata) ii) Ownership of the vahicle iii) Purpose of service. We have devided the transport sector into two category - state funded public transport (in our case WBTC) and vehicles with ownership. In the case of state funded i.e. WBTC(West Bengal transport corporation) we have brought a extra bus concept for charging scheduling. In case of purpose of service is commercial, having a rigid schedule already, the EVCS strategy proposed in [15] would be hazardous for service vehicles. Moreover, as generally the peak hours of load curve happens nearly 7:00-8:00 pm in night, BESS systems has to be introduced into the grid. Night peak shaving by DSRs like solar photovoltaic, would be impossible nearly without battery pack. It is possible if V2G(Vehicle to grid) technology is enabled but this wouldn't be a considerable amount. In our work, we have not considered V2G and PHEV in our studies. In our work all the charging stations are rooftop PV installed.

1.3 Objective

In our work a miniature model of the distributed, offline, mobility aware electric vehicle charging scheduling(EVCS) has been proposed considering one rooftop photovoltaic mounted charging station(PVCS), one route of West bengal transport corporation(WBTC). We have proposed WBTC to be fully electrified and one fourth of vehicles with ownership has been assumed to be fully electrified. Except load curve smoothing this would also be a huge step towards clean and somg-free city during winter. Firstly, an algorithm has been developed to propose the number of extra buses on the route, the battery pack capacity if it has to intake the PV generated energy during the underloading condition and discharge to grid during the overloading period, simultaneously charge the vehicles with ownership.If fully explored according to the proposed electrification of vehicles the potential of our model to smooth the load curve has been shown. Second, a traffic simulation has been done on an avege route. Status of all buses has been shown over the 24 hours considering the extra buses. Third, for over congestion of vehicle with ownership more than average we have proposed a surge pricing strategy.

Chapter 2

Survey of solar PV, transport and power industry in Kolkata

1. **Rooftop solar photovoltaic genaration data** Net meter reading of a rooftop solar panel installation,an array comprising of 4 poly-crystaline silicon solar panel at Department of Energy Studies, Jadavpur University, Kolkata, showed total generation of 3235.5 kw when checked on 2nd February, 2019 which was installed in last of November,2014. Total area of this installation is 6.47 m2 and tilt angle 22 degree south faced.

2. **Electric Vehicle average Consumption** AC 31 , Jadvpur 8b bus stand to Janakalyan Bus stopage Behala, a fully electrified Bus, under CSTC , model name TATA Electric STAR Bus Ultra, seating capacity 32 , standing allowed, battery capacity 125 kwh has been used for data collection. In Kolkata's road condition it showed consumption rate of 1.38 kwh/km. In case of increasing seat capacity or bad road condition in the modelling avergae consumption rate has been taken 1.45 kwh/km.

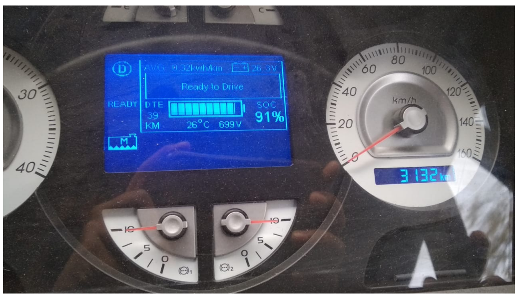


Figure 2.1: view of the display behind the steering wheel of the electric bus

3. **Electric Vehicle Charging Infrastructure:** Lake Depot Charging station has 7 chargers, AC/DC , 415V , 3-phase, 50 Hz, 200-750V rating manufactured by Shanhgai Tesus Power Co. Ltd. Among 7 chargers there is 1 fast charger of 120 kw charging rate, current rating 0-160 amp and another 6 is slow charger of charging rate 60 kw , current rating 0-80 amp.

4. **Load Curve** Typical monthly demand met pattern of 12 months has been collected from electricity demand pattern analysis POSOCO 2016 release. Taking any daily load distribution profile of one month, averaging the total demand over 24 hours, a average load line

Figure 2.2: first charger installation in lake depot

Figure 2.3: zoom out picture of the charger

Figure 2.4: Rating template of the DC charger

is superimposed onto the actual load profile. Subtracting the actual load from the average load line a "load flactuation curve" has been derived spanning 24 hours. In this "flactuation curve" positive outcome means underloading condition and negetive outcome means overloading condition. As Kolkata's average electrical energy consumption is nearly one-fifth of total demand West Bengal, in this model the load flactuation curve has been devided by 5 for kolkata.

5. **Kolkata Metropolitan Transport Industry**

    (a) WBTC has total 102 routes combining AC , non-AC, 60 bus stands , 11 bus depots. In case of new routes are introduced , we have taken 110 routes in calculation. 8B bus stand area is near 1285 m2 .Lake Bus Depot area is near 3600 m2 . Sulekha Petrol Pump near Jadavpur Bus stand has area of 640 m2 .

    (b) Total no of service cars (Ola + Uber+ Yellow Taxi) in kolkata is 45,160 (TOI ,March, 2016). Each 4-wheeler per day runs 150 km in an average.In case of E-car electricty consumption rate is 10 kwh/100 km.

    (c) Total no of Private car in Kolkata is 2,22,069 (TOI). Each private car per day runs 50 km in an average. d) There are 259 routes running daily supported by Private Buses in Kolkata.

    (d) A CSTC standard route S9 (Jadavpur 8B to Karunamayee, Saltlake) makes 65 trips per day, from both sides. (starrting from 5 am to 9 pm, per 15 minutes service). Trip distance 32 km.

