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Analysis of potential market share of electric vehicles and the demand for electric energy in a metropolitan area

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Abstract

Electrification of the private vehicle fleet (e-mobility) currently represents a key challenge to sustainable mobility, in keeping with the essential pathway to the road transport decarbonisation and the decrease of dependence on petroleum products. If combined with energy production from renewable sources, e-mobility is indeed one of the most promising answers to the undelayable need of reducing air pollution, especially in large urban areas. Besides, electrification of private road vehicles may produce several improvements from the energy saving perspective due to the high efficiency of electric motors, 3-4 times greater than combustion motors. Massive, High-resolution driving data privately-owned cars in the city of Rome is used to analyse daily driving patterns, and from those we deduce the range requirement for electric vehicles (EVs). In particular, we refer to the real case of the province of Rome (Italy) and use a large dataset of Floating Car Data (FCD): 150'000 vehicles travelling inside the province during May 2013, and 35,000 vehicles generated from the city of Rome and covering all the Italian territory during the entire year. We assumed that the current internal combustion vehicle users would not change their driving patterns even if the change to EVs and they will charge their vehicle only once daily (at home overnight). We analyse the users whose daily driving distance were entirely met and those who are willing to make some adaptations to current driving behaviours. Those adaptations are such like users charge their vehicle during the day, use an internal combustion vehicle, postponing some distances to another day. Analysis was made on the potential market share for EVs if users change to electric vehicles and carryout aforementioned adaptations. In the analysis we supposed a battery capacity of 30 kWh and a specific energy consumption of 0.16 kWh/Km. From the analysis we came to know that, 25% of the total fleet never exceed 150 Kms in one day, 56% of the total fleet never exceed 300 Kms in one day. Given the high mileage range promised by major EV manufactures, these users can easily adapt an EV without any adaptations. Those drivers who are willing to make adaptations for only 2 days in a year, the same 150 Kms can be travelled by 40% of the total fleet, if they adapt for 6 days, 61% of the fleet can cover that distance and an impressive 86% of the fleet can cover 150Kms if they are willing to adapt for 18 days in a year. So, despite range anxiety that is very much prevalent in the society.

Integrate with the supposed penetration rate, we computed the electric energy demand for 1 day out of a year to predict possible demand for electricity when vehicle users shift to electric vehicles. We analyse the locality of Tuscolana in the Rome metropolitan city and we got the

peak demand is 1.45 MW between the period of 18:00 and 20:00. There were 1792 conventional vehicles under our study on that day. The peak electric energy demand for all the 69700 families in the area has been calculated, which is 12.5 MW and compared that with the domestic electric demand.

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Abbreviations

CO2 - Carbon dioxide

EV - Electric Vehicle

BEV - Battery Electric Vehicle

EU - European Union

PHEV - Plug-in Hybrid Electric Vehicle

HEV - Hybrid Electric Vehicle

KW - Kilowatt

DC - Direct Current

CHAdeMO - CHArge de MOve

AC - Alternate Current

CC - Constant Current

TCO - Total Cost of Ownership

V2G - Vehicle to Grid

FCD - Floating Car Data

OBU - On-Board Unit

GPS - Global Positioning System

GPRS - General Packet Radio Service

RAM - Random Access Memory

NHTS - National Household Travel Survey

EVB - Electric Vehicle Battery

WH - WattHour

kWH - kiloWattHour

SOC - State Of Charge

NEDC - New European Driving Cycle

WLTP - Worldwide harmonized Light vehicles Test Procedure

EVSE - Electric Vehicle Supply Equipment

RES - Renewable Energy Sources

SG - Smart Grid

MW - Mega Watt

GW - Giga Watt

SM - Smart Meter

EMS - Energy Management System

AMI - Advanced Metering Infrastructure

MDMS - Meter Data Management System

HAN - Home Area Network

BPL - Broadband over PowerLine

PLC - PowerLine Communication

EVMS - Electric Vehicle Management System

ESS - Energy Storage System

VPP - Virtual Power Plant

DSM - Demand Side Management

ANM - Active Network Management

RFID - Radio Frequency IDentification

GHG - GreenHouse Gas

DER - Distributed Energy Resources

ESS - Energy Storage System

WECS - Wind Energy Conversion Systems

1. Introduction

The transportation sector can strongly contribute to the alleviation of greenhouse gas emissions [1]. In the European Union (EU) for instance, passenger cars and vans currently emit around 15% of total carbon dioxide (CO2) emissions. Hence, policy makers have set transport regulations to reduce CO2 emission from vehicles. Since these regulations consider the tailpipe, not the well-to-wheel emissions, purely electric vehicle counts as zero emission cars. [2]. The automotive industry has further developed EV through hybrid or pure electric powertrains, an effort partly supported by national and regional policy initiatives. Electric vehicles have several important advantages over conventional internal combustion engine vehicles for personal transportation. Electric vehicles do not require petroleum-based fuels, they would not contribute to mobile source air pollution in congested urban areas, and they have the potential to be considerably simpler to maintain. Electric vehicle(EV) could reduce global and local emissions from the transport sector. Yet the limited electric driving range of battery electric vehicles(BEVs) is technically and mentally a major hurdle for many consumers and impacts a BEV's utility. The variation in distances travelled by on individual on different days of the year is important for the utility of BEVs. Furthermore, long recharging times seem to impede BEV adoption as well. On the positive side, EVs can easily be charged at home for most car owners, potentially yielding more comfort since extra visits to gas stations become unnecessary. Another crucial factor that affects BEV market diffusion are the costs for the vehicle. A BEV typically has a higher investment cost and lower operating cost compared to a conventional vehicle. Given these special attributes of the vehicle, it is important to identify how to best utilise its strengths while mitigating its weakness.

The operation of the electric car itself is fundamentally very simple: the energy from the battery is used by the motor for driving and the power electronics helps in controlling the power flow. The electric motor together with the motor drive has the key benefit of providing close to full torque at all speeds and hence electric cars do not have gears and much simpler transmission system. Cooling of the traction batteries is becoming widespread practice to increase the battery lifetime. There are several types of electric vehicles, though the word 'electric vehicles' normally refers to battery electric/all electric/plug-in electric vehicles. The types of EVs are hybrid electric vehicles (series, parallel, series-parallel type), plug-in hybrid electric vehicles, battery electric vehicles and fuel cell electric vehicle. Based on the hybridisation rate, the hybrid electric vehicles can be further divided into micro, mild and full hybrids. In case of

micro and mild hybrid, the electric power is not large enough to propel the vehicle alone. The battery size and electric drivetrain power progressively increase as you move from a hybrid vehicle to an all-electric vehicle. The benefit of the PHEVs and HEVs compared to the BEVs is that the range anxiety is overcome for long distance drives due to the gasoline powered internal combustion engine. At the same time, this is the inherent disadvantage as well that these cars are not emission free at their tail-pipes.

Charging infrastructure for electric cars will play a key role for the uptake of EVs in the future. EV charging is possible by AC charging and DC charging. Typically, fast charging over 50kW is done using DC charging. There are several charging plug types (Type 1,2,3, CHAdeMO, Combo), charging modes (Modes 1,2,3,4) and charging power levels (Level 1,2,3). Type 1 chargers are predominantly used in USA/japan for AC charging and Type 2 chargers are predominantly used in Europe for AC charging. The charging process of a lithium battery has two distinct charging regions namely, the constant current charging (CC) region and the constant voltage (CV) charging region. Fast charging is typically done in the CC region. Currently, EV charging is uncontrolled and the charging starts as soon as the EV is connected and it occurs at a fixed power. With smart charging, the charging process can be changed both in time and power to be controlled based on say, solar energy production or energy prices. By smart charging, the EV charging can be made cheaper, more efficient and more environmentally friendlier. The challenge of infrastructure is a chicken-and-egg problem. For electric vehicles to dramatically expand, consumers need to have access to charging infrastructure. But for investors to build infrastructure, they want to be assured there's significant demand. There should be an intervention from the government to solve this problem by being a mediator between the EV manufactures and charging infrastructure investors. So that there will be an agreement in which required amount of charging infrastructures are made for a given number of electric car regionally or nationally.

Despite many benefits we can get from electric vehicles, there are a few disadvantages or more realistically speaking misconceptions about BEVs on society. Those are range anxiety, high price of EVs, lack of charging infrastructures etcetera. These problems, as they are usually addressed as, cause people to stick with their conventional vehicles. But, the mileage requirement, price of electric vehicles have been studied and found some positive results. If the users would not change their driving behaviours even after they change from conventional vehicle to electric vehicle, then most of the users do not want to worry about the lack of mileage provide by the electric vehicle manufactures.

While electric vehicles (EV) can perform better than conventional vehicles from an environmental standpoint, consumers perceive them to be more expensive due to their higher capital cost [3]. Recent studies calculated the total cost of ownership (TCO) to evaluate the complete cost for the consumer, focusing on individual vehicle classes, powertrain technologies, or use cases. It is a fact that the high price of the battery is the major contributor for the high price of the vehicle. Since battery is the major component of an electric vehicle. But many studies have been carried out on the possibilities of reduction of the cost of battery, even though it has been proved that there will be a price parity for electric vehicles to conventional vehicle by the year 2025. One of such study is about the Total cost analysis of electric vehicle and conventional vehicle. It is expected that the consumers should not only look at the initial purchase cost of the vehicle as many other costs occur during the ownership of a car. Existing studies show that the operating cost can be lower for EVs than for conventional vehicles [4]. Electric vehicles have the advantage that the price of driving the vehicle is lower due to cheaper electricity cost and the higher rate of efficiency of the motor. However, consumers tend not to consider the present value of these fuel savings. To compare the cost for consumers more comprehensively, including both capital and operating cost, researchers have applied the total cost of ownership (TCO) calculation method [5].

This thesis work analyses whether battery range limitations compatible with our gasoline enabled driving habits. It will analyse the travel behaviours of conventional vehicle users and evaluate how that make way for the EV penetration. Or in others, how current driving behaviours can be helpful for the users to shift to EVs. In this work, we also analysis the energy demand required for EV charging by taking in to account, the number of vehicle charging their EV at the end-of-the-day. For that we took a day out from a year and we plot the power demand graph for that day in the locality of Tuscolana, Rome. This study has been done with the help of the data collected by the FCD system operated under OctoTelematics for the year 2013. Cars are equipped with on-board unit (OBU) that stores GPS measurements and periodically, transmits them to the Data Processing Center. The OBU consists of a GPS receiver, a GPRS transmitter, a 3-axis accelerometer sensor, a battery pack, a mass memory, processor and a RAM. The OBU stores GPS measurements every 2 kilometres travelled or, alternatively, every 30 seconds when the vehicle is running along a motorway or some main urban arterials.

In this work, we refer to the real case of the city of Rome(Italy) and use a large dataset of Floating Car Data (FCD): 35000 vehicles travelling inside the province during the entire year of 2013.

The first chapter is the State-of-the-art, which has several sections related to Electric vehicle.

It is very much essential to know about the state-of-art technologies in the electric mobility system to understand it better. In this section we illustrate major elements of the e-mobility and try to explain what is out there in the market which will also help to understand my thesis better to all. First section describes about Electric vehicles. It depicts the various parts of an electric vehicles and their functions. It explains about the electric vehicle parameters like Nominal battery capacity, range, state of charge (SOC), Energy consumption etcetera. If we need to know how an EV work, we should know various parts of an EV. Since the parts are much simple when compared to conventional vehicle, it would not be difficult to the readers to understand them. Second section deals with the electric vehicle battery (EVB). Battery is the most vital part of any BEV. Since vehicles nowadays use mostly battery with Lithium element in it, we are concentrating more on lithium-based batteries. It also gives the idea on distinct types of battery, the relationship between battery capacity and the range of the vehicle, battery charging and discharging, Range anxiety, battery parameters.

The third section demonstrate the charging infrastructure. In this thesis work, some adjustments are suggested to be made for a portion of fleet who travel more than 350 Kms in a day. One of such adjustment is that the vehicle need to be charge in the day time. Various charging types, time needed to charge an EV, charging modes and cases are explained. Also, we assume that those who travel below 350 Kms will charge once in a day from their home. As discussed before, various level, mode and cases of charging are all mentioned here.

In the fourth section we mention about the smart grid. Smart grid comes along as a means to enhance power generation and distribution, which is more flexible, efficient, reliable and secured. This smart grid encompasses advanced technologies in communication, smart energy metering and advanced control and it can offer EVs as dynamic loads and potential dispatchable-distributed energy sources a flexible and optimized deployment in the power industry. Smart grid is one technology that every current and future EV users should have knowledge about. Since there are low power time during a day, an intelligent system to monitor them and provide adequate energy will be very essential in future. We also discuss about the vehicle to grid (V2G) technology. In the energy consumption analysis, we make use of the idea of Vehicle to grid to supply electrical energy from vehicle to the building in our case, during peak hours. In vehicle-to-grid, the excess electricity of energy stored by the vehicle is given out to the grid during the peak hours to make a balance in the power supply from the grid. Since when a lot of EV charge at the same time there will be an increase in the load, so that many of

them cannot charge their car. By using V2G, we can ensure that the electric supply is evenly distributed. Batteries have a finite number of charging cycles, as well as a shelf-life, therefore using vehicles as grid storage can impact battery longevity. Studies show that cycle batteries two or more times per day have shown large decreases in capacity and greatly shortened life. However, battery capacity is a complex function of factors such as battery chemistry, charging and discharging rate, temperature, state of charge and age. Most studies with slower discharge rates show only a few percent of additional degradation while one study has suggested improved longevity relative to vehicles that were not used for grid storage may be possible.

In the data analysis section, we firstly analyse the driving behaviour of the users and determine the possible electric vehicle market potential by assessing how much percentage of the users can shift to EVs without thinking a second thought. We also suggest for some adjustments so that many more vehicles can be included in the potential EV users. Secondly, we analyse the electric energy demand for the EVs. For that we take a region within the Rome metropolitan area. For this purpose, we take Tuscolana as we saw with the help of QGIS software that that region has more vehicle density. We determine the energy demand and the total demand for all the families living in that area to state hypothetically that this will be a possible scenario for Rome. We came to the conclusion that we can alleviate the peak hour demand by shifting much of those demand to off peak hour. It can be materialized by having a proper system of controlled charging, where a group of users should only able to charge their vehicle after 22:00 hrs.

Understanding the potential market for limited-range vehicles is important to planning research and development programs for electric and hybrid vehicles. Studies of consumer preferences and perceptions have shown vehicle range to be a very important vehicle attribute. So, it is very essential to analyse the daily distance travelled by the user to evaluate whether we can alter the scepticism of consumers that the EV cannot produce the range that they require. Assessing the energy demand will give us an idea on how to systematically control energy system so that it is well balanced.

2. Background Studies

Electric vehicles are new emerging technologies in the transportation sector. Many countries around the globe advocate the benefits of bringing EV revolution. It is undeniable that electric vehicles will reduce the greenhouse gas emission since automobile emissions are accountable for a major cause of air pollution. However, there are many factors we need to consider before the implementation of an e-mobility system. There are many disadvantages for an electric vehicle such as low mileage, high charging time, lack of infrastructure, high initial cost of the vehicle etcetera. There are few researches has been made these problems and found that there are solutions too. For example, one study indicates that the comparative cost efficiency of EV increases with the consumer's driving distance and is higher for small and for large vehicles [6]. In this thesis work, our major concern is: Are battery-range limitations compatible with our gasoline-enabled driving habits? Despite concerns about battery limitations, there is little published empirical analysis of driver range needs, in part due to lack of longitudinal vehicle and household travel data collected over extended time periods. For instance, one prior study of range and related questions studied a small set of vehicles sampled for a few days each and suggested that more than 95% of daily driving can be accomplished with 160 kilometres of electric range. [7]. Similarly, studies have found that about 75% of travel miles would be powered by electricity in a plug-in hybrid with 96 kilometres of range [8]. The problem with such studies reporting the number of limited-range trips is that the car buyers are likely to want a vehicle to cover most of their heterogeneous needs over time, not the needs of the average driver, nor even their own average travel profile. One of the longitudinal car travel survey was done in United States where data were conducted by GPS in the Atlanta, Georgia metropolitan area with a sample size of 470 cars that were observed 50 days to 3 years [9]. They found that the share of cars that is not used for short distance travel is rather low: only 9 % of the cars in the sample never exceed 100 miles within a day for one year. This finding contrasts with the results based on survey data covering only one day. Lin and Greene (2011) show that their results only based on uniform daily vehicle miles travelled differ significant from their results based on varying daily vehicle miles travelled considering the total energy use of PHEV's. Thus, the analysed surveys must consequently be longitudinally oriented (periods instead of single days). This requirement explicitly excludes data of the usually cross-sectional oriented national travel surveys. Several studies in the US (Gonder, et al., 2007; Bernard, 1996) try to estimate the potential of EV's with either National Household Travel Survey (NHTS) data or

GPS survey data of one day. [10] shows that 91 % of the vehicles that were used in the survey day travelled less than 161 km. These results may suggest the deduction that those cars could be replaced by BEVs. However, [11] notice that the lack of longitudinal data leads to an overestimation of EV's potential. The importance to automakers of the market sizes that correspond to EV-critical fuel features, such as range and recharge speed, motivates the present analysis. While there has been much discussion of the potential consumer acceptance of alternative fuels, such studies tend to focus on the required distribution infrastructure needed to mimic the convenience of the gasoline engine and filling station [12]. Research focused specifically on Electric Vehicle market acceptance tends to address social, market, or customer perceptions rather than needs dictated by travel patterns [13]. The present research is motivated by our belief that more detailed knowledge of how vehicle owners use their current gasoline cars can better inform the design of electric vehicles. In this paper, we use primary instrumented data to analyse daily driving distances, for all purposes combined, for all days in a year. Here we focus on daily driving range as a 'base case'. By assessing daily driving distances rather than individual trip distances, we conservatively assume that vehicle charging will be limited to a single daily charge event, probably at home and overnight, that the battery is full in the morning, and that no additional charging will take place between the various individual trips during the day.

Many studies have already proven that the vehicles who charge at the end of the day will increase the load at the evening hours. Because everyone need to charge their vehicles after they arrive at home. This can be avoided by shifting our focus to charge them at off-peak hours. A systematic controlled charging can be help us with this problem.

3. State of the Art

3.1 Electric Vehicles

An electric car is a plug-in electric automobile that is propelled by one or more electric motors, using energy stored in rechargeable batteries. There are three main types of EVs: hybrid electric vehicles (HEVs), plug-in hybrid electric vehicles (PHEVs) and battery electric vehicles (BEV or EV). There are many different potential HEV and PHEV configurations, but in general, a PHEV has an electric drivetrain like an EV, and a fuel-burning engine that can recharge the batteries periodically. The advantage of an HEV is that the fuel-burning engine, in general, is most efficient in only a small range of operating conditions. Also, at this most efficient operating point, the fuel-burning engine usually produces its lowest levels of emissions. Unfortunately, while driving, the engine in the car must run under a wide range of speeds and loads, and thus it is far less efficient and produces much greater emissions than it would if it could run at its most efficient point all the time. Electric drivetrains are also most efficient at only one point, but the reduction in efficiency for other speeds and loads is far less. Therefore, an HEV can run the fuel-burning engine at its most efficient point for battery charging and can use the electric drivetrain to take up all the slack under other conditions. In this way, emissions are much less than for the fuel-burning engine driving the car by itself, and fuel economy can be significantly improved. Hybrid technologies extend the usable range of EVs beyond what an all-electric vehicle can achieve with batteries only. Being a hybrid or plug-in hybrid would allow the vehicle to operate on only batteries within an urban area, and then switch to its combustion engine outside the urban area.

In this thesis I am only concentrating in BEVs. Since current battery EVs can provide most of the average range requirements and BEV is the category came under zero-tailpipe emission. Reduction of the pollutants are our major concerns as new policies on environmental safety has been proposing, need for emission free vehicle is more than ever.

The main benefit of the electric motor when compared to the internal combustion engine is its ability to provide peak torque at nearly all speeds, even at zero speed. This is achieved by a clever motor and motor drive design. So that electric car can accelerate at high speed and does not require multiple gears for its operation. This is the reason because Tesla Model S P100D became the third fastest accelerating production car ever produced, with 0-96 Kms per hour in 2.5 seconds. Keep in mind that the LaFerrari and the Porsche 918 Spyder that are quicker than

Models are small, 2-seater cars. While in comparison, the Model S is a four-door, family car with storage capacity and much lower cost. This show the huge performance benefits of electric cars over internal combustion engine cars.

3.1.1 Parts in an EV

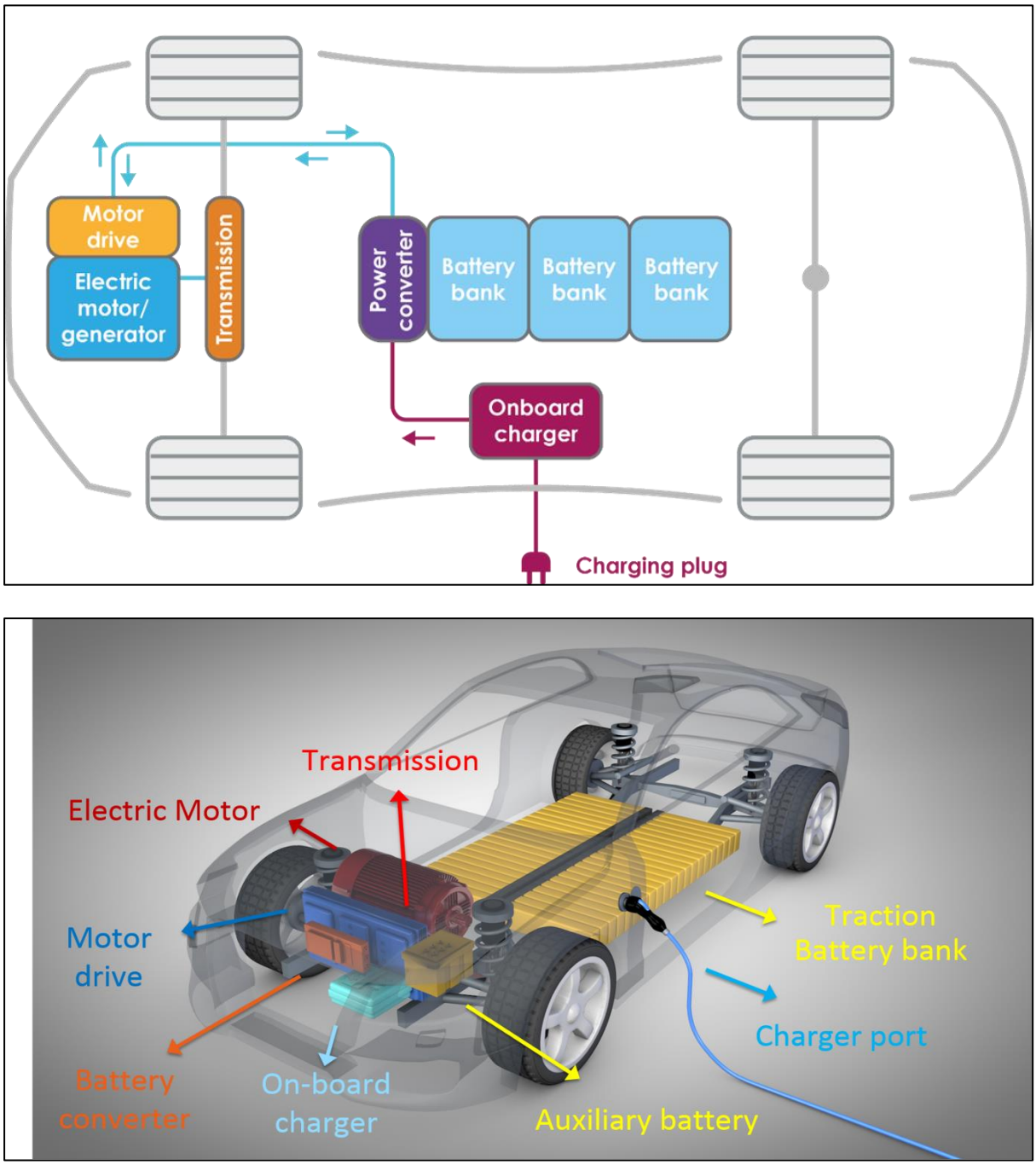

Fig.1 Parts of an EV

Fig.1 shows the majors parts of an EV. Transmission, electric motor, Motor drive, battery converter, on-board charger, auxiliary battery, charger port etcetera.

Charging port or vehicle inlet: It is a connector present on the electric vehicle to allow it to be connected to an external source of electricity for charging.

Power electronic convertor: A power electronic convertor is made of high power fast-acting semiconductor device, which act as high-speed switches. Different switching states alter the input voltage and current using capacitive and inductive elements. The result is an output voltage and current, which is at a different level to the input.

On-board charger: It is an AC-to-DC power electronic converter that takes the incoming AC electricity supplied via the charge port and converts it to DC power for charging the traction battery. Using the battery management system, it regulates the battery characteristics such as voltage, current, temperature and state of charge.

Traction battery pack: it is the high voltage battery used to store energy in the electric car and provide power for use by the electric traction motor.

Battery power convertor: It is a DC-to-DC power convertor that convers the voltage of the traction battery pack to the higher-voltage of the DC-bus used for power exchange with the traction motor.

Motor drive: It is a DC-to-AC (often referred as inverter) or at times DC-to-DC power electronic convertor, used to convert power from the high voltage DC bus to AC power for the operation of motor. The convertor is bidirectional for operating in both driving and regenerative braking mode.

Traction electric motor/generator: It is the main propulsion device in an electric car that converts electrical energy from the traction battery to mechanical energy for rotating the wheels. It also generates electricity by extracting energy from the rotating wheels while braking and transferring that energy back to the traction battery pack.

Transmission: For an electric car, usually a single gear transmission with differential is used to transfer mechanical power from the traction motor to drive the wheel.

Power electronics controller: This unit controls the flow of electrical power in the different power electronic converters in the electric car.

3.1.2 EV parameters

1. *Nominal battery capacity (E_{nom}, in Wh or kWh)*: It is total electric energy that can be stored in the battery. Alternately, it is the maximum amount of electric energy that can

be extracted from a fully charged battery state to the empty state. EV batteries have a battery capacity between 5 kWh to 100 kWh depending on the type of EV. The higher the battery capacity, the more energy it can store and the longer the time it takes to fully charge it. The battery capacity is often referred to as the energy content or energy capacity of the battery.

2. *State of charge, SOC (B_{SOC}, in %)*: The battery state of charge (SoC) is defined as the ratio between the amount of energy currently stored in the battery, E_{batt} and the total battery capacity, E_{nom}

$$B_{SOC}=(E_{batt}/E_{nom})\ 100$$

3. *Range (R_{max}, in km)*: It is the maximum distance that can be driven by an electric car when the battery is full. Usually an electric car is tested using a standardized driving cycle to estimate the range, e.g. New European Driving Cycle (NEDC), Worldwide harmonized Light Vehicles Test Procedure (WLTP) or the EPA Federal Test Procedure. The range can be expressed in miles, kilometre or other units based on the region. In this set of definitions, we stick to the European convention of using kilometre.

4. *Available Range (R, in km)*: It is the maximum distance that can be driven by an electric car based on the current state of charge of the battery.

5. *Energy consumption per kilometre (D, in kWh/km)*: When an electric car is tested using a standardised driving cycle, the EV efficiency is the energy consumed from the batteries per unit distance drive. In some cases, the energy drawn from the grid to charge the battery is considered as well. It can be expressed in kilowatt-hour per kilometre (or) kilowatt-hour per mile.

6. *MPGe or miles per gallon equivalent:* MPGe is the distance in miles travelled per unit of electric energy consumed by the vehicle. The ratings are based on United States Environmental Protection Agency (EPA) formula, in which 33.7 kilowatt-hours (121 megajoules) of electricity is equivalent to one gallon of gasoline.

7. *Motor power (P_m, in W):* It is the power delivered by the motor to the wheels for propulsion. The motor power is positive or negative based on whether the car is driving or under regenerative braking. The motor power can be expressed as a product of the motor torque, T_m and the motor rotational speed, w_m and the units normally used are watts (W), kilowatts (kW) or horsepower(hp). The rotational speed is normally expressed in radians per second (rad/s) or rotations per minute (rpm). The torque is normally expressed in newton-meter (Nm).

$$P_m = T_m * w_m$$

where

P_m is motor power (W)

$\mathbf{T_m}$ is motor torque (Nm)

$\mathbf{w_m}$ is rotation speed (rad/s)

an electric car must have a high range, low energy consumption per kilometre and a high MPGe. The following formula can be used to connect the above parameters

$$R = E_{batt}/D = (B_{SOC} /100) * E_{nom} /D$$

where
R is available range of EV (km)
$\mathbf{E_{batt}}$ is current battery capacity (kWh)
D is the Energy consumption per kilometre (kWh/km)
$\mathbf{B_{SOC}}$ is battery state of charge, SOC (%)
$\mathbf{E_{nom}}$ is nominal battery capacity (kWh)

In the data analysis section state of charge (SOC) is analysed to know the energy consumption of each vehicles in every class.

3.2 Electric Vehicle Battery

An electric-vehicle battery (EVB) or traction battery is a battery used to power the propulsion of battery electric vehicles (BEVs). Vehicle batteries are usually a secondary (rechargeable) battery. Traction batteries are used in forklifts, electric Golf carts, riding floor scrubbers, electric motorcycles, full-size electric cars, trucks, vans, and other electric vehicles. Electric-vehicle batteries differ from starting, lighting, and ignition (SLI) batteries because they are designed to give power over sustained periods of time. Deep-cycle batteries are used instead of SLI batteries for these applications. Traction batteries must be designed with a high ampere-hour capacity. Batteries for electric vehicles are characterized by their relatively high power-to-weight ratio, energy-to-weight ratio and energy density; smaller, lighter batteries reduce the weight of the vehicle and improve its performance. Compared to liquid fuels, most current battery technologies have much lower specific energy, and this often impacts the maximal all-electric range of the vehicles. However, metal-air batteries have high specific energy because the cathode is provided by the surrounding oxygen in the air. Rechargeable batteries used in electric vehicles include lead–acid, NiCad, nickel–metal hydride, lithium-ion, Li-ion polymer, and, less commonly, zinc–air and molten-salt batteries. The amount of electricity (i.e. electric

charge) stored in batteries is measured in ampere hours or in coulombs, with the total energy often measured in watt hours.

3.2.1 Lead-Acid Battery

Flooded lead-acid batteries are the cheapest and in past most common traction batteries available. There are two main types of lead-acid batteries: automobile engine starter batteries, and deep cycle batteries. Automobile alternators are designed to provide starter batteries high charge rates for fast charges, while deep cycle batteries used for electric vehicles like forklifts or golf carts, and as the auxiliary house batteries in RV's, require different multi-stage charging. No lead acid battery should be discharged below 50% of its capacity, as it shortens the battery's life. Flooded batteries require inspection of electrolyte level and occasional replacement of water which gases away during the normal charging cycle. Traditionally, most electric vehicles have used lead-acid batteries due to their mature technology, high availability, and low cost (exception: some early EVs, such as the Detroit Electric, used a nickel–iron battery.) Like all batteries, these have an environmental impact through their construction, use, disposal or recycling. On the upside, vehicle battery recycling rates top 95% in the United States. Deep-cycle lead batteries are expensive and have a shorter life than the vehicle itself, typically needing replacement every 3 years. Lead-acid batteries in EV applications end up being a significant (25–50%) portion of the final vehicle mass. Like all batteries, they have significantly lower energy density than petroleum fuels—in this case, 30–40 Wh/kg. While the difference isn't as extreme as it first appears due to the lighter drive-train in an EV, even the best batteries tend to lead to higher masses when applied to vehicles with a normal range. The efficiency (70–75%) and storage capacity of the current generation of common deep cycle lead acid batteries decreases with lower temperatures and diverting power to run a heating coil reduces efficiency and range by up to 40%. Recent advances in battery efficiency, capacity, materials, safety, toxicity and durability are likely to allow these superior characteristics to be applied in car-sized EVs.

A battery is essentially many electrochemical cells connected in series or parallel to provide voltage and capacity. Each cell contains a positive (cathode) and a negative (anode) electrode divided by an electrolytic solution, simply called as electrolyte, with dissociated salt that allows ion transfer between electrodes [14]. The electrical energy that a battery can give is a function of both the cell and its capacity which are dependent on the chemistry of the battery. Out of the common batteries used in various applications, lead acid, Nickel Cadmium (Ni-Cd), Nickel

Metal Hydroxide (Ni-MH) and Li-ion batteries have higher energy densities as shown in fig.2. Lithium ion battery is most commonly used nowadays because of its high energy density.

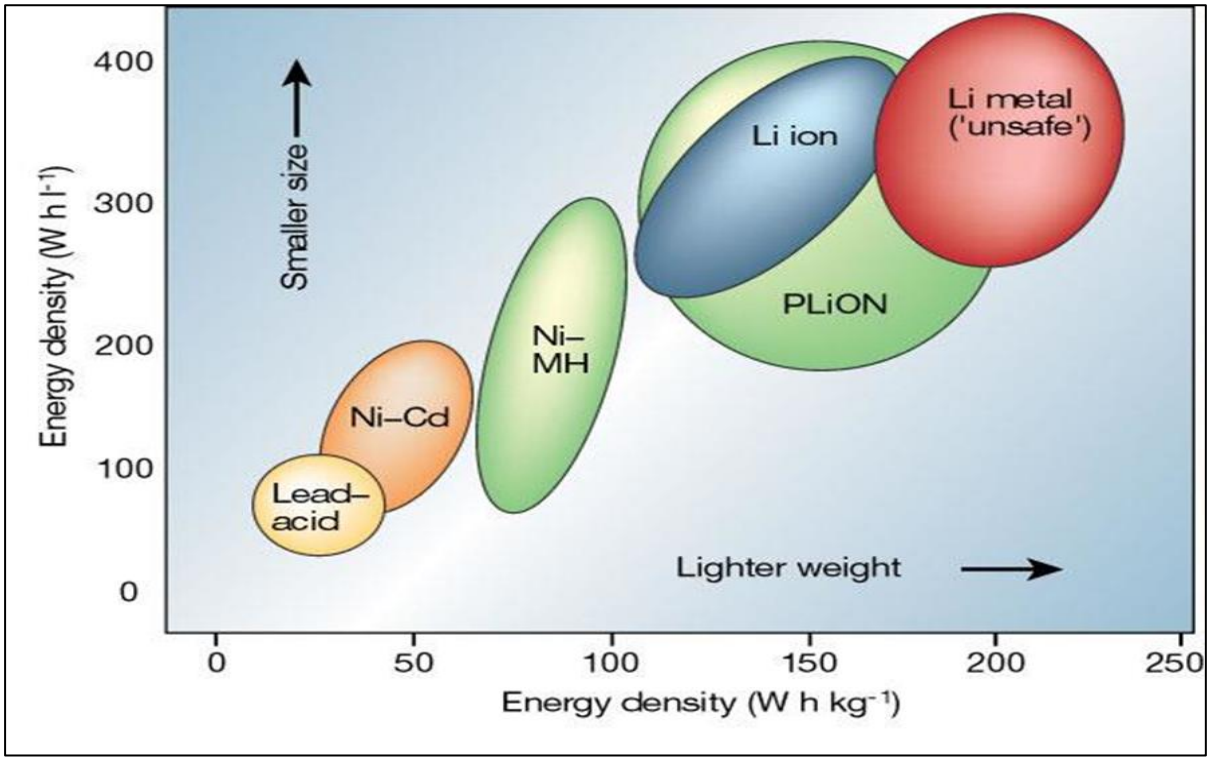

Fig.2 Gravimetric energy Vs Volumetric energy

From the fig.2, we can infer a few characteristics about distinct types of batteries used in EV. Li-ion battery has the Specific energy or gravimetric energy density which is the battery capacity per weight (Wh/kg) out of all. They have higher cycle life and low self-discharge rate than any other battery. Another advantage of Li-ion is minimal maintenance Ni-Cad cells require a periodic discharge to ensure that they did not exhibit the memory effect. As this does not affect the Li-ion battery, this process or other similar maintenance are not required. Tab.1 shows various specification of different batteries.

3.2.2 Nickel-metal hydride

Nickel-metal hydride batteries are now considered a relatively mature technology. While less efficient (60–70%) in charging and discharging than even lead-acid, they have an energy density of 30–80 Wh/kg, far higher than lead-acid. When used properly, nickel-metal hydride batteries can have exceptionally long lives, as has been demonstrated in their use in hybrid cars and surviving NiMH RAV4 EVs that still operate well after 100,000 miles (160,000 km) and

over a decade of service. Downsides include the poor efficiency, high self-discharge, very finicky charge cycles, and deficient performance in wintry weather.