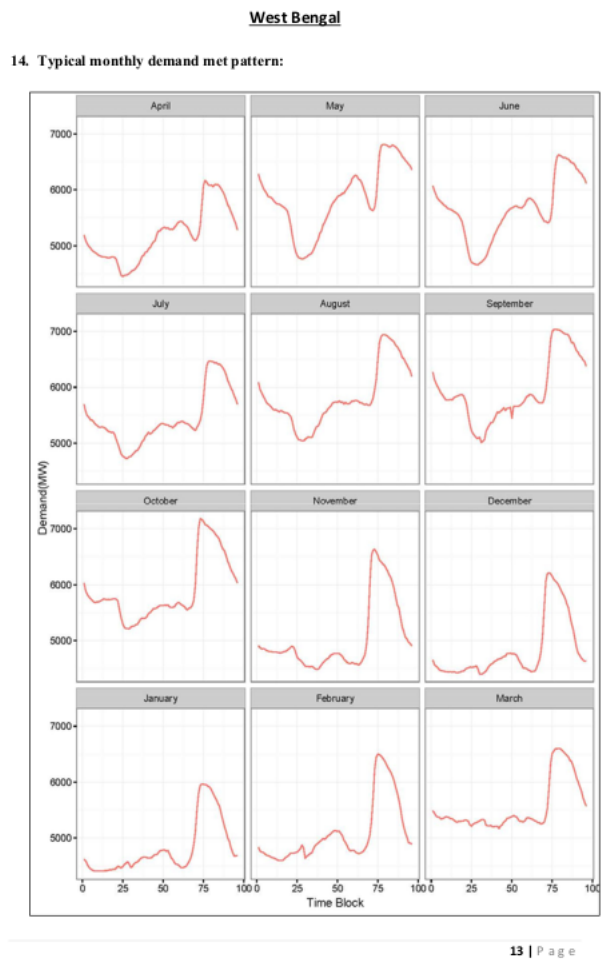


Figure 2.5: Load curve patterns monthly in West Bengal givevn by POSOCO

Chapter 3

Calculations based on survey

- Seventy percent area of bus stands and bus depots and all commercial buildings of Kolkata has been proposed to be installed with rooftop solar panels. In this process total area available for rooftop installation comes out to be 10,13,000 m2 .(60 bus stands, 11 bus depots, 70 petrol pumps, 200 commercial buildings rooftop each having 4500 m2 convertable to PV installation)
- Taking solar insolation average from NASA ,it can be stated that equator facing Polycrystalline silicon solar panels are 6.8 percent efficient in kolkata's weather and dust condition.Most importantly, by taking real data all the factors hampering panel efficiency has been averaged out. For example, average radiation of May is 5.39 kwh /m2 /day. So, in case of May average solar generation from rooftop installation all over kolkata per day will be (0.0068*5.39*10,13,000=) 37.12 Mwh.
- If the panels are south faced with tilt angle equal to latitude, from "JRC European Commission Photovoltaic Geographical Information System - Interactive Maps" putting latitude, longitude, tilt angle as inputs and solar panel efficiency 6.8 percent solar generation potential in terms of electrical power(in MW) has been listed by every 15 minutes of the day.
- If the panels are south faced with tilt angle equal to latitude, from "JRC European Commission Photovoltaic Geographical Information System - Interactive Maps" putting latitude, longitude, tilt angle as inputs and solar panel efficiency 6.8 percent solar generation potential in terms of electrical power(in MW) has been listed by every 15 minutes of the day.
- Similarly, from the load flactuation curve ,underloading and overloading depth in terms of electrical power(MW) has been listed by every 15 minutes of the day.
- Electricity consumption to suffice S9 route daily 3.05 Mwh electric energy is needed depending on the survey results.
- In this way to suffice WBTC (all 110 routes has been assumed to be electrified, per route 3.05 Mwh) energy is needed =336.34 Mwh.To cater all other forms of road transportions (25percent of service cars, private cars,private bus routes has been assumed to be electrified), the energy required is 930 Mwh. Total underloading or overloading area of May load fluctuation curve is 2574 Mwh. So percentage share of energy to suffice WBTC & unscheduled transports with respect to the area, is 13.05 percent and 36 percent respectively.

Chapter 4

Methodology of our proposed plan

We have only one month and chose the month May as the overloading duration of load fluctuation curve is higher than rest 11 months as shown in Fig3. In case of may we can explore the maximum size needed for the stationary battery pack. All the algorihm has been run on May for example.

4.1 Proposed PVCS Model

The idea with the objective of smoothening the load curve ,has twofold manifestation, that is, firstly, when the grid is in underload condition, EV's are to be put in charging condition correspoding to the depth of underloading ,secondly, when the grid is in near peak overloading condition, stationary BESS units storing daily photovoltaic generation will discharge to grid through a bidirectional AC/DC converter. The proposed EVCS algorithm[algorithm 1] is depicted below under some subparts:-

1. In the load fluctuation curve total area of under-loading is equal to total area of over-loading.
2. PV generations will be stored in the battery bank during under-loading condition and through battery bank the stored PV energy will be released to grid during over-loading condition.
3. As other transports except WBTC can not be scheduled , it has been assumed that throughout the 96 intervals of a day there will be a constant demand of these type of electric vehicles. And it is per battery station 0.028 Mwh/intetrval [=930 mwh/96/341 (where from survey 930 mwh is the daily energy demand for other transports and total no of battery bank station possible is 341)].
4. Only WBTC buses will be scheduled keepng extra buses in all routes. CSTC buses will be charged only when grid is in under-loading condition.
5. when in any interval grid is in underloading condition
   (a) Grid will charge the CSTC buses and other transport vehicles corresponding to the depth of underloading (underloading area of this interval)that is 13.05 percent and 36 percent of underloading area of the interval respectively.
   (b) PV generation output will be stored in the battery bank. (total PV generation of kolkata from the solar photovoltaic power generating stations as considered in this study is 16.16 percent of total overloading area of load fluctuation curve)

(c) If 36 percet of the underloading area is greater than 0.028 Mwh, the difference will be stored in battery bank.(Unscheduled road transports are to be supplied by each photovoltaic station is 0.028 Mwh per interval constantly)

(d) Otherwise, battery bank & grid will combinedly fulfill the 0.028 mwh demand for unscheduled transports per interval.

6. when in any interval , grid is in overloading condition

   (a) From the battery bank other transport buses will get charged.

   (b) The stored solar energy will be released to grid corresponding to the over-loading area.

   (c) No CSTC buses will be charged in this time.

   (d) If need of grid in the interval is greater than solar generation of the interval, then battery bank and PV generation will combinedly fill the demand of grid and vice-versa.