Specifications	Lead Acid	NiCd	NiMH	Li-ion[1] Cobalt	Li-ion[1] Manganese	Li-ion[1] Phosphate
Specific energy (Wh/kg)	30–50	45–80	60–120	150–250	100–150	90–120
Internal resistance	Very Low	Very low	Low	Moderate	Low	Very low
Cycle life[2] (80% DoD)	200–300	1,000[3]	300–500[3]	500–1,000	500–1,000	1,000–2,000
Charge time[4]	8–16h	1–2h	2–4h	2–4h	1–2h	1–2h
Overcharge tolerance	High	Moderate	Low	Low. No trickle charge		
Self-discharge/ month (room temp)	5%	20%[5]	30%[5]	<5% Protection circuit consumes 3%/month		
Cell voltage (nominal)	2V	1.2V[6]	1.2V[6]	3.6V[7]	3.7V[7]	3.2–3.3V
Charge cutoff voltage (V/cell)	2.40 Float 2.25	Full charge detection by voltage signature		4.20 typical Some go to higher V		3.60
Discharge cutoff voltage (V/cell, 1C)	1.75V	1.00V		2.50–3.00V		2.50V
Peak load current Best result	5C[8] 0.2C	20C 1C	5C 0.5C	2C <1C	>30C <10C	>30C <10C
Charge temperature	–20 to 50°C (–4 to 122°F)	0 to 45°C (32 to 113°F)		0 to 45°C[9] (32 to 113°F)		
Discharge temperature	–20 to 50°C (–4 to °F)	–20 to 65°C (–4 to 49°F)		–20 to 60°C (–4 to 140°F)		
Maintenance requirement	3–6 months[10] (toping chg.)	Full discharge every 90 days when in full use		Maintenance-free		
Safety requirements	Thermally stable	Thermally stable, fuse protection		Protection circuit mandatory[11]		
In use since	Late 1800s	1950	1990	1991	1996	1999
Toxicity	Very high	Very high	Low	Low		
Cost	Low	Moderate		High[12]		

Tab.1 Diverse types of EV batteries

3.2.3 Lithium-ion battery

Lithium-ion (and similar lithium polymer) batteries, widely known by their use in laptops and consumer electronics, dominate the most recent group of EVs in development. The traditional lithium-ion chemistry involves a lithium cobalt oxide cathode and a graphite anode. This yields cells with an impressive 200+ Wh/kg energy density and good power density, and 80 to 90% charge/discharge efficiency. The downsides of traditional lithium-ion batteries include short

cycle lives (hundreds to a few thousand charge cycles) and significant degradation with age. The cathode is also somewhat toxic. Also, traditional lithium-ion batteries can pose a fire safety risk if punctured or charged improperly.

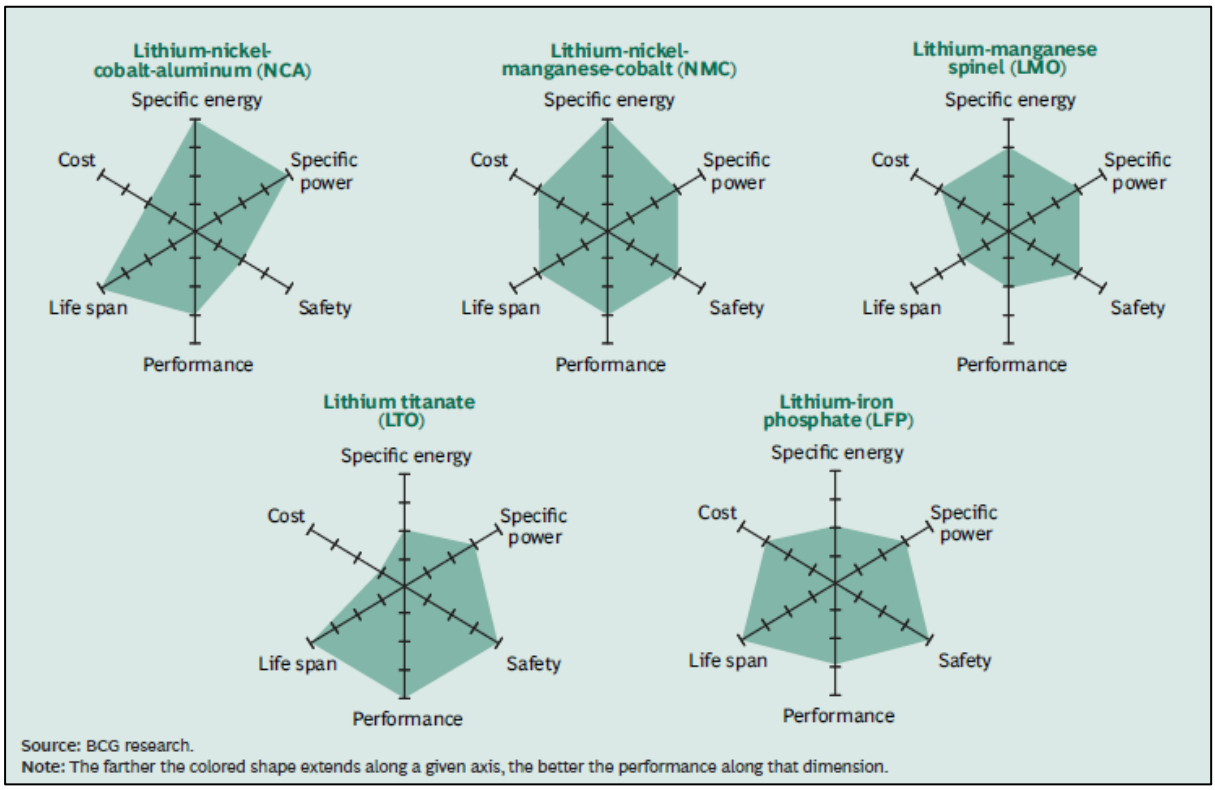

Fig.3 Different Li-ion batteries

The fig.3 shows diverse types of lithium-ion battery. Lithium-ion comprise a family of battery chemistries that employ various combinations of anode and cathode materials. Each combination has distinct advantages and disadvantages in terms of safety, performance, cost and other parameters. The most prominent technologies for automotive applications are lithium-nickel-cobalt-aluminium, lithium-nickel-manganese-cobalt, lithium-manganese spinel, lithium titanate, and lithium-iron phosphate. The technology that is currently most prevalent in consumer applications is lithium-cobalt oxide, which is generally considered unsuitable for automotive applications because of its inherent safety risks.

Chemical Name	**Material**	**Abbreviation**	**Short form**	**Notes**
Lithium cobalt oxide	LiCoO2	LCO	Li-Cobalt	High Capacity
Lithium Manganese oxide	LiMn2O4	LMO	Li-manganese or spinel	Most safe, lower capacity than Lco

Lithium iron phosphate	LiFePO4	LFP	Li-phosphate	excellent safety and long-life span
Lithium Nickel Manganese Cobalt	LiNiMnCoO2	NMC	NMC	Excellent specific energy
Lithium Nickel Cobalt Aluminium Oxide	LiNiCoAlO2	NCA	NCA	Gaining importance in electric powertrain and grid storage
Lithium Titanate	Li4Ti5O12	LTO	Li-titanate	Gaining importance in electric powertrain and grid storage

Tab.2 Chemical structure of different Li-ion batteries

All automotive battery chemistries require elaborate monitoring, balancing, and cooling systems to control the chemical release of energy, prevent thermal runaway, and ensure a reasonable long-life span for cells. Above figure shows no single technology wins along all six dimensions. Choosing a technology that optimizes performances along one dimension inevitably means compromising on other dimensions. Tab.2 shows chemical structure of different Li-ion batteries.

There are many advantages and disadvantage for Lithium. The advantages are they last long, mining is environmentally friendly, light-weight etcetera. The downside is that initially, it is more expensive.

3.2.4 Range Anxiety

Range anxiety is the fear that a vehicle has insufficient range to reach its destination and would thus strand the vehicle's occupants [15] [16] [17] [18]. This is one of the major barriers for the large-scale adoption of BEV. Studies shows that Range anxiety is exaggerated. A recent study [19] concluded that most daily trips can be accomplished within the range of an inexpensive electric vehicle. The two issues are intertwined in the simple questions of, "Do I have enough charge to get there and do I have enough charge to get back?" A survey found that 71.7% of the respondents were more inclined to purchase a PHEV if charging stations were located at either their place of work or their trip destination [20]. While PHEVs are different from BEVs,

with BEVs requiring a charger and PHEVs having an ICE for backup, a lack of chargers even for PHEVs will reduce the battery benefit and thus the economic benefit.

We know that we would not get the complete range a EV manufacturer offer but, there are few ways in which we can get the maximum out of that:

- Be diligent with the throttle.
- Use climate control conservatively
- Plan the most efficient drive route
- Strategize drive modes
- Use right tyres

3.2.5 Battery Range

	Battery Capacity (kWh)	Combined Avg. Range (km)	Efficiency (kWh/100km)
2017 Nissan Leaf	30	172	17.4
Tesla Model S	100	539	18.6
Tesla Model X 90D	90	414	21.7
Kia Soul EV	30.5	150	20.3
Smart Fortwo ED	17.6	145	12.1
Mitsubishi i-MiEV	16	100	16
Ford Focus Electric	23	122	18.9
Chevrolet Bolt EV	60	383	15.7
BMW i3	33	156	21.2
Fiat 500e	24	160	15

Tab.3 Battery range of various BEV models

The range is main parameter for the electric vehicle (EV) especially from the customer side. Range of electric vehicles has long been considered a major barrier in acceptance of electric mobility [21]. Numerous factors influencing EV range. The first group of factors influencing EV range is vehicle design and the second is driver influence. The most significant design parameter for EV is the battery capacity. Increasing the amount of batteries is the simplest way to increase EV range. For long journeys could be used range extender [22].

The Tab.3 shows the battery capacity, Combined Avg. Range (km), Efficiency(kWh/100km) of several BEVs.

3.2.6 Battery Capacity

Battery Capacity is a reference to the total amount of energy stored within a battery. Battery capacity is rated in Ampere-hours (AH), which is the product of Current and the hours to total discharge.

There are several factors that govern battery capacity. They are:

- Physical size – the amount of capacity that can be stored in the casing of any battery depends on the volume and plate area of the actual battery. The more volume and plate area the more capacity one can store in the battery.
- Temperature – capacity, energy store decreases as a battery gets colder. Elevated temperature also influences all other aspects of the battery.
- Cut off voltage – to prevent damage to the battery, batteries have an internal mechanism that stops voltage called the cut-off voltage, which is typically limited to 1.67V or 10V for a 12V battery. Letting a battery self-discharge to zero destroys the battery.
- Discharge rate – the rate of discharge, the rate at which a battery goes from a full charge to the cut off voltage measures in amperes. As the rate goes up, the capacity goes down.
- Battery history – deep discharging, excessive cycling, age, over charging, under charging, all reduces the capacity.

It must be noted that the range of an electric car is dependent on various parameters of which four are important.

- Energy consumed by the car. When a car travels at a higher speed, generally more energy is consumed due to friction and air resistance. Hence, less driving range is possible.
- Efficiency of the battery. It depends on several parameters including the ambient temperature, discharging current and the aging of the battery.
- Driving style. City driving is very different from highway driving. This is the reason why EPA provides separate fuel economy estimates for MPGs for city, highway and combined.
- Energy consumed by on-board accessories like air conditioning system, battery cooling system etcetera.

There are many other factors which influence the range of an EV. Mostly users would not get the mileage that the manufactures promise. But they can ensure they will get the deserved amount by taking care of above mentioned factors.

3.2.7 Battery parameters

The battery is the most important part of the EV. It determines the cost of the EV to a substantial extent and its range. Hence, understanding the battery performance parameters is very important. It forms the basis of understanding battery charging. Let us now look at a few main performance parameters we should know:

1. *Nominal voltage (V_{nom}, in V)*: It is rated voltage of the battery when it is fully charged. When a battery is discharged or is loaded, the voltage reduces gradually to a lower value, V_{batt}
2. *Nominal current (I_{nom}, in A)*: It is rated current of the battery for charging or discharging. Typically, the actual charging/discharging current $I_{batt} <= I_{nom}$. Further, electric cars normally have much higher peak discharging current than the peak charging current.
3. *Ampere-hour (Q_{nom}, in Ah)*: An ampere hour is a unit of electric charge that corresponds to the charge transferred by a steady current of one ampere flowing for one hour, or 3600 coulombs. The commonly seen milliampere hour (mAh) is one-thousandth of an ampere hour (3.6 coulombs). The total amount of energy that can be stored in the battery can be calculated by the product of battery ampere hours and battery nominal voltage. The effective ampere hour of a battery is determined by the charging/discharging current as described by Peukert's law. This results in the following formula:

$$\boxed{E_{nom} = Q_{nom} V_{nom}}$$

4. *Charge/discharge Efficiency (in %)*: When charging or discharging a reversible battery, neither can all the energy sent to a battery be

effectively stored nor can all the available electric charge inside a battery be retrieved successfully. The efficiency is used to represent the ability of a battery to store/retrieve electric charge or energy. The efficiency of a battery is not always constant even in one cycle, and it depends on the SOC, cell temperature and current. When we talk about efficiency, generally it refers to the overall cycle efficiency, which means the efficiency of a whole cycle.

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3.3 Charging Infrastructure

3.3.1 Charging station

An electric vehicle charging station, also called EV charging station and EVSE (electric vehicle supply equipment), is an element in an infrastructure that supplies electric energy for the recharging of electric vehicles, such as plug-in electric vehicles, including electric cars and plug-in hybrids.

As plug-in hybrid electric vehicles and battery electric vehicle ownership are expanding, there is a growing need for widely distributed publicly accessible charging stations (some of which support faster charging at higher voltages and currents than are available from residential EVSEs). Many charging stations are on-street facilities provided by electric utility companies or located at retail shopping centres and operated by many private companies. These charging stations provide one or a range of heavy duty or special connectors that conform to the variety of electric charging connector standards.

Charging stations fall into three basic contexts:

a) Residential charging stations
b) Charging while parked (including public charging stations).
c) Fast charging at public charging stations > 40kW.

Battery capacity and the capability of handling faster charging are both increasing, and methods of charging have needed to change and improve. New options have also been introduced (on a small scale, including mobile charging stations and charging via inductive charging mats). The differing needs and solutions of various manufacturers has slowed the emergence of standard charging methods, and in 2015, there is a strong recognition of the need for standardization.

Although the rechargeable electric vehicles and equipment can be recharged from a domestic wall socket, a charging station is usually accessible to multiple electric vehicles and has additional current or connection sensing mechanisms to disconnect the power when the EV is not charging.

3.3.2 Residential charging

In our analysis, we are assuming that all the vehicles will charge from home once a day. When they come back from work or somewhere else, they will connect their vehicle with the charging station built in their home and they can change until battery is fully charged. A home charging station usually has no user authentication, no metering, and may require wiring a dedicated circuit. Some portable chargers can also be wall mounted as charging station. They can charge their EV at home using a standard 3 pin plug with a EVSE cable or wall mounted home charging point.

- Electric car drivers choose a home charging point to benefit from faster charging and built-in safety features.
- Charging an EV is like charging a mobile phone- plug in overnight and top up during the day.
- It is useful to have a 3-pin charging cable as a backup charging option.
- An EV will have either a Type 1 plug or a Type 2 plug. One must choose a charging point with a plug that is compatible with their car.

To charge from home, one must either a Level 1 charging station (120V) or Level 2 charging station (240V).

There are few advantages if the drivers charge their car at home.

- They can start their day with a 100% charged EV.
- Low cost charging.

3.3.2.1 Level 1 charging

The level 1 charging station is slower. It only provides 1 to 1.5 kWh of charging per hour. For most vehicles on the market, a complete charge takes between 3 to 5 hours depending on the size of the battery. In SAE terminology, Level 1 charging refers to using a standard house outlet to charge your electric vehicle. This will take a long time to fully charge your car but when your EV is only used to commute or travel short distances, a full charge is not needed.

Charging Level	Power Supply	Charger Power
Level 1	120VAC Single Phase	1.4 kW @ 12 amp (on-board charger)
Level 2	240VAC Single Phase up to 19.2 kW (up to 80 amps)	3.3 kW (on-board)
		6.6 + kW (on-board)
DC Fast Charge Level 2	200 – 450 VDC up to 90 kW (approximately 200 amp)	45 kW (off-board)

Tab.4 Different charging levels

3.3.2.2 Level 2 charging

240-volt AC charging is known as Level 2 charging. Level 2 charging is like household appliances. Level 2 chargers range from chargers you can install in your garage such as ones sold by Tesla to many chargers in public spaces. They can charge an electric car battery in 4–6 hours. Level 2 chargers are often placed at destinations so that drivers can charge their car while at work or shopping. Level 2 home chargers are best for drivers who use their vehicles more often or require more flexibility. With a residential level 2 charging station, the electric vehicle charges faster during the first hours of charging according to the battery capacity and its SOC. Tab.4 shows different charging levels.

3.3.2.3 Level 3 charging

Level 3 charging is also known as DC fast charging. The organization CHAdeMO is working to standardize fast chargers. Level 3 chargers use a 480 V plug and can charge an EV in around 30 minutes. The Tesla Supercharger is the most ubiquitous in the United States and can charge a Tesla Model S in around 20 minutes. Tesla reports that they have 1,043 supercharging stations around the world with more on the way.

3.3.3 Charging time

Time to charge an EV can be as little as 30 minutes or up to 12 hours. The time it takes to charge depends on the size of the battery and the speed of the charging point. In our analysis, as we assume that they will come home at around 18:00 Hrs and leave in the morning at 06:00

Hrs. According to the European market segment [23], most cars (40%) are Class A, which needed less hours of charging. About 87% of total cars sold in Europe in 2017 are either Class A or class B or Class C.

- A typical EV (Nissan LEAF 30 kWh) takes 4 hours to charge from empty with a 7kW home charging point.
- 3.7kW home charger provides about 24 Kms per hour of charge.
- 6.6kW home charger provides about 48 Kms per hour of charge.
- Charging rates can differ based on the ambient temperature, the SOC and maximum charging rate of the vehicle.