The algorithm is like

Algorithm 1 System Algorithm

$j = i + 1$

$A_i = 1/8(a_i + a_j) \leftarrow$ (+)area of the interval

$B_i = 1/8(b_i + b_j) \leftarrow$ (−)area of the interval

$W_i = 1/8(w_i + w_j) \leftarrow$ PV generation of the interval

$\sum x_i = 36$ percent of $\sum A_i = (0.028 * 96)$

$y_i = 13.5$ percent of A_i

$\sum A_i = \sum B_i = Area$

$\sum W_i = 16.16$ percent of Area

$S_i = 16.16$ percent of B_i

$\sum S_i = \sum W_i$

for strating from one 96 consecutive intervals **do**

  $m = i - 1$

  $output_i = y_i/0.015 \leftarrow$ scheduled charging unit of wbtc as charger has 60 kw rating

  $s2g_i = S_i$

  $g2s_i = x_i + y_i$

  $battery_i = battery_m - 0.028 + x_i + w_i - y_i$

end for

a matrix and b matrix are column matrix of 96 intervals listing the power of positive and negative load fluctuation curve respectively.Ai is the underloading area of the particular interval calculated approximately by trapizoidal area determination method. Similarly Bi is the overloading area of the particular interval Wi is the PV generation in Mwh of the interval. As total generation of solar power is 16.16 percent of the total overloading area.So aggregator to grid (S2Gi) energy sharing is 16.16 percent of the overloading area of this interval. yi is the percentage share of energy by wbtc which is 13.5 percent of the positive area i.e. the underloading area. xi is the energy required for the vehicles with ownerships which is to be ideally 0.028 Mwh per interval. But it would not match properly. Here comes the primary estimation of battery pack such that it will store the wi and release 0.028 i.e. the constant demand of the vehicles with ownership and will store the excess of xi . It will store also the wi and release yi in the same interval.

4.2 Traffic simulation

In our scheme an aggregator based smart traffic control has been presented for WBTC buses.And the next part is for the transport with ownerships a pricing strategy has been depicted. As in [25], an MSS based EVCS has been proposed for transports with ownership, but there is problem in their proposition. Because in case of service vehicles or previously scheduled vehicles if they are in emergency it wouldn't be proper treatment to postpone their charging requirement. In that case we have proposed a OL-FCA based surge pricing strategy for the vehicles with ownership.

4.2.1 For WBTC automated traffic algorithm

A miniature model of CSTC S9 route has been programmed succesfully. The route is a [2*5] route matrix in which every element of the matrix naming alphabetically 'a-j' , denotes the current position of one bus. Matrix element (1,1) that is element 'a' is the exit point of 8B bus stand, element 'j' is the entrance of 8B bus stand, similarly 'e' & 'f' elements are entrance and exit point of Saltlake Bus stand. Route distance is 16 km and average speed is 16 km/hour. We have taken average speed everywhere for simplicity.

As per algorithm 1 no of extra buses will be 6. Minimum no of Bus is 10 makes sumtotal of 16 buses in the S9 route. The rule of charging is

1. Based on SOC and the next every bus will get a fuzzy score entering the bus stop.

2. Two types of charger there are fast & slow. Depending on the score and $output_i$ of Algorithm 1 higher score P no of buses will get charged by fast charger and second higher Q no of buses will get charged by slow charger. Such that $2P + Q = output_i$.

3. Rest of the buses in bus stop will gt an idle time upto next interval.

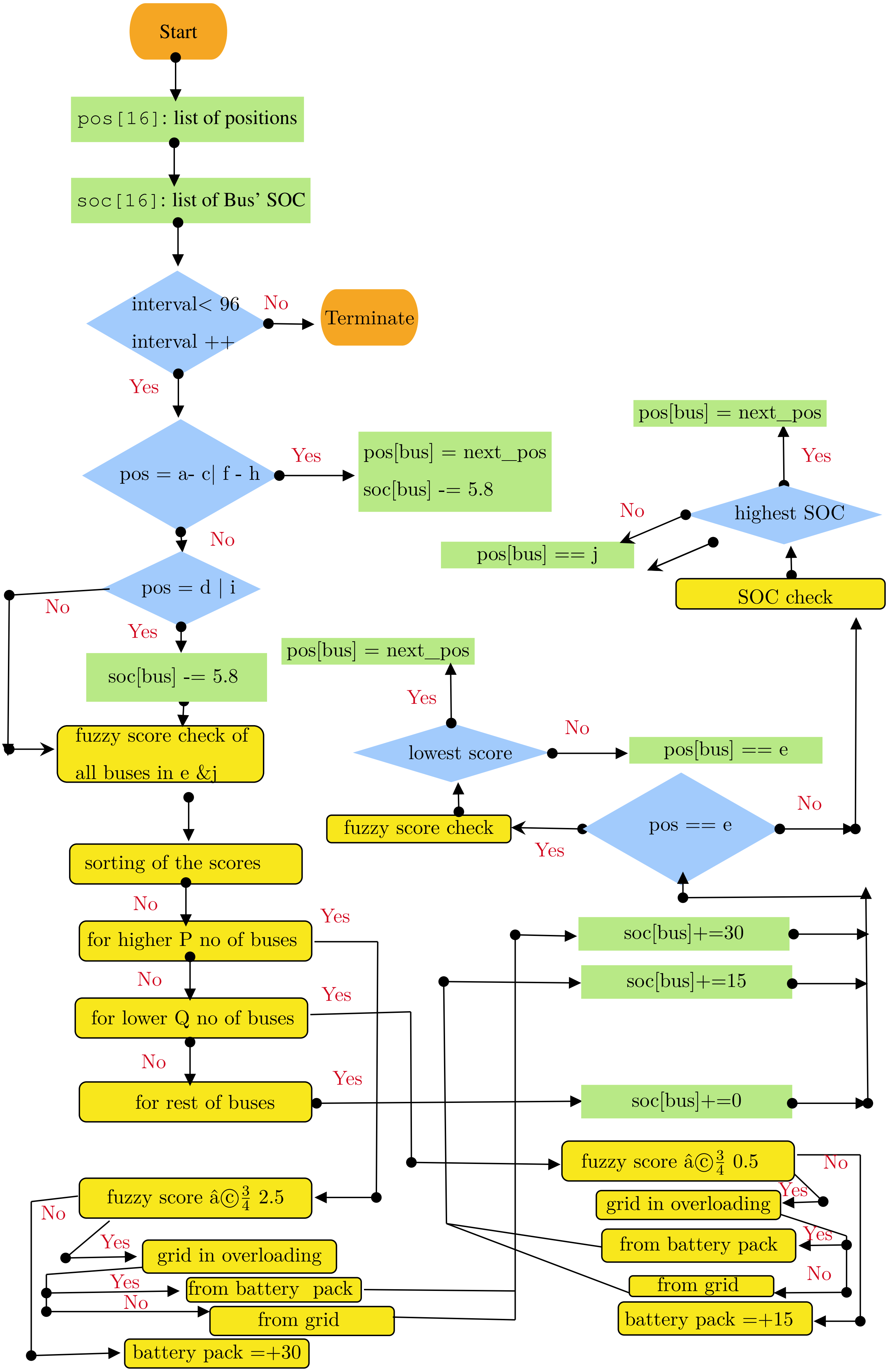
4. If the Bus score throw it under higher P but the score is < 2.5, the fst charger will charge the stationary battery pack. Similarly, if the Bus score throw it under less higher Q but the score is < 0.5, the fast charger will charge the stationary battery pack.

5. In the exit point of bus stop both side separately at that instant which bus has the highest SOC value will go for the next trip.

6. When a bus requires charging, if the grid is in underloading condition it will get the energy from direct grid but if the grid is in overloading condition it will get the energy from battery pack. In that case the battery pack will be higher for the bus stops than other charging station among 341 charging stations all over Kolkata ciy.

7. There will be no charging facility available on the route.

8. As WBTC services end up before 11 pm on the day and grid overloading stops after 1 AM in an average the buses will start getting charged upto trip starts. The charged distribution should be such that before the scheduled time of first trip all the get equal SOC.



Start
pos[16]: list of positions
soc[16]: list of Bus' SOC
interval< 96
interval ++
No
Terminate
Yes
pos = a- c| f - h
Yes
pos[bus] = next_pos
soc[bus] -= 5.8
No
pos = d | i
No
Yes
soc[bus] -= 5.8
fuzzy score check of
all buses in e &j
sorting of the scores
No
for higher P no of buses
Yes
No
for lower Q no of buses
Yes
No
for rest of buses
Yes
fuzzy score â© 2.5
No
Yes
grid in overloading
Yes
from battery pack
No
from grid
battery pack =+30
pos[bus] = next_pos
Yes
highest SOC
No
pos[bus] == j
SOC check
pos[bus] = next_pos
Yes
lowest score
No
pos[bus] == e
pos == e
No
fuzzy score check
Yes
soc[bus]+=30
soc[bus]+=15
soc[bus]+=0
fuzzy score â© 0.5
No
Yes
grid in overloading
Yes
from battery pack
No
from grid
battery pack =+15

4.3 Proposed OL-FCA for score marking of WBTC buses

As an alternative to random charging of PEV batteries,we have taken advantage of the sophisticated smart grid communication backbone and implements an OL-FCA that will improve grid performance and automatically coordinate PEVs.The Fuzzy inference system has 5 inputs and one output to determine the score of each bus as depicted below. SOC input has benn give a triangular membership function,rest are crisp input , defuzzification method is centroid method.

4.3.1 Fuzzification of SOC

To fuzzify the SOC content of Bus battery the triangular membership function has been used. There is six domains of SOC level defination. They are - very high, high, moderate, low, very low, emergency. The membership design is such that a bus battery will get full membership of the domain if amount of SOC defines the domain properly. WE have considered that SOC will rarely go below 30 percent as the most efficient working condition of Li-ion battery is between 30 percent to 90 percent. The membership function is

$$\mu_{soc} = \begin{cases} 4 - \frac{x}{10} & \text{if } 30 \leq soc \leq 40 \\ 5 - \frac{x}{10} & \text{if } 40 \leq soc \leq 50 \\ 6 - \frac{x}{10} & \text{if } 50 \leq soc \leq 60 \\ \frac{x}{5} - 12 & \text{if } 60 \leq soc \leq 65 \\ 14 - \frac{x}{5} & \text{if } 65 \leq soc \leq 70 \\ \frac{x}{10} - 7 & \text{if } 70 \leq soc \leq 80 \\ \frac{x}{10} - 8 & \text{if } 80 \leq soc \leq 90 \end{cases} \}$$

4.3.2 FIS rules for score determination

Rules for deciding the score has been gievn in the following table:

4.4 OL-FCA based surge pricing strategy for others

In case of transport under ownership we have gave most priority to business of owner. The surge price factor has to be acted upon an average price based on the infrastructure static cost. The surge pricing is dynanmic. Based on the time the vehicle approaches for charging and other parameters the owner may get a bonus or penalty. Again we have have taken advantage of the sophisticated smart grid communication backbone. While a car owner will feel his/her vehicle to be charged he/she will see for nearby charging station. For each charging station nearby the owner will see a surge price per charging station by distributed mobile comuting technnology which is feasible. The surge price will be decided by the OL-FCA algorithm as depicted below. There is 5 inputs

1. SOC level
2. If the vehicle take charging from the charging station, by adding this vehicle in that particular interval vehicle congestion is higher or loer than average (0.058 Mwh). So this is a crisp type input whose value is 0 for less than equal to 0.058 Mwh , 1 for greater than 0.058 Mwh ,
3. In that intetrval the grid is underloading or overloading condition. This is also a crisp input whose value is 0 for underloading condition & 1 for overloading condition.