3.3.4 Charging while parked

Some users in our study drove more than 350 Kms some days in a year. If they are ready to make some adjustments, more users can shift to EVs. Some of the adjustment includes charging during the day. They can charge when they are at office; they will get a lot of hours as they are working. Or when they are doing some other activities such as shopping or watching movies they will get necessary hours needed to charge their vehicles. They can charge from a commercial venture for fee or free, offered in partnership with the owners of parking lot. This charging may be slow or high speed and encourages EV owners to recharge when they take the advantage of any nearby facility.

3.3.5 DC Fast charging

DC Fast Chargers supersede level 1 and level 2 charging stations and are designed to charge EV quickly with an electric output ranging from 50kW to 120kW. Most modern fully-electric vehicles can be equipped with DC quick charge capability. It can deliver 100Kms of range in 10-30 minutes. These chargers may be at rest stops to allow for longer distance trips. It can deliver more power to the vehicle which enable the EV to run much higher distances that with a AC charging. Many DC power charging stations are implemented in the United States. CHAdeMO and Combined charging is two major DC power suppliers. When CHAdeMO prioritize on Japanese and American car manufacturers, Combined charging focus on European vehicles. In the Tab.5, we can see the time required to charge various electric vehicles. Tab.5 shows the time to complete full charge for various BEV types. And Tab.6 shows number of combined charging systems installed in various European countries.

BATTERY ELECTRIC VEHICLES			TIME TO COMPLETE A FULL CHARGE (IN HOURS)	
			Plug-in, 240V NEMA 14-50 outlet, 7.7 kW Max Power Delivery Rate	120V standard household outlet 1.4 kW Max Power Delivery Rate
VEHICLE	ACCEPTANCE RATE (kW)	BATTERY SIZE (kWh)	LEVEL 2 HCS-40PR 32A Max Charging Current	LEVEL 1 Cordset 120V, 12A (provided with car)
BMW ActiveE	7	32	4.5	23
BMW i3 2014-2016 (60Ah battery)	7.4	23	3	16
BMW i3 2017 (60 AH battery)	7.4	23	3	16
BMW i3 2017 (90 Ah battery)	7.4	32	4.5	23
Chevy Bolt	7.2	60	8.5	43
Chevy Spark	3.3	23	7	16
Coda	6.6	31	4.5	22
Fiat 500E	6.6	24	3.5	17
Ford Focus EV	6.6	23	3.5	16
Ford Focus EV 2017	6.6	33.5	5	24
Honda Clarity	6.6	25.5	4	18
Hyundai Ioniq	6.6	28	4	20
Kia Soul	6.6	27	4	19
Mercedes B Class B250e	9.6	28	3.5	20
Mitsubishi i-MiEV	3.3	16	5	11
Nissan Leaf 2011-12 (3.3kW onboard charger S Upgrade, SL & SV Model)	3.3	24	7.5	17
Nissan Leaf 2013-16 S (3.3kW onboard charger)	3.3	24	7.5	17
Nissan Leaf 2013-15 (6.6kW onboard charger, S Upgrade, SL & SV Model)	6.6	24	3.5	17
Nissan Leaf 2016 (6.6kW onboard charger, S Upgrade Model)	6.6	24	3.5	17
Nissan Leaf 2016 (6.6kW onboard charger SL & SV Model)	6.6	30	4.5	21
Nissan Leaf 2017 S (3.3kW onboard charger)	3.3	30	9	21
Nissan Leaf 2017 (6.6kW onboard charger, S Upgrade, SL & SV Model)	6.6	30	4.5	21
Nissan Leaf 2018 S (3.3kW onboard charger)	3.3	40	12	29
Nissan Leaf 2018 (6.6kW onboard charger, S Upgrade, SL & SV Model)	6.6	40	6	29
Smart Car	3.3	17.6	5.5	13
Smart For Two	7	17.6	2.5	13
Tesla Model 3 Standard	7.7	50	6.5	36
Tesla Model 3 Long Range	9.6	70	9	50
Tesla Model S 60 Single	9.6	60	8	43
Tesla Model S 70 Single	9.6	70	9	50
Tesla Model S 85 Single	9.6	85	11	61
Tesla Model S 90 Single	9.6	90	11.5	64
Tesla Model S 60 Dual	19.2	60	8	43
Tesla Model S 70 Dual	19.2	70	9	50
Tesla Model S 75 & 75D	11.5	75	9.5	54
Tesla Model S 85 Dual	19.2	85	11	61
Tesla Model S 90 Dual	19.2	90	11.5	64
Tesla Model S 100D & P100D	17.2	100	13	71
Tesla Model X 60 Standard	11.5	60	8	43
Tesla Model X 75 Standard	11.5	75	9.5	54
Tesla Model X 90 Standard	11.5	90	11.5	64
Tesla Model X 60 Upgrade	17.2	60	8	43
Tesla Model X 75 Upgrade	17.2	75	9.5	54
Tesla Model X 90 Upgrade	17.2	90	11.5	64
Tesla Model X 100D & P100D	17.2	100	13	71
Tesla Roadster	17.2	56	7.5	40
Toyota Rav4	9.6	41.8	5.5	30
VW e-Golf (3.6kW)	3.6	24	6.5	17
VW e-Golf (7.2kW)	7.2	24	3.5	17

Tab.5 Time to complete a full charge for BEVs

Country	Total	December 2017	November 2017	October 2017	September 2017	August 2017	July 2017	June 2017
1. Germany	875	54	43	34	37	58	26	17
2. UK	699	20	9	18	17	9	11	7
3. Norway	441	9	1	67				11
4. France	427	17	8	28	18	18	7	20
5. Sweden	310	7	12	19	8	11	5	5
6. Austria	177	11	5	9		4	1	4
7. Switzerland	152	5	2	2	4	2	2	6
8. Denmark	148	1		7		2	1	1
9. Netherlands	138	5		1			3	2
10. Spain	82	4	1	1				
11. Italy	79	4	12	3	27	1	3	1
12. Finland	79			7				10
13. Belgium	63	5	1	3	12	2		6
14. Czech Republic	46	5	1	4	1	3	3	
15. Ireland	40							
16. Poland	36	11	2	10	4			2
17. Slovenia	32			1				
18. Slovakia	28				2			
19. Iceland	24	1	1	4	2			
20. Lithuania	23	10		2		1		2

Tab.6 Number of Combined Charging System installed in Europe.

They may also be used regularly by commuters in metropolitan areas, and for charging while parked for a shorter period. Common examples are CHAdeMO, SAE Combined Charging System, and Tesla Superchargers. This type of charging is extremely useful for those who do not have enough time to wait for their car to get charged. Tab.7 shows features of major EVs.

	AC charging (1 or 3 phase charging/ maximum power in kW	Battery storage Capacity (kWh)	Approximate range (km)	Off-board DC charge option
Renault Zoe	1 or 3/43	22/41	240/400 (NEDC)	No
Tesla Model S 75D	1 or 3/22	75	490 (NEDC)	Yes (Tesla)
BMW i3	1 or 3/11	22/33	190/300 (NEDC)	Yes (Combo)
Nissan Leaf	1/7.4	24/30	200/250 (NEDC)	Yes (CHAdeMO)
Ford Focus Electric	1/6.6	33.5	185 (EPA)	Yes (Combo)
Chevy Bolt	1/7.4	60	383 (EPA)	Yes (Combo)
Chevy Volt PHEV	1/3.3	16	60 (EPA)	No

Tab.7 Features of major EV models

3.3.6 Charging Modes

3.3.6.1 Mode 1

This mode entails slow AC charging via a regular electrical socket. There is no communication between the vehicle and the charging point. It is required to provide an earth wire to the EV and have an external means of protection against faults. In many countries, this form of charging is considered to be unsafe and is illegal.

3.3.6.2 Mode 2

This mode provides for slow AC charging from a regular electricity socket. In addition, the charging cable is equipped with an In-Cable Control and Protection Device (IC-CPD), that is responsible for control, communication and protection (including residual current protection).

3.3.6.3 Mode 3

This mode entails both slow or semi-fast charging via a dedicated electrical socket for EV charging. The charger (or charging station) has an EV specific socket, generally corresponding to Type 1 or Type 2. A charging cable is responsible for the control, communication and protection of the charging process. This mode is commonly used for public charging stations and can facilitate integration with the smart grid. This type of charging can be used commonly for residential charging purpose.

3.3.6.4 Mode 4

Mode 4 uses a dedicated electrical socket for EV charging like mode 3. The charger typically has a charging cable with an EV charging plug. Mode 4 is specifically used for DC charging, which is recommended for fast charging of an electric vehicle. In the case of dc charging, the AC/DC convertor is located within the charging station. The control, communication and protection are built into the charging station.

Fig.4 shows various modes of charging an EV and Tab.8 shows modes and charging types of EV. As we discussed above, control and communication between vehicle and infrastructure is unavailable in mode 1 makes it unsafe.

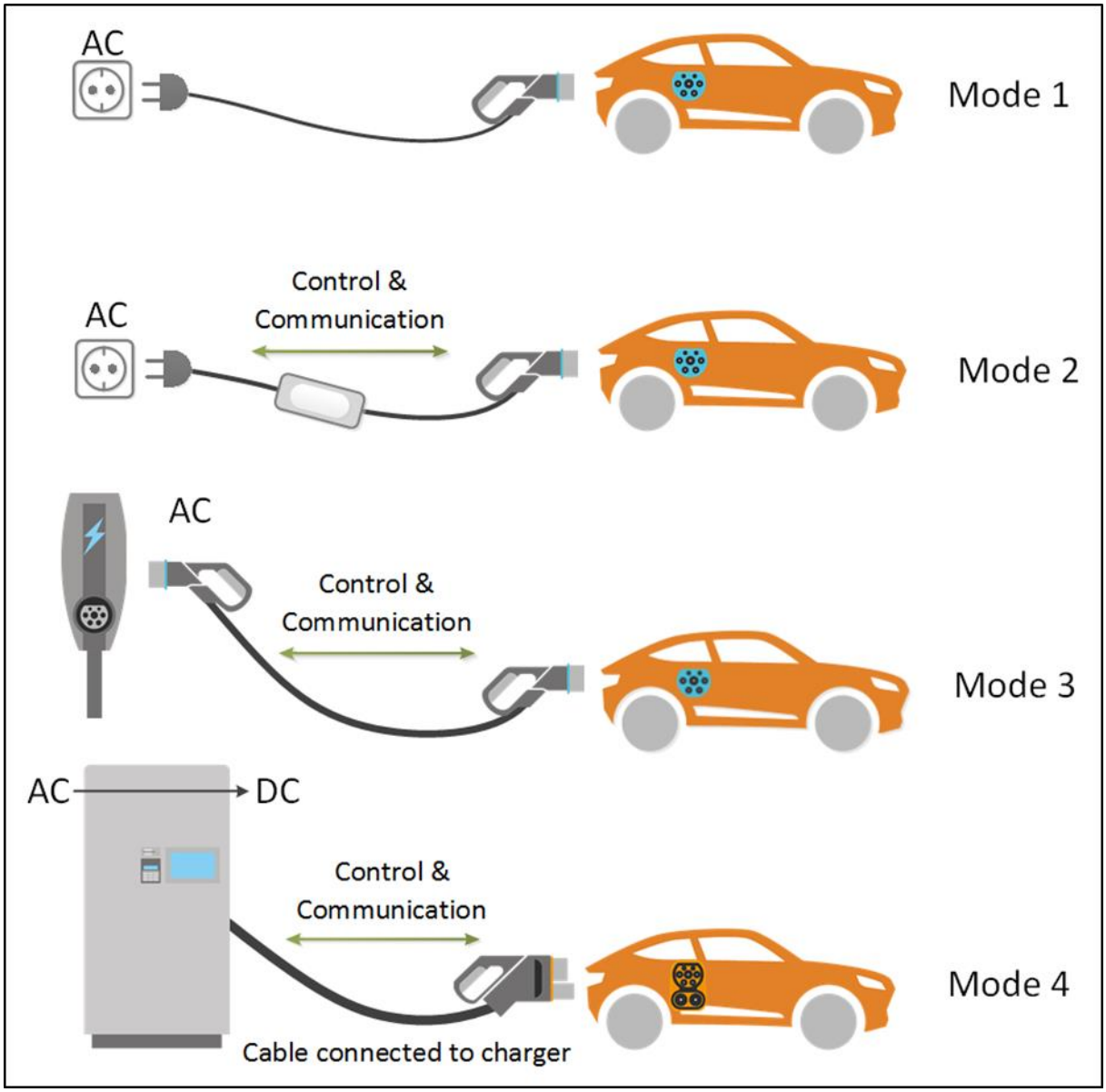

Fig.4 Modes of charging an EV

	Mode	Dedicated socket	Control, communication and protection system	AC/DC charging	
	1	No	No	AC	
	2	No	Yes	AC	
	3	No	Yes	AC	
	4	No	Yes	DC	

Tab.8 Modes and charging type

3.3.7 EV charging cases

There are also three charging cases depending on the location of the charging cable of the charging system.

Case A: The EV charging cable is connected to a domestic power outlet on one end and has a dedicated connector for EV charging on the other end, like a Type 1 or Type 2 connector. The charging is done using the vehicles on-board charger. This case is usually associated with mode 1 or mode 2.

Case B: The charging cable has a dedicated connector for EV charging on both sides like a Type 1 or Type 2 connector. The charging is done using the vehicles on-board charger, usually mode 3. This is the most currently used configuration for public charging with a high degree of flexibility.

Case C: In this case, one end is fixed to a dedicated charging station, supplying DC charge through the cable to the vehicle. This case is generally used for mode 4. The EV connector is chosen to be compatible with EV inlet.

3.4 Smart Grid

Electric vehicles are gaining more and more popularity due to fewer emissions and lower oil dependency. The number of EVs in the globe would be over 35 million by 2022 [24]. And EVs sales per year in US would be over 2.4 million by 2024 [25]. However deep penetration of EVs comes with a large magnitude of charging demand and causes heavy impact on the power grid such as branch and transformer congestion [26]. One effective solution to mitigate the impact is to associate local power generation such as renewable energy sources (RESs) with the charging infrastructure. For example, SolarCity provides solar power system for Tesla EVs charging [27]; SunPower supports Nissan Leaf charging with solar power [28].

Smart Grid is a next-generation electricity network equipped with communications and control systems. Those added controls make it possible to efficiently and dynamically manage energy supply and demand. The key is to be able to fine-tune how much energy is generated, and how much energy is needed at any given moment. An electric vehicle is critical because it can communicate with the grid and respond to calls for storing and discharging energy.

Technologies that play a role in the Smart Grid can be grouped as follow:

- Smart meters, which automatically relay detailed energy consumption data back to the utility at regular intervals and may even respond to remote control signals.
- Grid sensors, distributed throughout grid infrastructure and feeding information on, for example, transformer health and distribution efficiency back to their owners and operators.

EVs are well suited to the Smart Grid for several reasons:

- They have ample energy storage
- They present easy access for control signals
- They are geographically dispersed

Once connected to the Smart Grid and operated as grid resources, EVs can soak up excess energy, pump in extra power, and help maintain a reliable flow of electricity.

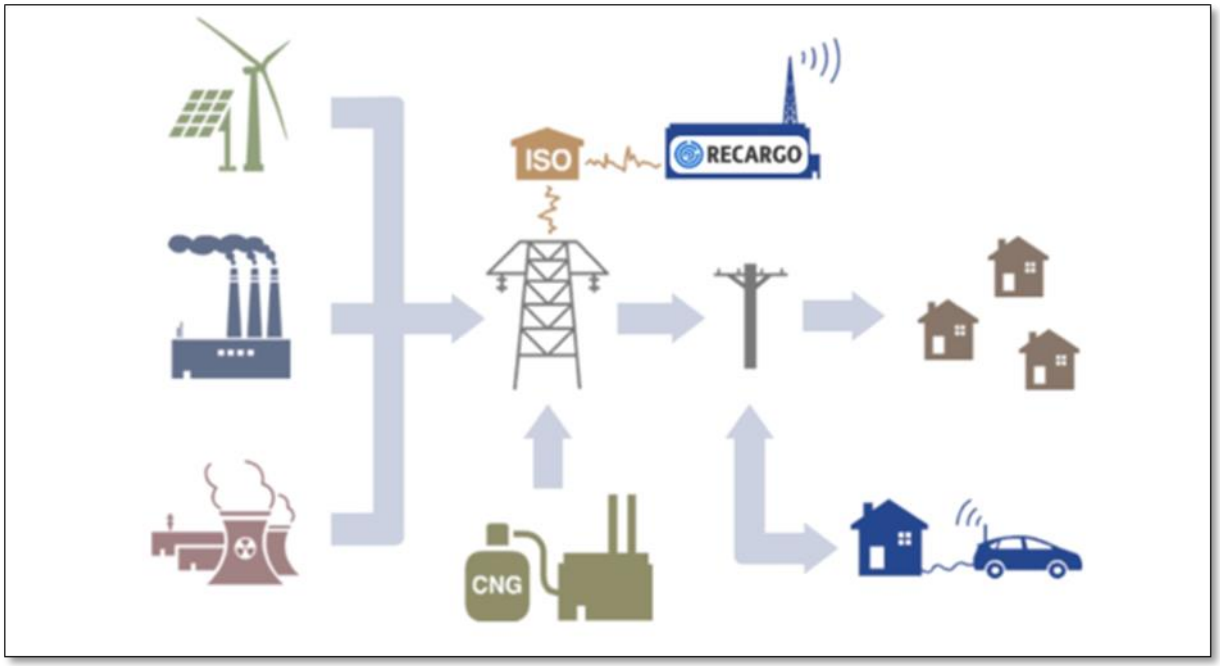

Fig.5 Smart Grid model

The EV aggregator model: PlugShare supplies ancillary services to the grid via remote control optimization of EV charging, smoothly and efficiently integrating with other sources of generation and demand on the grid. Fig.5 shows a smart grid model.

The ability to store energy is incredibly useful to the grid. When too much energy is being produced with massive amounts of wind energy and little demand for it having storage means energy can be pulled off the grid and reserved for use at later peak times. When there is too little energy to meet needs in a location, electricity can flow out of storage and onto the grid. The flow of energy into and out of storage can also support basic operations of the grid, like

maintaining the electrical frequency of the system so critical to overall stability. Despite the value of storage, even the most advanced electrical grids typically have very little of it. Battery storage in stationary battery packs is expensive and technically challenging to build at a large scale. For example, valley sites for dams used for pumped storage where energy is used to move water uphill, for release downhill through turbines when needed are rare. Consequently, there is a large and mostly unmet need for more energy storage.