SOC condition	Can make the next half trip				Score
	Immediately?	After charging of 15 minutes	After charging of 30 minutes	After charging of 45 minutes	
Very high (>=80%)					0.25
High (70%=<Soc<80%)	Yes				0.5
	No	Yes (slow charging)			1
Moderate (60%=<Soc<70%)	Yes				0.75
	no	Yes (slow charging)			1.25
	No	No	Yes (slow charging)		1.75
Low (50%=<Soc<60%)	Yes				2.5
	No	Yes (slow charging)			3.25
	No	No	Yes (slow charging)		4
	No	No	No	Yes (slow charging)	4.5
Very low (40%=<Soc<50%)	Yes				2.75
	No	Yes (slow charging)			3.75
	No	No	Yes (slow charging)		4.25
	No	No	No	Yes (slow charging)	4.8
	No	No	Yes (Fast charging)	No	5
Emergency (Soc<40%)					4.8

Table 4.1: FIS rules for WBTC score determination

4. How many time before the owner tries to book ? We have assumed booking can be done from only 1 hour before.
5. The duration of charging. It should be a multiple of 15 minutes in our case and at most it can be 1 hour.

4.4.1 Fuzzification of SOC

Triangular membership function. The membership function is

$$\mu_{soc} = \begin{cases} 1 - \frac{x}{40} & \text{if } 0 \leq soc \leq 40 \\ \frac{x}{60} - \frac{2}{3} & \text{if } 40 \leq soc \leq 100 \end{cases}$$

4.4.2 Fuzzification of booking time

It has been gievn a exponential membership function. The owner has to pay high if he/she needs an immediate charging. The membership function is :

$$\mu_{booking\_time} = \begin{cases} \frac{e^{t-15}}{0.5} & \text{if } t \leq 15 \\ \frac{e^{t-60}}{0.5} & \text{if } 15 \leq t \leq 40 \end{cases}$$

4.4.3 Fuzzification of booking time

This has been given a triangular membership function. The owner has to pay high if he/she wnt to book charging more than 30 minutes i.e. for 45 minutes or 1 hour. The membership function is:

$$\mu_{charging_duration} = \begin{cases} \frac{t}{30} & \text{if } \Delta t = 15, 30\ minutes \\ \frac{t}{30} - 1 & \text{if } \Delta t = 45, 60\ minutes \end{cases}$$

The FIS logic system for private vehicles are as follows in the table 2.

SOC percentage	Congestion over or under? (Mwh)	Grid underloading or overloading?	How many minutes before booking occurred?	Charging time requirement in minutes	Surge price factor to be added with charging price
<=40	<=0.028			15 or 30	-1
				45 or 60	0.25
>40	<=0.028	underloading		15 or 30	0
				45 or 60	0.5
		overloading		15 or 30	0.75
				45 or 60	1
<=40	>0.028	underloading	<=15 minutes	15 or 30	-2
				45 or 60	-0.75
			Greater than 15 minutes	15 or 30	-4.5
				45 or 60	-3
		overloading	<=15 minutes	15 or 30	2.5
				45 or 60	3.5
			Greater than 15 minutes	15 or 30	0.5
				45 or 60	1.5
>40	>0.028	underloading	<=15 minutes	15 or 30	-1.5
				45 or 60	-0.5
			Greater than 15 minutes	15 or 30	-3.5
				45 or 60	-2.5
		overloading	<=15 minutes	15 or 30	3
				45 or 60	4.5
			Greater than 15 minutes	15 or 30	0.75
				45 or 60	2

Table 4.2: FIS rules for surge pricing determination for vehicles with ownership

Chapter 5

Results

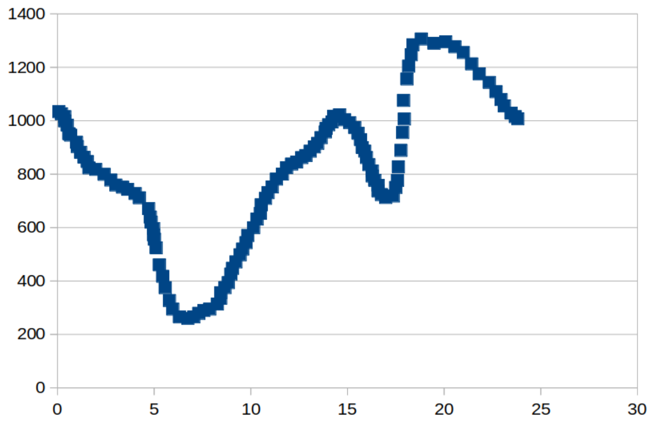


Figure 5.1: load curve of month may

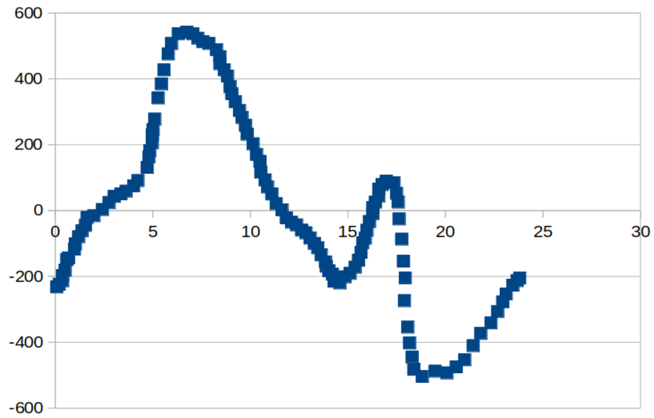


Figure 5.2: load fluctuation curve of month may in MW

Matlab results are as followed

The actual load fluctuation curve and the curve after proposed treatment is like
Due to WBTC the extra battery pack capacity in the bus stands will be In the matlab results x-axis represents here the percentage of day length where starting or 100 percent means 12 O'clock

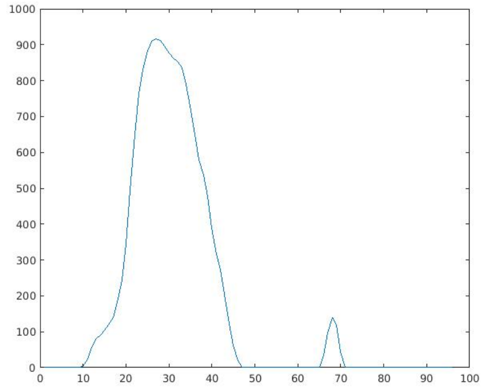


Figure 5.3: energy drawn from grid in Mwh per interval

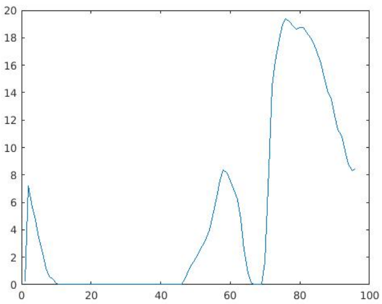
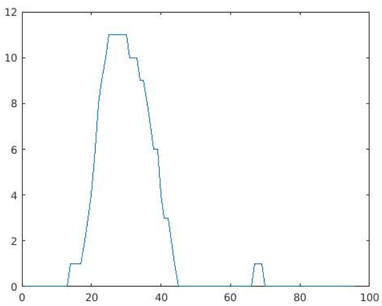


Figure 5.4: energy given to grid Mwh per interval



unit.jpg

Figure 5.5: Number of WBTC buses charging schedule per bus stand per interval

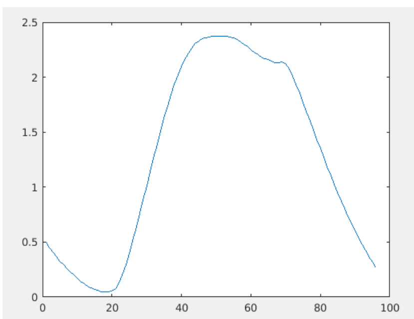


Figure 5.6: battery energy storage over 96 intervals in a battery bank station in Mwh

in night. The battery pack capacity for the bus stands would be 2.67 Mwh(Figure 5.9) & other charging station is 2.4 Mwh.(Figure 5.6) So totally in Kolkata city by our proposed strategy total battery capacity would be 834 Mwh. That is still lesser than 960 Mwh(Figure 5.11) which is the

State 0 means the bus is in rest , state 1 means the bus is in running condition. State 0 to 1 means the bus is starting the trip & 1 to 0 means the bus is ending the trip.

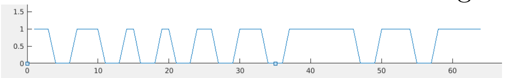
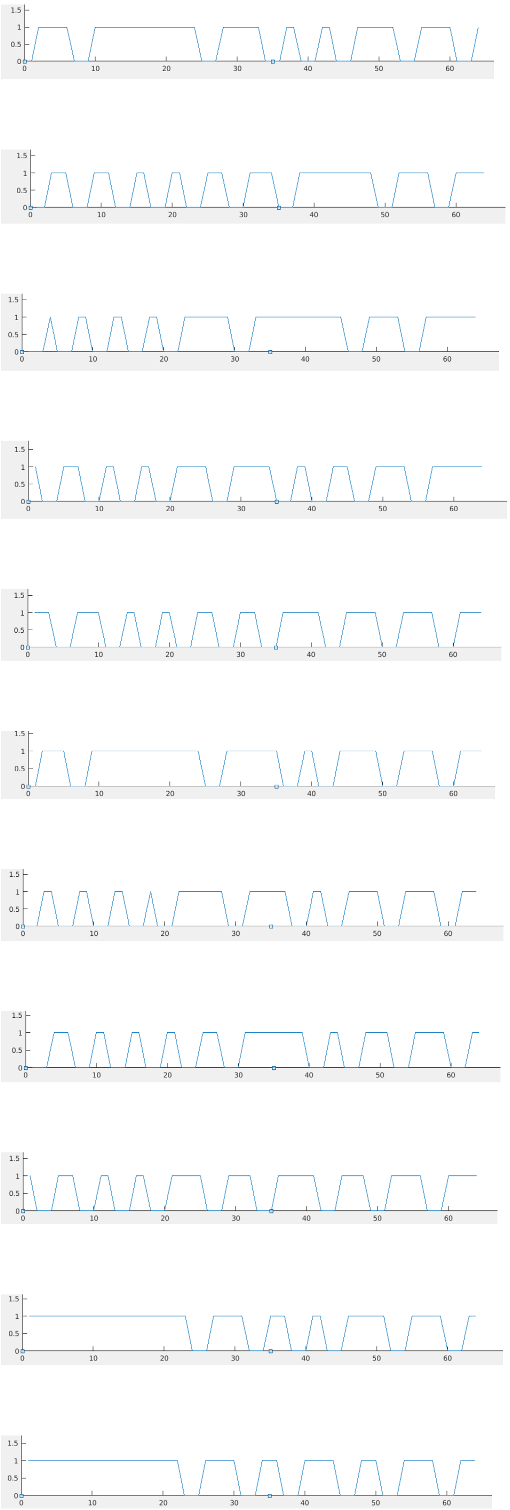
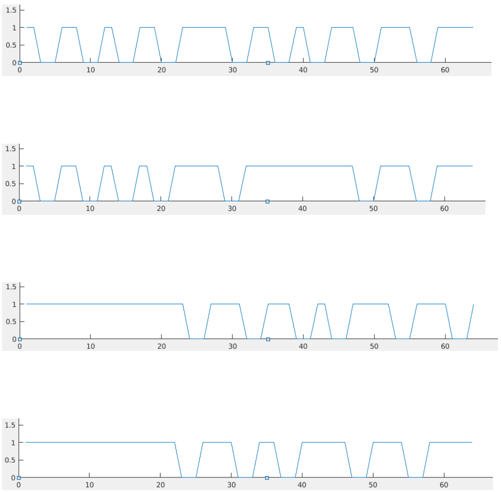


Figure 5.7: bus 1 position starting from 6:00 am to 10 pm



capacity if the same improvement was done only by BESS without any electrical vehicle penetration. The improvement in load curve smoothing by the strategy is shown in terms of energy given to the grid by the proposed system in Figure 5.10. Positive value means energy delivered to grid by the