Consider this: when an electric vehicle is plugged into the Smart Grid, the network doesn't "care" about its make or model, visual design or zero-to-60 performance. To the Smart Grid, the vehicle is nothing more than a unit of storage with a given charge and discharge rate.

Compared with the consumption of the energy grid, a single EV battery has a tiny capacity and is best suited to providing backup power to a household or buffering energy from rooftop solar panels. But think about what happens when there are millions of new EVs on the road, as we fully expect in the next decade. When they arrive, electric vehicles will suddenly become a powerful force in the Smart Grid—the energy storage mechanism so desperately needed.

Charging EVs with RESs further decreases greenhouse gas emission and even reduces charging cost. However, RESs such as solar and wind energy significantly vary over time because of the great dependence on weather conditions. They are usually characterized by intermittency and in dispatchability [29]. These characteristics make it very challenging to coordinate EVs charging with other grid load and renewable generation. On the other hand, smart grid (SG) technologies enable two-way communications between the power grid and power consumers such as EVs. In the context of SG, the power grid can embrace a large scale of EVs with intelligent charging coordination. Along this line, many recent research efforts have studied EVs interacting with RESs in the SG environment.

There are many other EV coordination reviews have been made [30-33]. Results from my analysis shows that at least 85 percentage of vehicles in a given month were parked. In this case, they can remain connected to grid and be ready to deliver the energy stored in the batteries under the concept of vehicle to grid (V2G) in traduced by [34].

Some of the major challenges that the present world economy faces are energy security, sustainability, pollution and climate change impacts. Renewable energy is the energy which is collected from renewable sources such as sunlight, wind, rain, tides, waves and geothermal heat. Renewable energy often produces energy for electric generation, air and water heating/cooling and off-grid energy services other than for transportation purposes. Renewable

energy is derived from natural processes that are replenished constantly. One study prove that 100% renewable transportation is feasible [35]. Transport is fundamental in the current globalized economy as it allows the exchange of goods, communication between citizens and is one of the causes of suburbanization in cities [36]. However, one of the major problems arising from the transformation of the global transport system is a high dependence on fossil fuels. Oil is the main energy provider in the transport energy mix, over 94% of the total energy demand for transport is provided by oil, 3% by natural gas and other fuels, 2% by biofuels and 1% by electricity.

Wind energy is playing a crucial role in supplying renewable energy. According to Global wind energy council, worldwide wind power capacity reached 318,137 MW in 2013 with an increase of nearly 200,000 MW in the past five years [37]. To improve the efficiency of electricity generated by wind energy, it is important to choose beneficial locations for wind farms. Solar energy can be converted into concentrating solar power plants or photovoltaic (PV) solar panels. Solar power plants utilize mirrors or lenses to focus sunlight, creating sufficiently elevated temperature to drive traditional steam turbines or engines to generate electricity, while PV solar panel generates electricity by solid-state semiconductor that converts sunlight into electricity directly. Hydropower generates 16.6% of worlds total electricity and 70% of all renewable electricity. Since water is about 800 times denser than air, even a slow flowing stream of water can yield considerable amounts of energy.

China for the year 2020 has set a goal to install 150–180 GW of wind power and 20 GW of PV solar power. This huge penetration of the RES into power system will require large energy storage systems (ESS) to smoothly support electric grids so that the electrical power demand and operating standards are met at all the times. In this case, the EV fleets are the possible candidate to play a key role as the dynamic energy storage systems using the V2G context. To this point, the EVs can be aggregated and controlled under the virtual power plant (VPP) concept model. While the EVs are providing these opportunities through charging and discharging of their battery packs, a number of challenges are imposed to the power system grid. These challenges compel the changes on the planning, operation and control of the electric grid. To the utility, the EVs are both the dynamic loads which are difficult to schedule but also a potential back up for the electric grid. Similarly, the vehicle owners have some notion that possessing an EV will substantially increase an extra operating cost when compared to owning an ICEV. Hence, an attractive scenario is needed to merge them so that a sharing of load can be realized between the two parties. Fig.6 shows share of energy from renewable sources.

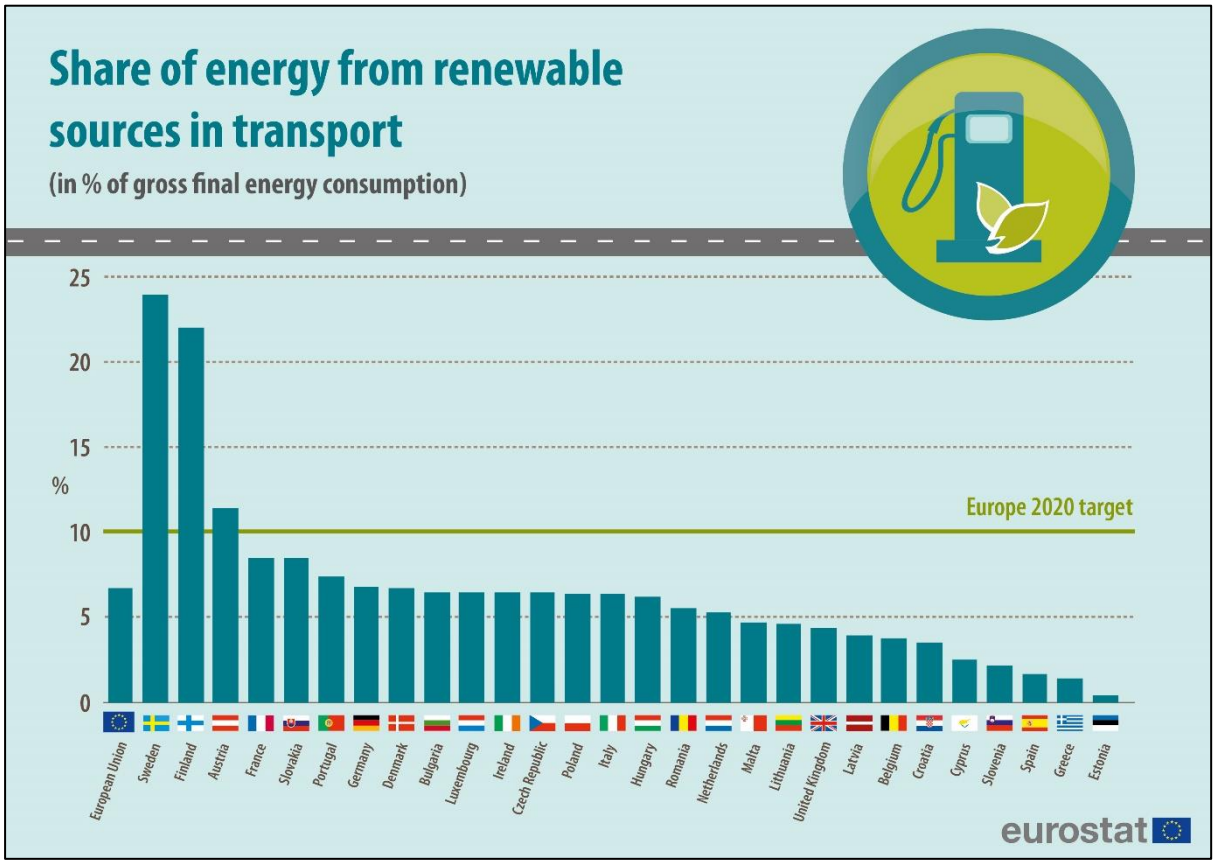

Fig.6 Share of energy from renewable sources

The electricity generation cost has a direct influence on both EVs charging providers and consumers. To reduce the electricity generation cost, the interaction between EVs and RESs has been studied by researchers. [38] developed a hierarchical control algorithm to reduce electricity generation cost, via scheduling EVs charging demands to accommodate fluctuation of electricity generation by wind energy. The hierarchical control algorithm is divided inti three levels with different time scales. The top-level controller solves the scheduling of wind energy and conventional energy utilization with an hour scale. The middle-level controller schedule of EVs charging demands with a sub-hour scale. The bottom-level controller utilizes the power grid frequency deviation to conduct real time control of EVs charging.

For EVs charging providers, they aim at increasing their profit or benefits for providing charging services. Renewable energy can be utilized to help realize this objective. It can be considered from the perspective of increasing investment benefits or the management of electricity deliver. [39] consider increasing investment benefits from demand side management (DSM) perspective by using EVs as flexible demand. Among various active network managements (ANM), the autonomous regional active network management system is

formulated by linear programming problem. In the proposed ANM with DSM, renewable energy utilization and investment benefit are improved. [40] propose an effective scheme for wind energy providers to improve the profits. To achieve this objective, the authors studied the feasibility of using EVs as a storage medium. Meanwhile, they adopt the VPP of wind farm, which can be regarded as a single entity composed of some wind power producers and EVs in the electricity market. The revenue earned by a VPP is modelled by linear programming. [41] formulate charging of electric vehicles and wind energy by stochastic programming. The key components of SG include bulk and real-time purchase of electricity, penalties of selling back electricity to the grid operator and the flexible demand for EVs. An aggregator is utilized to coordinate EVs charging in a controlled manner. The objective is to maximize the profit of the aggregator.

Penetration of more distributed energy resources (DERs) into the energy market is shifting the power generation and distribution industries. The DERs feature variability of time and space of the power production and consumption which results in the more complex and challenging energy management system of the traditional power grid. Smart grid comes along to improve power generation and distribution, which is much more flexible, efficient, reliable and secured. Smart grid encapsulates advanced technologies in communication, smart energy metering and advanced control. It provides EVs as dynamic loads and potential dispatchable-distributed energy sources a flexible and optimized deployment in power industry.

3.4.1 EV smart charging

We mentioned about potential undesirable impacts of uncontrolled EV charging such as the overloading of the power system facility and increased power demand leading to a less efficient electricity supply. One must understand that there are many advantages for smart charging strategies [42]. Smart-charging schemes can pursue various objectives. Some studies focus on the minimization of system or charging costs in the electricity market [43] which in most cases leads to a valley-filling type of charging. Other studies do not model the supply side explicitly but rather try to find some intelligent ways to avoid undesirable impacts on the electric grid network [44]. It has been observed that an optimized algorithm is very crucial to effectively schedule and utilize in an intelligent manner the benefits of the EV niche market. With the large EV penetration into the power systems, many constraints coexist in the real-world implementation scenarios which must be optimized for the better solutions. The constraints are not constant, but they do vary depending on the objectives of the deployed EV system, such as minimization of the charging cost, GHG emissions or losses in the power system, a few to

mention. The authors in [45] presented a day-ahead energy resource scheduling for smart grid by considering participation of the DERs and V2G. A modified particle swarm optimization approach is used for intelligent optimal scheduling. Besides, the EVs are controlled to respond to the demand response programs. The overall operating cost reduction demonstrates the efficacy of the smart EVs scheduling in the smart grid environment.

An optimized price algorithm pertaining the scheduled EV charging and V2G operation is proposed in [46]. To facilitate this intelligent charging, the Radio Frequency Identification (RFID) tag technology is also used. The authors involve EV owner via web mobile application to acquire information and to have control over the EV charging by using parameters like the desired SOC, arrival and departure times or the option for the V2G services to maximize profit. The scheduled charging scheme reported to be cost effective. It resulted in 10% and 7% savings for drivers with flexible charging scheme and enterprise commuters, respectively. In addition, a 56% reduction of the peak power demand is attained with the driver variable charging scheme.

3.4.2 Advanced Metering Infrastructure with EVs

Energy management system (EMS) in smart grid is accomplished by measuring, analysing and reporting the energy use or demand in near-real time phenomenon. Smart metering is a core component in the effort to realize online EMS functionalities in the smart grid. In the integration of the EVs into the power grid, a smart meter (SM) plays a significant role in obtaining the near-real time information of the power demanded or consumed. Hence, the SMs make the process of energy forecast such as day-ahead or intraday forecast and energy pricing more feasible [47,48]. Fig.7 shows the overview of AMI architecture.

These are the fundamental roles of the SMs in the smart grid operation. To this end, the advanced technologies in the smart metering are necessary to accommodate the dynamic EV loads. Hence, the advanced metering infrastructure (AMI) is a framework that embraces the real time smart metering and communication as a single unit.

The figure below depicts an overview of the AMI solution for the EV interactions with the smart grid. It represents collection of data of energy usage or demanded using SMs. The SMs communicate data collected through the communication technologies like BPLC or WiMAX in a particular Field Area Network (FAN), Local Area Network (LAN) or HAN.

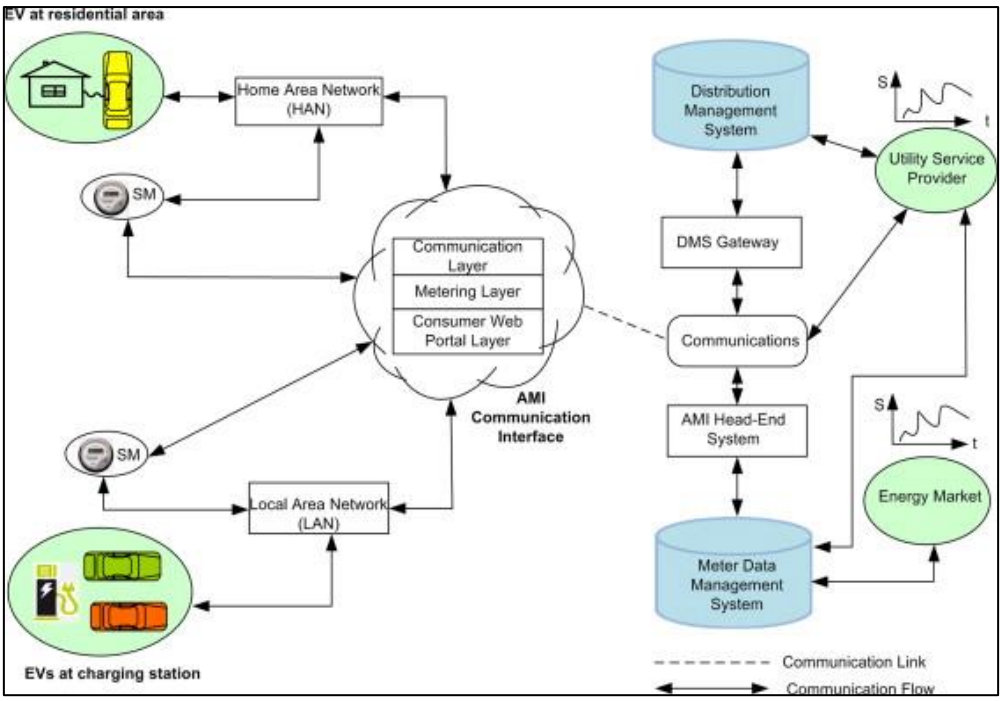

Fig.7 Overview of AMI architecture in V2G interface

These data are received at the AMI head-end system prior to the MDMS which is responsible for the data management, storage and analysis. The EV utility can access the energy information through MDMS. By sing customer web portal, the human machine interface can be realized between the EVMS, MDMS, utility service provider and energy market.

The AMI system encloses within itself numerous technologies and applications that are combined as a single functional unit. They include meter data management system (MDMS), home area network (HAN), SMs, computer hardware, software, advanced sensor networks and various communication technologies. These technologies can be wireless or broadband over powerline (BPL)/power line communication (PLC) that facilitates a bi-directional communication link between the utility network, smart meters, various sensors, computer network facilities and EV management system (EVMS) [49]. The information collected by the AMI can be used to employ intelligent decision and control system. It is concluded that the deployment of EVs using AMI platform can manage to reduce the peak energy consumption by 36%. It shifts 54% of the energy demand to the off-peak hours. Hence, it reduces the stresses of power system during peak demand.

3.4.3 Advanced communication and control network infrastructure with EVs

A bidirectional communication network of the smart grid infrastructure enables many demand response technologies, which control several distributed energy resources over enormous dispersed geographical areas. Wireless communication is an ambitious solution for V2G applications in this case and include low cost and wide area coverage. Depending on the EV integration model into the smart grid, communication solutions can be envisioned in two different scenarios. Primarily, the communication link from advanced systems like EVMS, to the SMs. Secondly, between SMs and grid operators' data centre.

But New challenges are coming up with the EVs deployment in the power industry on monitoring, communication and control architecture due to its dynamic mobility nature. An advanced SM must be able to allow the EVs to be connected to a different aggregator, energy supplier or visiting network when they are away from its HAN or LAN. One study [50] shows the advanced development in wireless communication appears in favour to smart metering facilities. This is an attractive case for the EV applications as most of the EVs are spatially dispersed in the real world. For successful operation of the EVs, they must be able to connect at any time (wherever charging point is available) for recharging their batteries or supplying power to the grid. The GO or EV aggregator, in this case must be able to identify a electric vehicle in the near-real time environment for billing the demanded power. On the other hand, the EV must obtain the time of use or real time pricing trends from the energy market to deliver power to the grid.

Moreover, wireless sensor network (WSN) is an emerging control network which has gained popularity in smart grid. Recently, some researches have shown promising applications of the WSN in the DG and microgrid (MG) operation. By using the same concept, the wireless sensor network can be adopted to enhance the EV penetration. The challenges are still high in adopting WNSs for the EV applications especially in the V2G services. These challenges include shorter ranges as compared to other wireless technologies, which result in packet delays and decreasing success ratio as the number of hops is increased. In [51] the information system for the V2G application based on the WSN is proposed. The vehicle-grid operator communication is distributed wirelessly to improve the grid demand profile, EV reliability and data delivery with minimum number message broadcast. This study is one of the attempts to realize the advanced EV system with the WSN architecture for supporting V2G transactions. Apart from that,

ZigBee technology has been investigated and tested by various researchers, particularly for the EV applications [52]. The ZigBee technology is simple and requires low bandwidth for its implementation. However, the issues like communication interference with other devices sharing the same transmission line, small memory and communication delays need to be addressed to allow ZigBee technology to be reliable and effective for the V2G applications.

Tab.9 shows various wireless communication technologies for V2G application.

S/N	Technology	Operating frequency	Covered distance
1	ZigBee	868 MHz (Europe)	10–100 m
		915 MHz (North America)	
		2.4 GHz (Worldwide)	
2	Near Field Communication (NFC)	13.56 MHz	5–10 cm
3	Bluetooth	2.4 GHz	1–100 m
4	IEEE 802.11p	5.85–5.925 GHz	500–1000 m
5	WiMAX	2–6 GHz	2–5 km

Tab.9 Wireless communication technologies for V2G application.

On the other hand, the cyber-security for the communication network between EV and utility or power market should be assured to prevent the smart grid from the cyber-attacks such as price tampering and system congestions by malicious software. These are some major issues as the deployed EV to the grid network is impotent as it can prone to cyber-attacks. And it is also necessary to provide secured EV services at the visiting networks. If these issues are not taken care they would reduce the effective benefits and reliability of the EVs in the energy market [53]. They provide with a battery-state aware authentication scheme (BASA) to address the issue for V2G networks. In BASA, an aggregated identifier is proposed during the charging to Fully charged state transition to ensure that EVs can be authenticated without disclosing their real identities, selective disclosure-based challenge-response authentication is presented during the Fully charged to discharging phase to realize anonymous data transmission, an aggregated-status is reported during the discharge-to-charging transition in order to hide a EVs power level from an aggregator. The figure below shows communication network architecture and functionalities for the EV interactions with the smart grid. The wireless communication technology to be employed depends on the distance between communicating hot spots and the amount of data to be transmitted. In this figure, the smart mobile phone is used as an interface between the EVMS, charging point and aggregator via GPS or/and Bluetooth-enabled functionalities. Fig. 8 shows EV communication network architecture with smart grid.

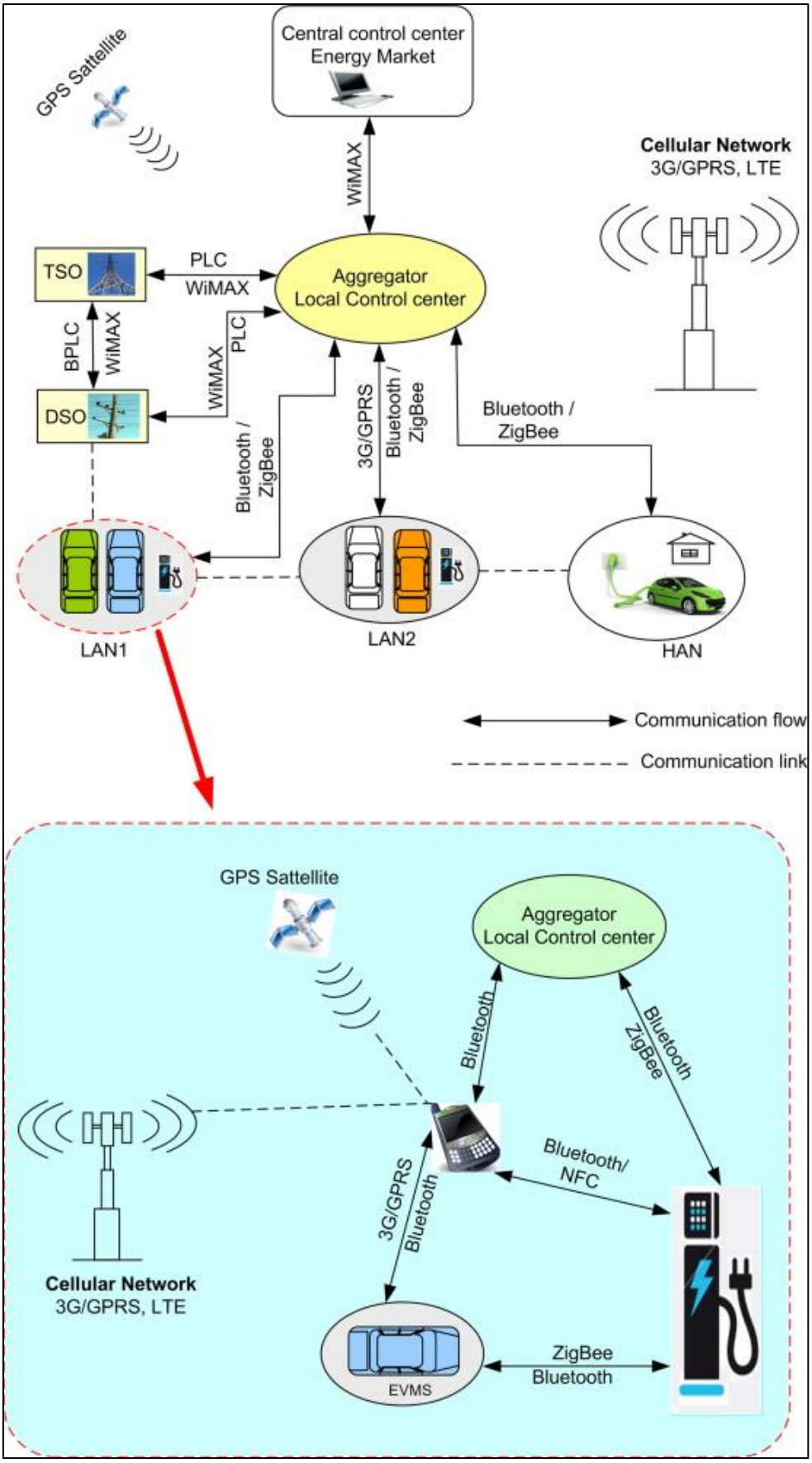

Fig.8 EV Communication network architecture with smart grid

All the statuses from the EV are communicated to the outside environment through the CAN gateway. The WiMAX protocol represents a long-distance communication scenario that covers communication between the aggregator, energy market and utility (TSO/DSO). To increase reliability in the smart grid environment, the Near Field Communication (NFC) protocol can be used to automatically support Bluetooth pairing and intuitively reduce more than eight user interactions to establish Bluetooth connection [54].

3.4.4 Renewable energy sources integration with EVs

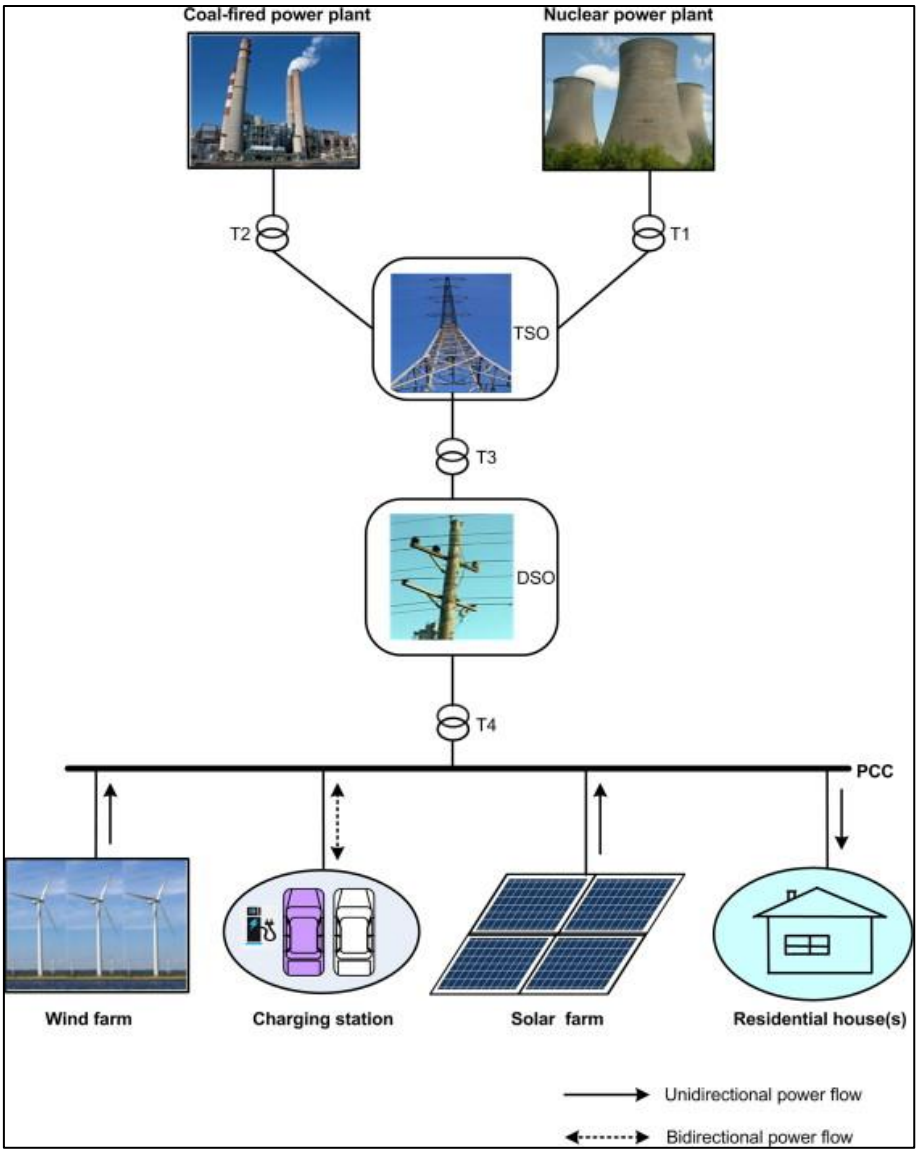

Fig.9 Wind and PV solar energy sources integration into electric grid with EVS

Even though increase penetration of RES into the electric power system is appealing, they suffer from an unpredictable and intermittent power supply especially from wind and PV solar

energies. They are variable with time. Most studies show integration of wind energy conversion system (WECS) and PV solar systems into power system is mature [55]. a solution to balance the electricity generation from this RES on grid can be materialized by adopting stationary energy storage systems (ESS) or controllable dispatch loads [56]. The stationary ESS absorb or supply electricity in the case of excess and low power generation respectively. But this system delays the increase penetration of RES into power system due to its high investment cost. Above fig. illustrates the integration of wind and PV solar energy sources into the power grid with EVs. The electric vehicles are aggregated at charging station located at public area or office and can be used to suppress power fluctuations from this RES in the V2G mode. Here Ti stands for the power transformer in the electric grid, where

i = 1,2, 3,..n. Fig.9 shows wind and PV solar energy sources integration into electric grid.

3.5 Vehicle to Grid System

Electric vehicle can be integrated into power systems and operate with different objectives such as the dynamic loads by drawing power from the grid or dynamic ESS by feeding power to the electric grid. It is worth mentioning that the latter is referred to as Vehicle to grid. The limited EVs as resources, their spatial-location and low individual storage capacity make them unrealizable for the V2G services. In this case, many EVs are aggregated in diverse ways depending on the control schemes and objectives to realize the V2G concept [57]. The aggregation of the EVs as a single controllable distributed energy source can participate in energy market for supporting electric grid in regulation and system management.

The interaction of electric vehicle with smart grid is an attractive system which draws the attention of various scholars in this area. There are numerous application schemes of EV technology in the power market under the smart grid context. Lots of smart grid and V2G technologies are essential to integrate EVs into the smart grid in an efficient manner and are yet under development stages. For example, [58] review V2G impact on distribution systems and utility interfaces. There are many European V2G project going on. One among them is the NewMotion V2G project which is carried out by Mitsubishi motors, Enel, NewMotion, Nuvve and TenneT. It is a High-end smart technology which optimizes the use of renewable energy. NewMotion, one of Europe's biggest providers of smart charging solutions for electric driving-announces the implementation of V2G. They consider EVs as energy buffers. There will be stability by maintaining supply-demand dynamics, based on the request from Grid system operator.

Increasing number of EVs poses a threat to the recharging batteries as the increase the load demand. If these charging are intelligently coordinated, we and distribute this big shift of load. But this need advanced control and communication incorporated for both electric grid and EVs.

The availability of wireless communication, GPS facility and smart metering that we discussed before are becoming more obvious in the current infrastructures. the smart charging technology and communication facilities will be envisioned as an extended service to this wireless infrastructure in place. The smart meter can be configured as firmware rather than hardware while encapsulating roaming services to cope with the EV mobility nature for the dynamic pricing and other data exchange purposes to enable intelligent EV scheduling.

4. Data Analysis

4.1 Potential EV market penetration analysis

This analysis is based on a high time-resolution database of vehicle use, previously collected to study traffic patterns, drivers' behaviour and vehicle emissions. In contrast to most studies that rely on self-reporting and odometer readings, this database was generated by data acquisition hardware installed on the sample vehicles. The data that we took for this analysis refers to the real case of the province of Rome (Italy) and use a large dataset of Floating Car Data (FCD): 150'000 vehicles travelling inside the province during May 2013, and 35,000 vehicles generated from the city of Rome and covering all the Italian territory during the entire year. The database consists of details such as distance travelled, speed, date and time values, state of the vehicle, geographical position etc of 35,000 vehicles of that year. Since computation for all the vehicles are extremally tedious we chose to do that for a sample of 1913 randomly chosen vehicles. The data analysed are of different category with which we can understand the suitability of using Electric vehicle in the city.

In this data analysis section, we have decided to work on the key parameters in which we can analyse the daily distance requirement for a driver and how that data will make him fit for the acceptance of an EV. Firstly, we plot a graph (fig.10) on the average distance travelled and the percentage of fleet. Here, we found more vehicles travelled less average distances. With the data that we have, we days of vehicle use, and the distance travelled where we categorize the days in a year into 12 clusters and find how much percentage of the fleet travels for each cluster. In another word, we could be able to find the percentage of fleet who travelled more days in a year. Even if they travelled more days that would not be a problem for them to change to EV if they travel an average distance less that the proposed mileage from an EV. That is what the graph (fig.11) is all about. For each and every cluster we formed, we found the average distance travelled by that much vehicles. The average value shows a good sign for EV adaptation.

Next, we find the maximum daily distance travelled by each vehicle (fig.12). We found that only 15% of the total fleet travelled more than 600Kms a single day. But still EV is a viable option because more vehicle travelled 101-150 Kms a day. This analysis was done to understand how extend each driver could travel with their car. And from the sample of data that we have, we can say that most drivers can buy an EV for their daily travelling purposes.

The next computation was on the cumulative distribution of the maximum daily distance for the vehicles (fig.13). The cumulative distribution, for a given value of daily driving, is defined to be the fraction of the fleet that never exceed that distance in the study year. In our case, if we take 200 Kms, around 38 % of users never travelled more than that much Kms in an entire year. This data will help us to know how short numbered those are who travel long distance.

Until now we know that the vehicles that travel below a certain distance mark from the las analysis. But we also want to know how flexible that can be if the users are ready to make some adjustment few days in a year. We make use of the days and find some adjustment days for 2, 6 and 18 days and saw how the previous graph change. It came to our attention that if the users are ready for an adaption, more users can travel a given Kms. The adaptations that they need to take are reducing their distance travelled for those days planned to travel long to another day, use a conventional vehicle, recharging their vehicle during the day time. Since our analysis is in an assumption that the vehicle will only recharge only one in a day while they come back from work or somewhere else to the home. So, there would not be any difficulties for making a provision for recharging en route.

Alternatively, rather than only distance travelled analysis we monitored the percentage of fleet those were on use and those were in parking lots. We have the data on the number of vehicles that were on the road and from that we found the parked vehicle fraction. The analysis was done only for a month, the month of May. The data we have was with 15 minutes interval in between and we take the average of those values to do the calculations. It has been found out that at least 85 % of vehicles were parked during the entire month. What we find from our analysis is congruent with that of similar previous analysis. Most of the cars were parked during the entire period.

Although electricity has many advantages as a vehicle fuel, it has two disadvantages: storing it is more bulky and expensive (batteries versus a sheet metal tank) and refuelling is slow. The former implies that the initial electric vehicles will have less range than gasoline, and the later implies that they cannot be quickly refuelled en route. The range and refuel questions are most acute for electric vehicles(EVs), which derive motive power exclusively from onboard electric batteries. One technical approach to range is the Plug-in Hybrid Electric Vehicle(PHEV), which can be refuelled by either electricity or liquid fuels. We focus here on electric vehicles, because they present the more challenging range problem in need of this thesis driving-distance analysis.

Fig.10-Average Distance Vs Fleet percentage depicts the Average distance driven by the fraction of 1865 vehicles. The average distance range of each vehicles were computed and categorised in to 13 groups. Each group consist of 15 Kms range. Then the percentage of the fleet for each group were found out and represent it graphically. From the graph it is evident that most distance range travelled by the vehicle is 31 to 45 Kms (about 26% of total fleet).

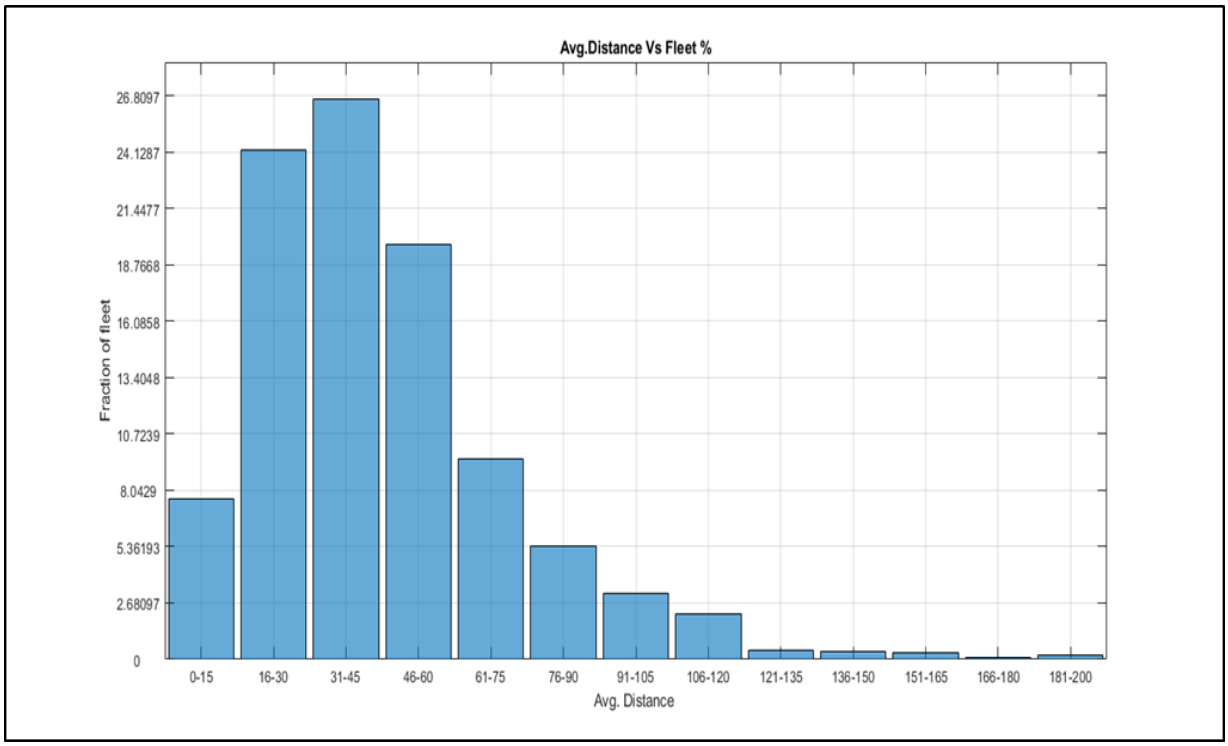

Fig.10 Avg. Distance Vs Fleet percentage

The second highest distance group was 15 to 30 Kms travelled by around 24 percentage of users. It is evident from the graph that the number of uses is reducing steadily from 45 Kms mark. Since then the number of vehicles travelled starts to decrease until it reaches a point where only 0.25% of total fleet travelling between 166 to 200 Kms. This is a very good result for the Electric vehicles as almost all the electric vehicle travels 50 Kms range. Only less than 8 percent of the fleet travelled between 0 and 15 Kms. Days with no driving at all are not shown in this histogram. The vast majority of daily range need is in the 0-50 Kms range. Excluding days of zero driving, the mean daily driving range is 44.6 Kms and median is 39 Kms.