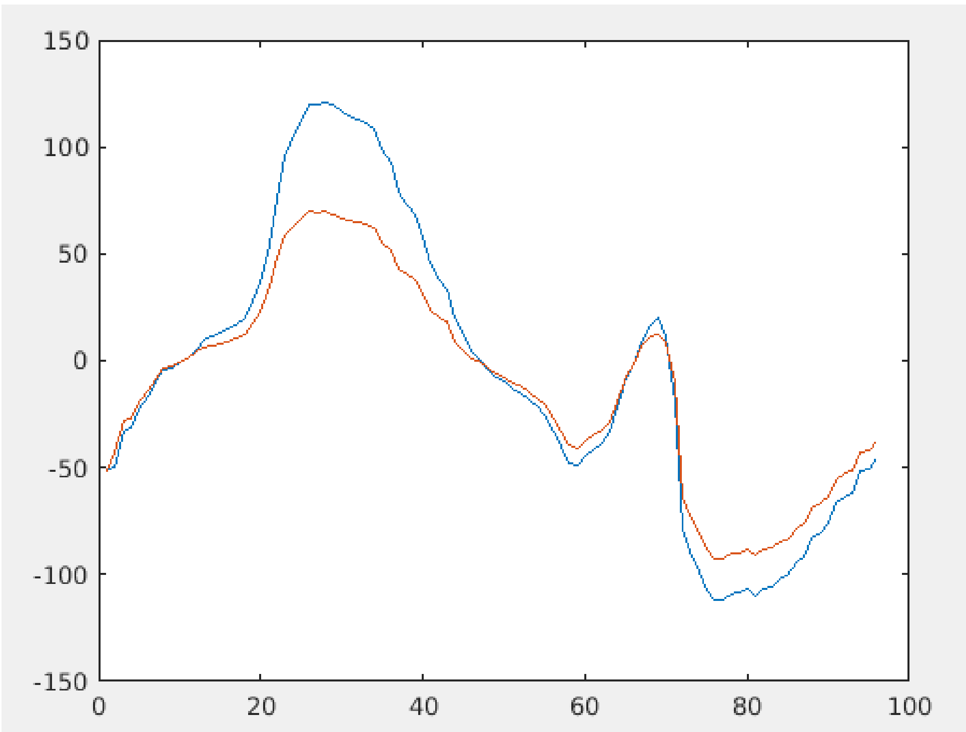


Figure 5.8: Blue- actual load fluctuation curve, red- after treatment

the system and negative value means energy given to the grid by the system.
Area of overloading of the grid previously was 2574 Mwh(Blue curve Figure 5.8) and now by calculating from the new condition of grid he overloading area is near to 1600 Mwh(Red curve of Figure 5.8).Therefore, efficiency of our proposed plan for load curve smoothing comes out to be 37.8 percent.

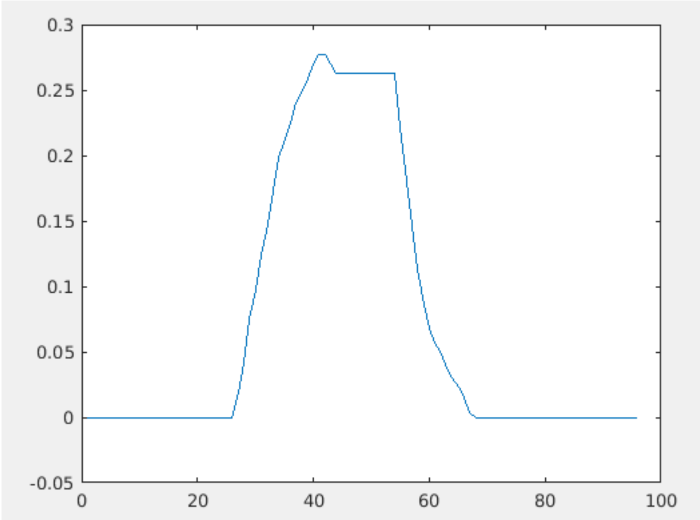


Figure 5.9: extra battery pack capacity due to WBTC

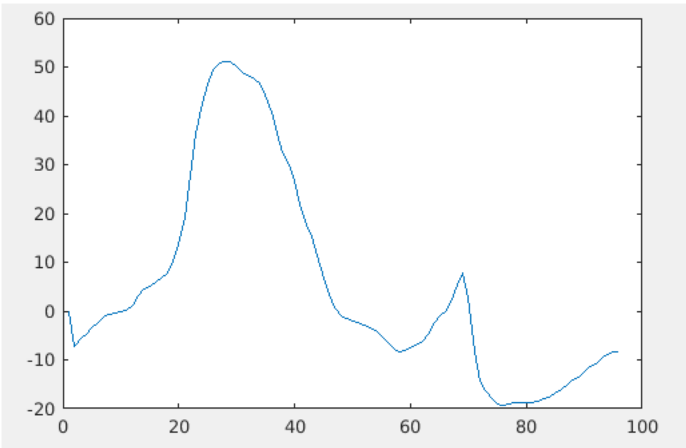


Figure 5.10: Improvement of grid condition afeftr introducing our charging strategy

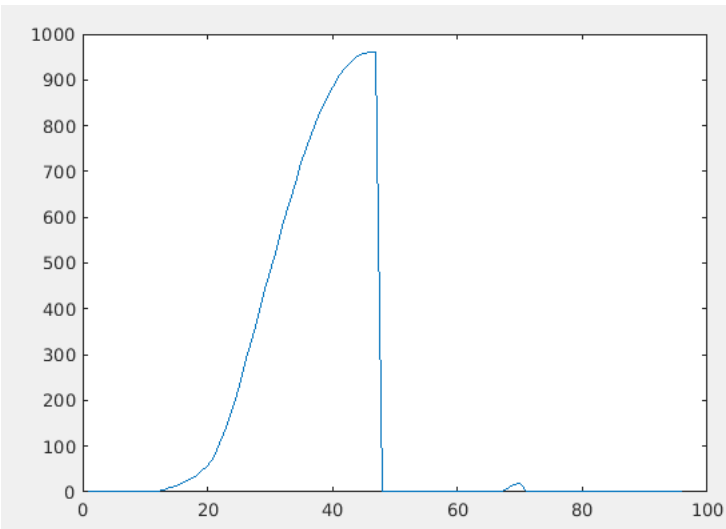


Figure 5.11: Capacity of the battery it the same improvement was done only by BESS