4.1.1 Days of vehicle use and mileage

The next analysis compares how many days the vehicle is used with daily distance driven. Number of fleet observed was 1865 vehicles. In this analysis each vehicle is characterised by

two parameters: the number of days on which that vehicle was used during the year and the average distance driven during those days when it was used. In contradiction with the previous graph, here in the x-axis we took the days in a year and clustered them in to 12 groups and the value corresponding to each group in both the percentage of vehicle and the average distance the travelled were found out. For this analysis, we found out, for each vehicle, the number of days they travel in the year. And the data points on the t-axis were converted in to the percentage of 1865 vehicles. And for each group of vehicles, the average distance travelled by them in the year were also recorded.

Fig.11 Daily Travel in Kms Vs days of vehicle use is a graph in which 1865 vehicle were grouped between 30 days so that 12 groups are shown for the year, with the last subset have 36 days. In the top graph, for each subset, the sample mean is indicated with marker, and 95% confidence limits of the mean are indicated with the error bars.

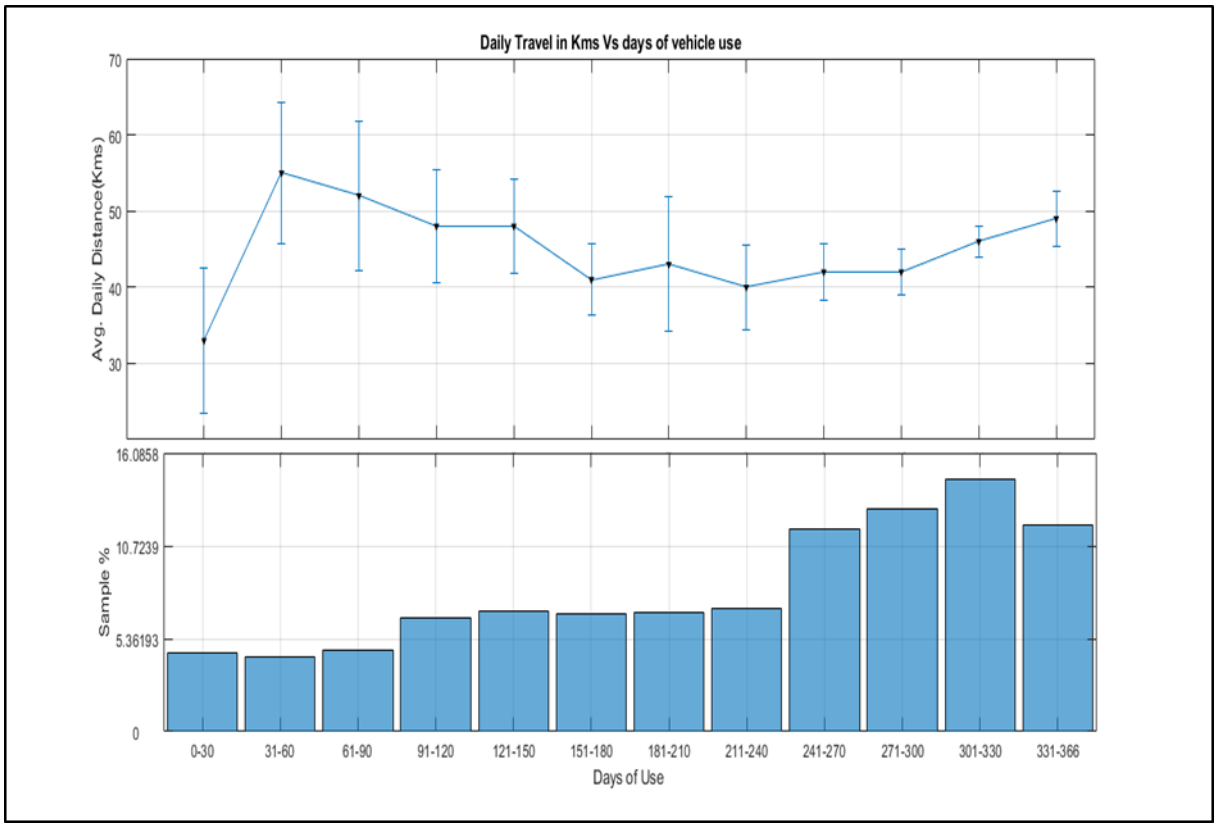

Fig.11 Daily Travel in Kms Vs days of vehicle use

And in the bottom graph of the fig.11, the population of each subset is shown, as a percentage of 1865 vehicle. It reveals little relationship between the frequency of use of a vehicle and its average daily miles of travel. The correlation coefficient(r) between these variables is -0.05.

The low r coefficient means there is a little linear relationship between how many days a vehicle is driven, and how far it is driven on those days. From the graph, we can infer that the vehicles that travelled 30 days or less in a year has an average distance travelled of 33 Kms, with less than 5% of total vehicle travelling that distance. Most vehicles (about 15.5% of total fleet) travelled between 300 and 330 days in a year with an average mileage of 46 Kms. Within the data, we can subdivide in to three classes of vehicle travelled between 0 to 90 days, 91 to 240 days and rest of the days with very little variation in the average distance among those subgroups.

4.1.2 Maximum daily travel distance

The histogram below (Fig.12) shows one day for each vehicle, the day that vehicle drove the furthest. It can be seen as the worst-case scenario for EVs.The distribution of maximum daily mileage for the 1865 vehicles is shown as a histogram with bin sizes of 50 miles. This was done by monitoring the maximum distance travelled on one by each user for one year. There are instances when a vehicle travelled only 1 Km and vehicle travelling 1465 Kms in a single day. Even though the range is wide, the distribution is not linear.

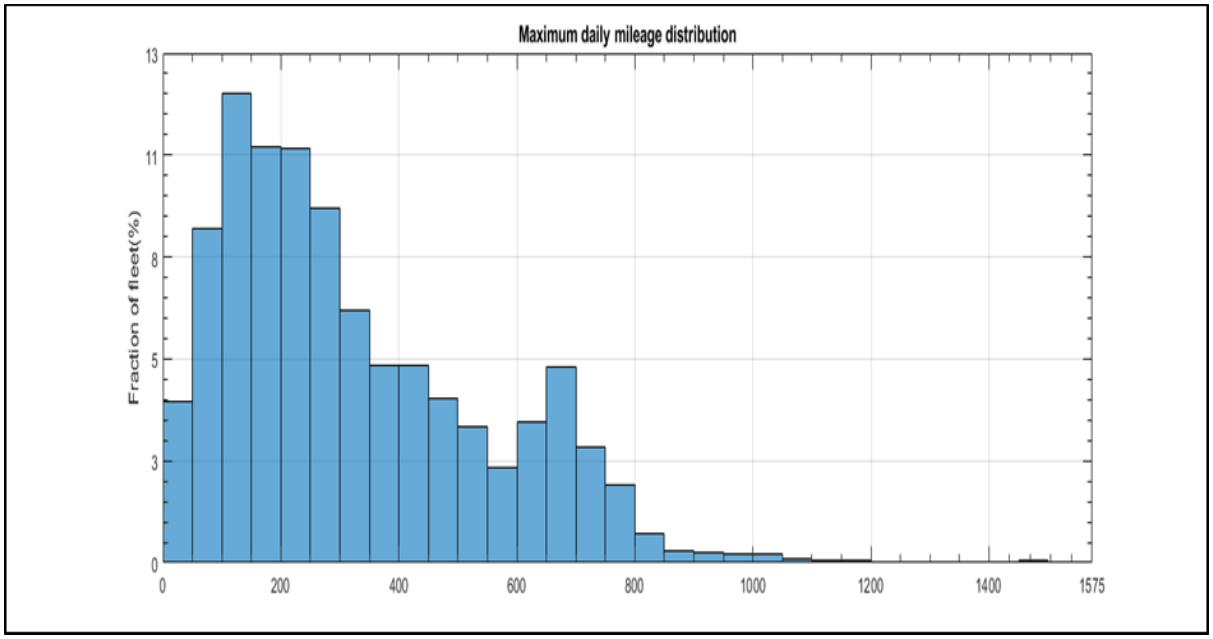

Fig.12 Maximum daily mileage distribution

No adjustments have been made for vehicles with less than a full year of data, but these vehicles were in the study an average of 357 days, so any bias from missing data should be small. Most vehicle were travelled their maximum daily distance in a range between 101 to 150 Kms. That

was almost 12 percentage of the fleet. There are presents of vehicles until 1200 Kms but after that no vehicles travelled in between 1200 Kms and1420 Kms. When comparing with the distance range of its vicinity groups, more vehicles travelled in between 651 to 700 Kms range. This distribution of fleet's maximum travel in fig.12 shows 3% or more of the fleet in each bin from zero to 600 kilometres. Few cars exceed a daily travel maximum of 700 Kms. Only 9 vehicles (0.4%) exceed 1000 Kms, none exceed 1500 Kms. The diminution of driving from 700 to 1000 Kms can be interpreted as a physical limit imposed by road speed limits and human exhaustion. The mean value in this distribution is 324 Kms and median values is 260 Kms.

Fig.13 is the cumulative distribution of the maximum daily distance for the same 1865 vehicles. The cumulative distribution, for a given value of daily driving, is defined to be the fraction of the fleet that never exceed that distance in the study year. For example, an electric vehicle with a range of 150 Kms, charged only once per day, could substitute for 25% of the fleet. Conversely, for the remaining 75% of the fleet, that same 150 Kms EV would have failed to address the driver's range needs on at least one day during the year.

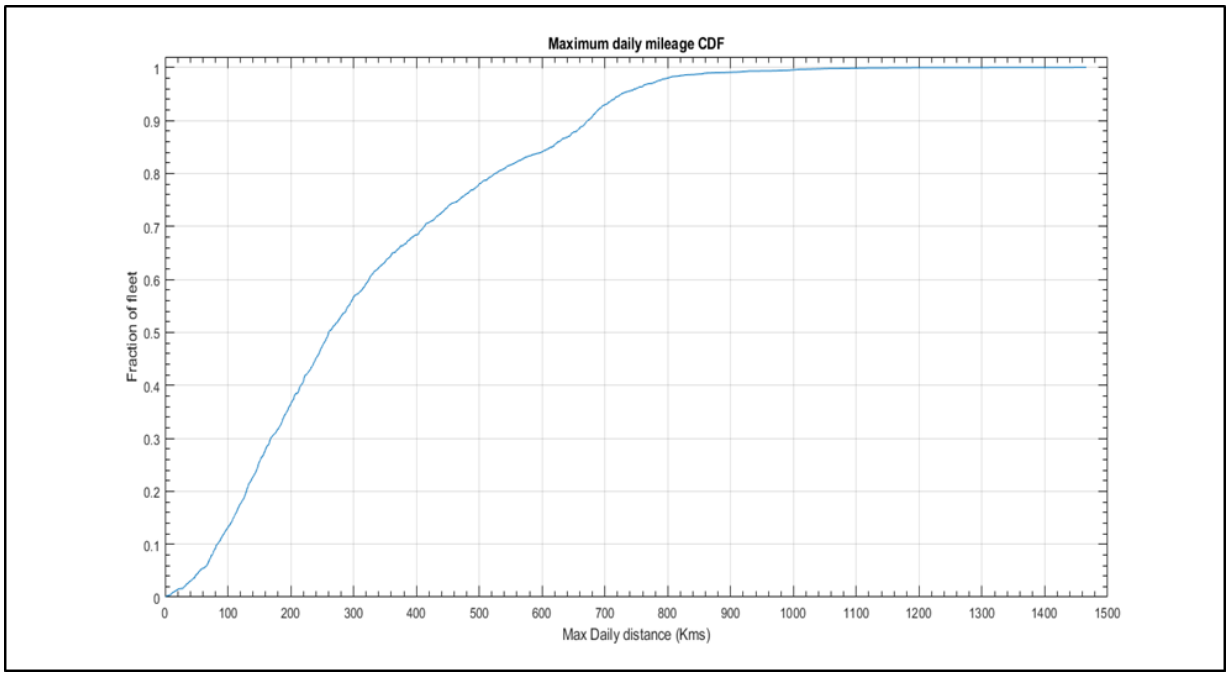

Fig.13 Maximum daily mileage CDF

Similarly, at the 50% mark, an EV would require 260 Kms of range to fully substitute for half of the vehicle fleet. We can see that the percentage of vehicles who travelled more than 1000 Kms are negligibly small. Again, by "fully substitute" we mean that for 25% and 50%, of

drivers, an electric vehicle with 150 and 260 Kms range, respectively, would satisfy all driving needs, every day of the year, with no change from their gasoline vehicle habits.

4.1.3 Days requiring adaptation

The previous analyses examined the distance travelled and the number of days each vehicle was used. Drivers who never exceed a given range in a day are potential users of limited-range vehicles without adaptation. In this section, the data are analysed based on the notion that a driver might be willing to adapt their driving behaviour on some number of days. By "adapt driving behaviour" we mean either (1) substituting a liquid fuel vehicle (use another car in the household or rent a gasoline car), (2) recharging during the day or en route, (3) delaying part of the travel until the next day (e.g. instead of three side errands after work, two are done one day and the third the next day), or (4) choosing a different mode of transport (commuter rail, bus, air, etc.).

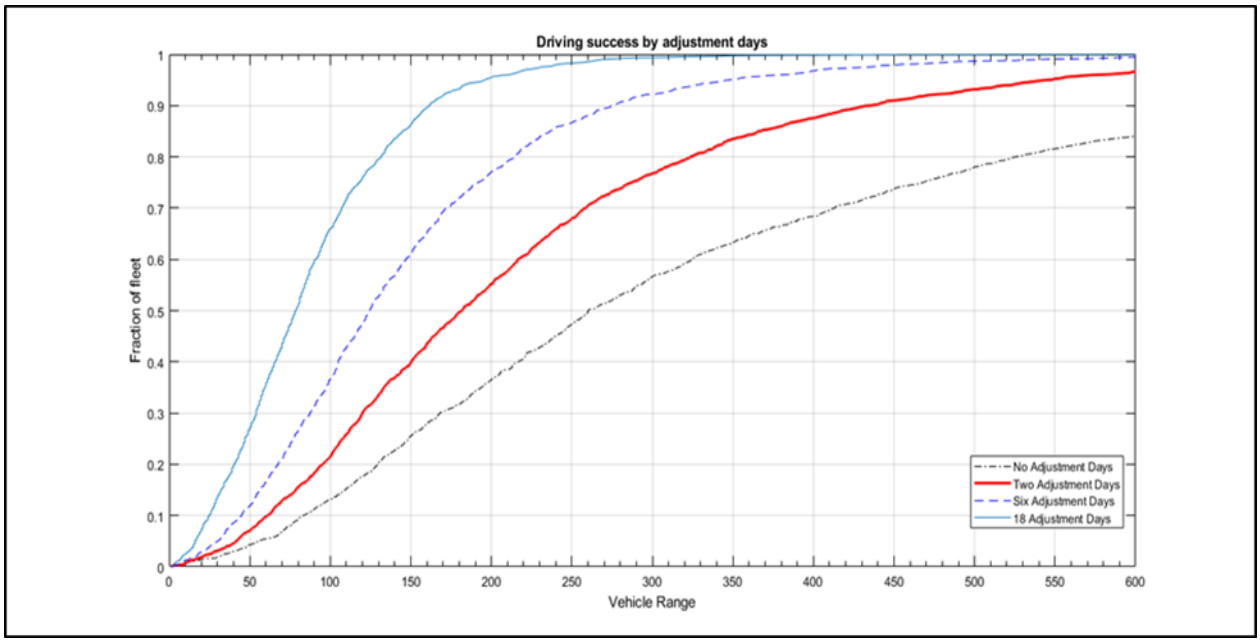

Fig.14 Driving success by adjustment days

The advantages of making such kind of adaptations are evident from the plot. More vehicles can travel a given distance means more users can change from conventional vehicle to the electric cars. We can reap the benefits from using the EVs in most of the days in a year by this way. Even though vehicle sharing within a household might be so simple as not to qualify as an "adaptation", we include it to tabulate without judgment all changes required to adapt to limited range. The need for adaptation is assessed in terms of three factors: Given a vehicle

with X miles of range, Z% of the study drivers would find that vehicle fully satisfies their current driving patterns on all but Y days of the year. On those Y days, they must make some form of adaptation, as itemized above. In these terms, the analyses for Figs. 12 and 13 Y set to zero, whereas, in the following analysis, the implication is that a person might be willing to adapt a few days a year.

In Fig.14 the fleet fraction values are on the y-axis and picks four representative numbers of days of adaptation to describe the surface. The four lines represent zero, two, six, and 18 days of required adaptation. The "No adjustment days" line depicts the same information as the cumulative distribution function in Fig.13, though the axes scale has changed. In Fig.14, if we start with 150 Kms on the x-axis, move up to the red line (2 adaptation days), then look left to the y-axis, we see that 40% of drivers have driving patterns consistent with this EV range, if they would tolerate 2 adaptations per year. As shown earlier, EVs with 100 Kms range could replace about 14% of all cars with zero driver adaptations. Fig.14 shows that, if the drivers were willing to adapt on 2 days in the year, those 100-mile EVs would meet the needs of 21% of drivers. Or, if owners were willing to adapt six days per year, the same 100-mile EV would meet the needs of 38% of drivers.

If we shift the range of an EV from 150 Kms to 200 Kms, we can see that 56 percent of vehicles can travel if the adapt for 2 days as compared to 40% for 150 Kms. That is a 40 percent increase. When they adopt for 6 days in a year, 78 % users can adapt with that when compared to 60 % for 150 Kms. And the number again soars up for 18 days adaptation. It will be 95% of users for 200 Kms to 88% for 150 Kms.