Chapter 6

Discussions

Electric vehicle charging schedule has got many different intelligent strategies to be implemented. There is a need of real time control but in case control system becomes very cost consuming and complex, this should be avoided. In our case we have not considered V2G technology, long distance vehicles. Adding one more consideration that we have considered only PVs as DGs, excluding wind energy systems and bio-gass energy systems. We have designed our system nearest possible to our reality. All the data driven outputs are based on real time survey. We have worked on based on an

survey based averaging model. All the data are current data. But there will be a gradual increase in electric demand for all the sectors including domestic, industrial and transport. So in case of increase, the system parameter i.e. battery capacity will change. We have not consider that in our study. But in case of market implementation , first the system parameters has to be decided by those two algorithm. As an energy balancing solution The Australian Energy Market Operator's

(AEMO's) South Australian Fuel and Technology Report[5] published earlier this month shows that battery storage is now competitive with other large scale solutions for energy balancing,i) Gas peaking plants 218 dollars per MWh,ii)Solar thermal 137 dollars per MWh, iii)Pumped hydro 161 dollars per MWh,(the cost of pumped hydro would be significantly variable depending on the scale and size of the project and other factors such as proximity to power lines) iv) Lithium Ion batteries 216 dollars per MWh.There is a sharp declining of battery pack cost over the years. So , it can be considered that as time passes by, in near future BESS technology would be the most economical solution for energy balancing. Instead of the proposed strategy, if energy balancing of grid and

electric vehicle charging schedule were taken care of separately, BESS capacity for Kolkata would be 980 Mwh. In our case, proposed capacity for current scenario came out as 834 Mwh along with a charging schedule for EVs in the city. In case of private vehicles we gave highest priority to

the business of the owner. Our system is capable of charging vehicle whenever necessary without disturbing the energy balance of grid.

Chapter 7

Cost savings

The energy consumption pattern has been studied for different types of public transport vehicles in Kolkata.Pertaining to the present condition of passenger transport in Kolkata, the rising fuel cost and environmental concern, a considerable share of the conventional public road transportation modes has been considered for replacement by battery-operated counterparts.

As per our survey concluded that per day total energy needed by WBTC transport in terms of electrical Mwh is 336 unit. It also concluded that per day an average service taxi travels 150 km and a personal taxi travels 50 km per day in average.We also surveyed a WBTC bus can travel 1 km by 1.45 kwh energy whereas a taxi can make it by 0.10 kwh. A diesel driven bus take 0.31 l of diesel per km and a taxi can make it by 0.8 l of diesel.

Paper [14] showed that the cost of electricity per vehicle per day by conventional grid is Rs 7.95/kWh, by PV technology is Rs. 12.77/kwh and in case of diesel it is Rs. 18.78/kwh.
Calculating from these datas it can be derived that WBTC can save Rs. 3.6 lakhs per day if it transform all the transport conventional to electric vehicle. One service taxi can save Rs. 153 Rs in this manner and one personal taxi can save nearly 50 Rs. per day by getting electrified.

Chapter 8

Environmental Impact Analysis

Environmental pollution has been one of the major concerns in recent times. Transport sector has played the role as one of the major contributors of air pollutants.

In case of Kolkata, the road transport sector has an emission level of 129.54 tons of CO, 65.59 tons of NOX , 51.02 tons of HC, and 10.13 tons of PM a day [14].These pollutants have been formed mainly due to the combustion of the fuel used for vehicle propulsion (in most cases, diesel). The combustion of 1 l of diesel emits 2.71 kg of COx , 8.9 g of SOx , and 2.9 g of NOx.

The emissions per unit of electricity are estimated to be in the range of 0.91 to 0.95 kg/kWh for COx , 6.94 to 7.20 g/kWh for SOx, and 4.22 to 4.38 g/kWh for NOx during the period 2001-02 to 2009-10 [18].

As per the survey conducted total distance travelled per trip of WBTC is 32 km. To cover 64 trips per day ,then calculating all 110 routes of WBTC , total energy needed for WBTC is (32*64*110*1.45=) 336 Mwh (electricity consumption 1.45 kwh/km) and (32*64*110*0.31=) 73559 l of disel (diesel consumption 1.45 kwh/km)per day. Therefore , the same bus run by diesel would

emit (73559*2.71=) 200 kg of COx but if run by battery pack it would emit (336000*0.95=) 319.2 kg of COx. So in this scenario,for totally electrified WBTC emission of Cox will increase by 119.2 t . similarly SOx will increase by 1.65 t and NOx by 0.19 t.

Chapter 9

Conclusions

We believe that this work has considerable potential to smooth demand fluctuation profile and consequently improve EV adoption rate with a limited cost , both economical and computational. As from the survey we got that the unschedued electric bus in Kolkata mainly kept on charging during 12:00-2:00 pm and 12:00 am -2:00 am. , it can be concluded that the unscheduled vehicles charging time mostly coinsides with peak overloading hours of grid which is very uncomfortable for grid. Huge amount of low frequency oscillations can be caused by unscheduled operation and that is a serious threat to steady state operation. Our work brings some important facts to be noticed very carefully in the context of smart city planning i.e. firstly , after one or two decade when there will be a large penetration of electric vehicles into the grid , we can not design a load curve smoothing technique without taking into consideration of EV charging profile. In our work we have shown that if the same amount of smoothing was done by BESS not considering EV penetration , the battery pack size would be larger than that of our proposed plan in spite of our proposed plan considers electric vehicle penetration of the total city. There comes the success of the charging schedule which we have entitled by the term â˜Harmonization of transport sector and power sectorâ™. In case of vehicles with ownership the surge pricing strategy should be such that it would be profitable from both aggregator and consumerâ™s point of view. Therefore , here comes out an extra responsibility of the researcher to detetrmine the slab with the objective of profit maximizing from both supplier and consumerâ™s point of view. Last but not the list from the cost saving anaysis and environmental impact analysis , it has been clear that electrification of vehicles is a cost effective decision , though a more environmentally damazing technology if not solely the demand of EVs is met by renewable sources. In that case, our study also shows that more emphasis should be given to solar-gassifier hybrid , wind energy and other forms of renewable energy.

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