4.1.4 Time-of-day driving pattern

To analyse the time at which vehicle are used during weekday and weekend we plotted the fig.15 and fig.16. Number of vehicle on a given time in the study area has been taken and divide that by the total number of vehicle for that whole month to get the vehicle used fraction. This study was done only for the month of May 2013 to reduce the amount of data. The average value for every 15-min is taken into the graph.

The data input was for every 15 minutes to get 2976 data points (31 days * 24h * 4 15-min intervals per hour). The result was then plotted along with the one standard deviation and minimum value.

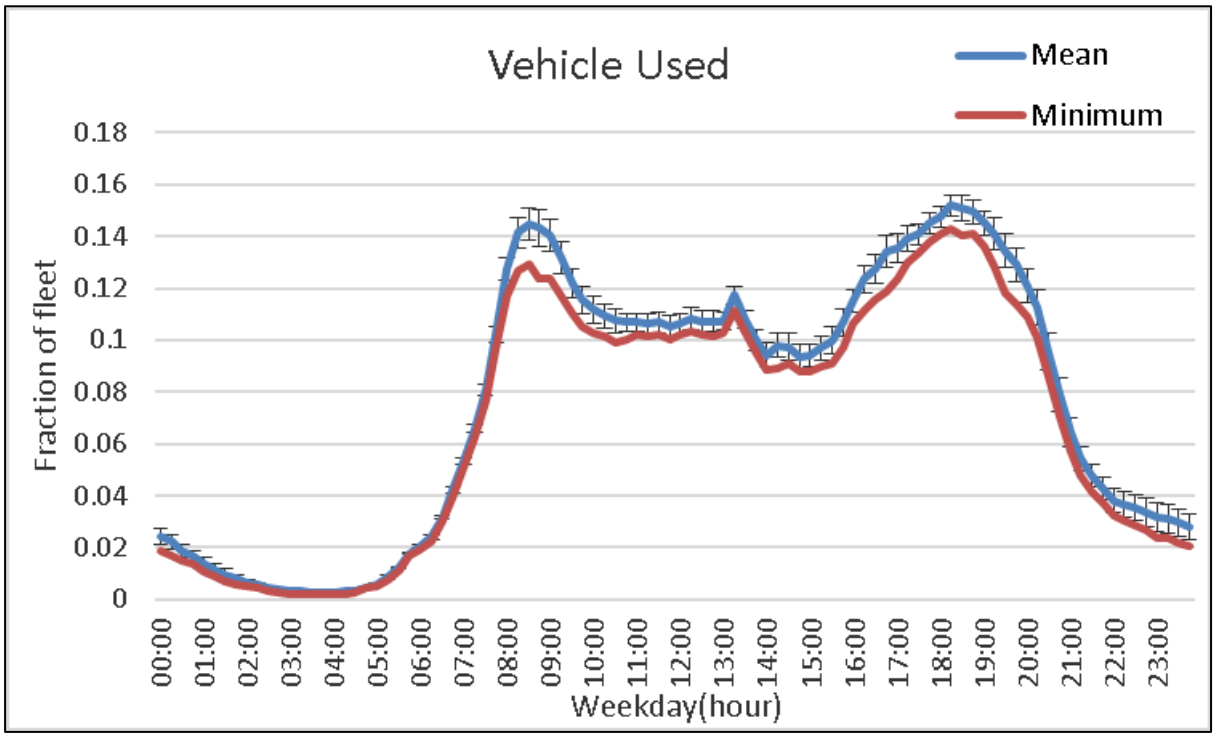

Fig.15 Fraction of vehicle by time-of-usage (Weekday)

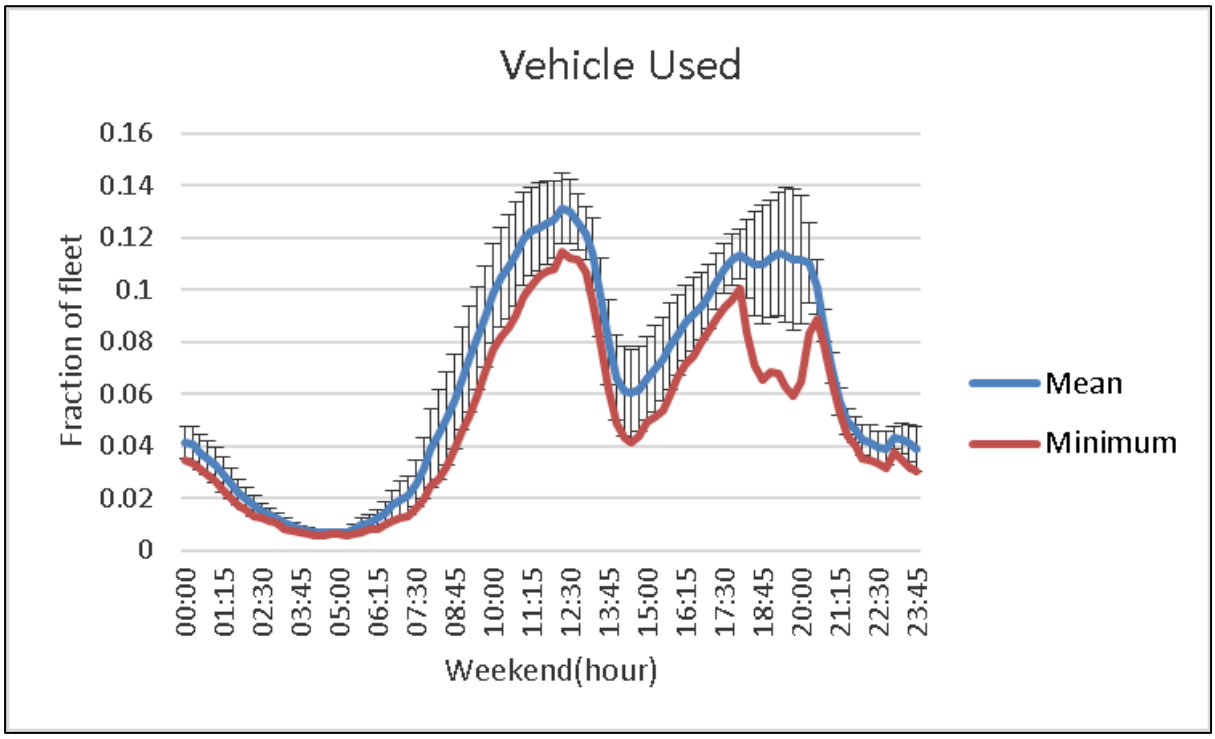

Fig.16 Fraction of vehicle by time-of-usage (Weekend)

In the fig.15 and fig.16, blue line shows the Mean value at which vehicles are used, redline shows the minimum values and the error bar shows One standard deviation from the mean. From the graph (fig.15) it can be understood that most of the vehicles are used in the morning and evening peak hours (8-9 am and 6-7 pm) on weekdays. About 15% of the total fleet were used on that period. Whereas in the early morning hours little or no vehicles were used. But instead on the weekend (fig.16), vehicles were more used between 11:30 to 12:30 (about 13%) and 17:30 to 18:30 (about 11%).

4.1.5 Parked Fraction

Here for finding the parked fraction we took the same data that we used for the previous analysis but this time we used the number of vehicles that were on the parking spaces. Parked fraction analysis was done on a 15-min time increment throughout the month. The data was collected for the month of May of the same year. As utilities and automakers plan for substantial number of electric vehicles, two statements about electrical load have been made without definitive empirical support. The first is that there will be a large load on the power grid when drivers return home and plug in after work, said to be between 5 and 6 pm. The second, countervailing statement is that vehicles will complement electric load, even in the absence of time- or price-based charging signals, because they are parked overnight and are either driving or parked away from home during the day when loads are high. These expectations may be tested against our driving data.

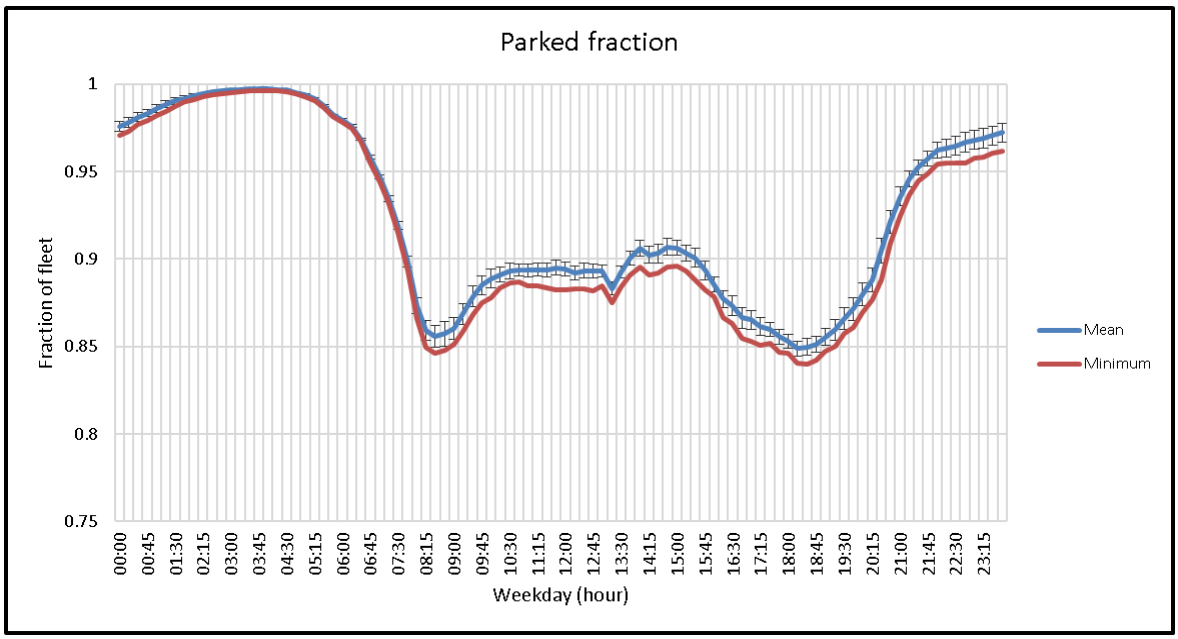

Fig. 17 Fraction of fleet by time of parking(Weekday)

The same vehicle trip data can be used to examine the rate at which these vehicles enter the parked state, at high time resolution. Because we have processed the database into trips, a calculation of the ‘‘simple parked vehicle count’’ is, for any one minute, the number of vehicles in the study at that time minus the number traveling at that time.

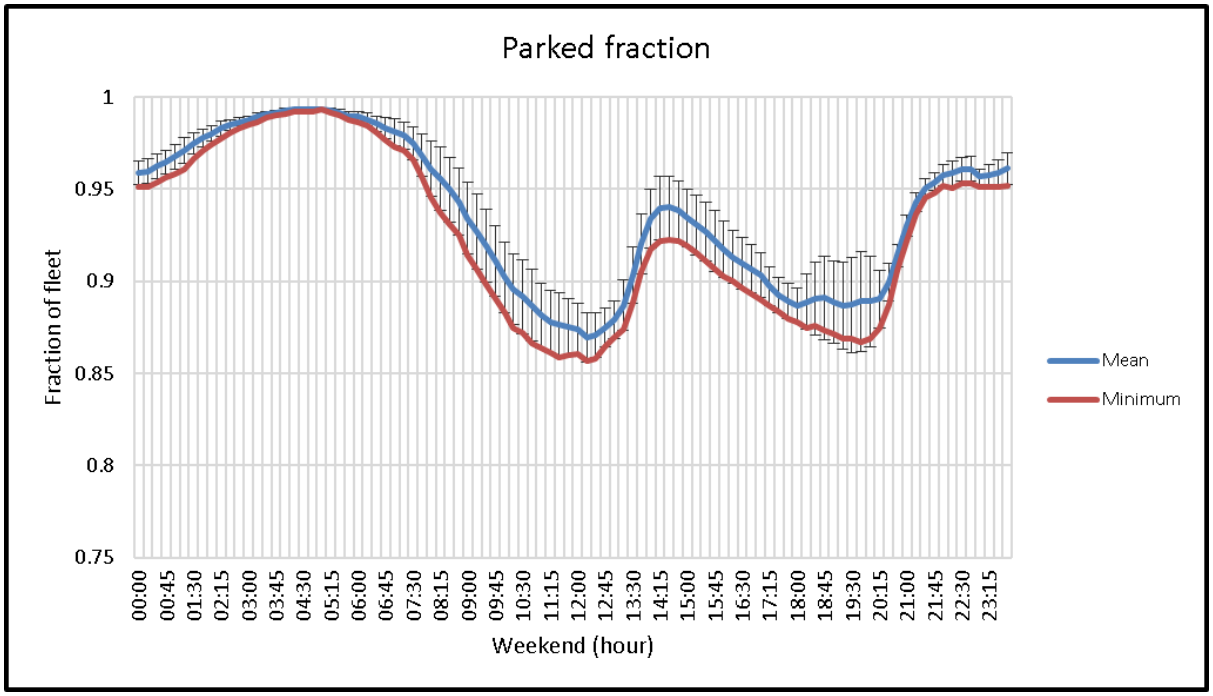

Fig.18 Fraction of fleet by time of parking(Weekend)

The result is based on 28965 vehicles drove during that month with 2976 data points (31 days * 24h * 4 15-min intervals per hour). Fig.8-depicts the Fraction of vehicles parked in each 15-min interval on weekdays. It is obvious from the graph that at the 8:30 am weekday rush hour, on average 86% of the vehicles are parked. Number of vehicle parked increases steadily up to midnight, when on an average about 97% of vehicles parked. In the evening peak hour at 6, 85% of the vehicles parked.

Fig.18 shows that of weekend. The average of 28965 vehicles is shown in blue line, while 1 standard deviation of distribution is shown by error bars. And the monthly minimum, that is, the minimum fraction of vehicles parked during that 15-min segment on any day during the month is plotted in thick red line.

For the weekend the least percentage of vehicle parked is at 12 noon in the morning section and 7 pm at the evening section. More vehicles were parked in the early morning hours of 4 am. Here also the blue line and red line shows the average and minimum respectively.

From the graph it is obvious that most of the vehicles were parked most of the time. The result that we obtained is similar to that has already been done in the same analysis by different authors.

The next analysis is to determine how quickly the fraction of the vehicle fleet that is parked increases, which is relevant to whether a sudden load might be imposed on the electrical grid. The concern about rapid load increase assumes of electric vehicles reaching their trip end, parking and beginning to charge in the absence of intelligence in the

charging equipment. The rate of change in vehicles parked at each time interval compared to the preceding time interval, using 15-min intervals, is presented Fig.19.

In Fig.19, the net fraction of cars parking in each 15-min interval is plotted in a heavy blue line. That is, an increase in the number of parked cars is indicated by positive numbers (increasing load) and a decrease is indicated by negative numbers (reducing load). Fig.19 shows a weekday pattern of vehicles leaving for work (negative numbers) between 5:00 and 7:45 am and arriving at work (positive numbers) between 7:45 and 9:00 am. The corresponding departure from work from 4:30 to 5:30 pm and net arrival at home (arrivals > departures) from 6:00 pm to 12:00 am can also be seen.

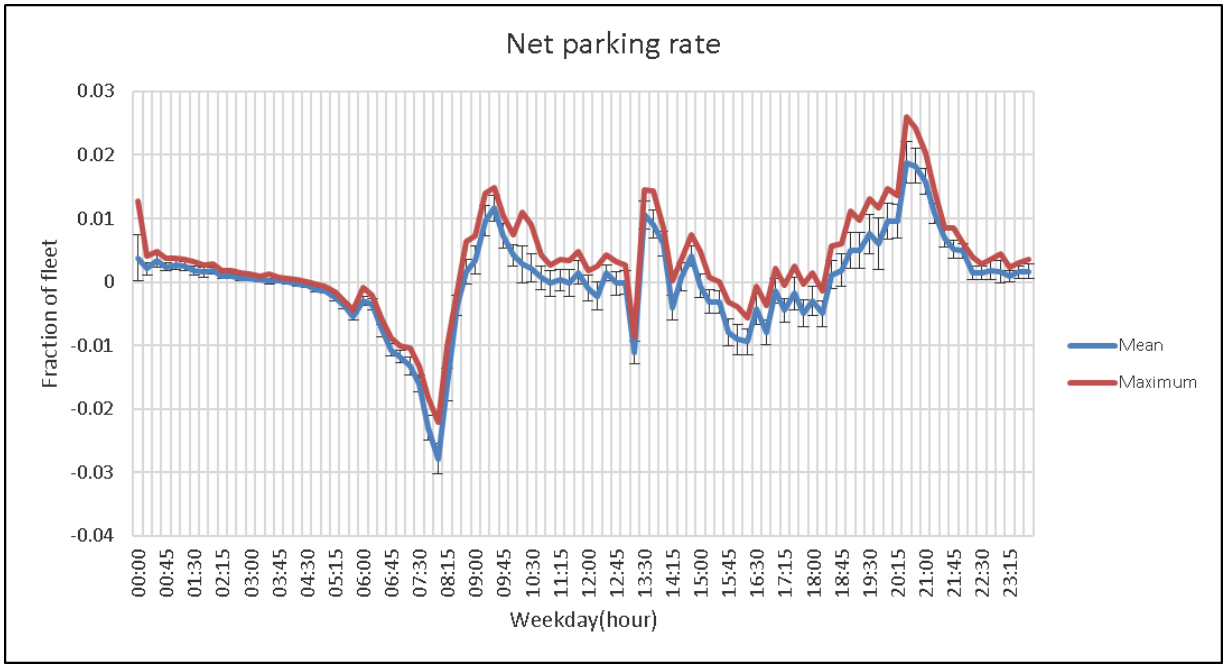

Fig.19 Net parking rate (Weekday)

Although the patterns are clear, the magnitude of the effect is very small, exceeding 0.5% of the fleet per 15-min increment only between 6:30 and 7:40. The sharpest increase in parked

vehicles, at about 8:30 pm, is less than 1% of the study vehicle fleet in 15 min, and less than 4% in the worst 60-min span. Again, the standard deviation is indicated by the error bars around the mean, and the maximum value throughout the year is indicated as a thin red line. It should be noted that Fig.19 plots net vehicles parked. Hence if one vehicle departs and two parks, there is a net increase of one parked.

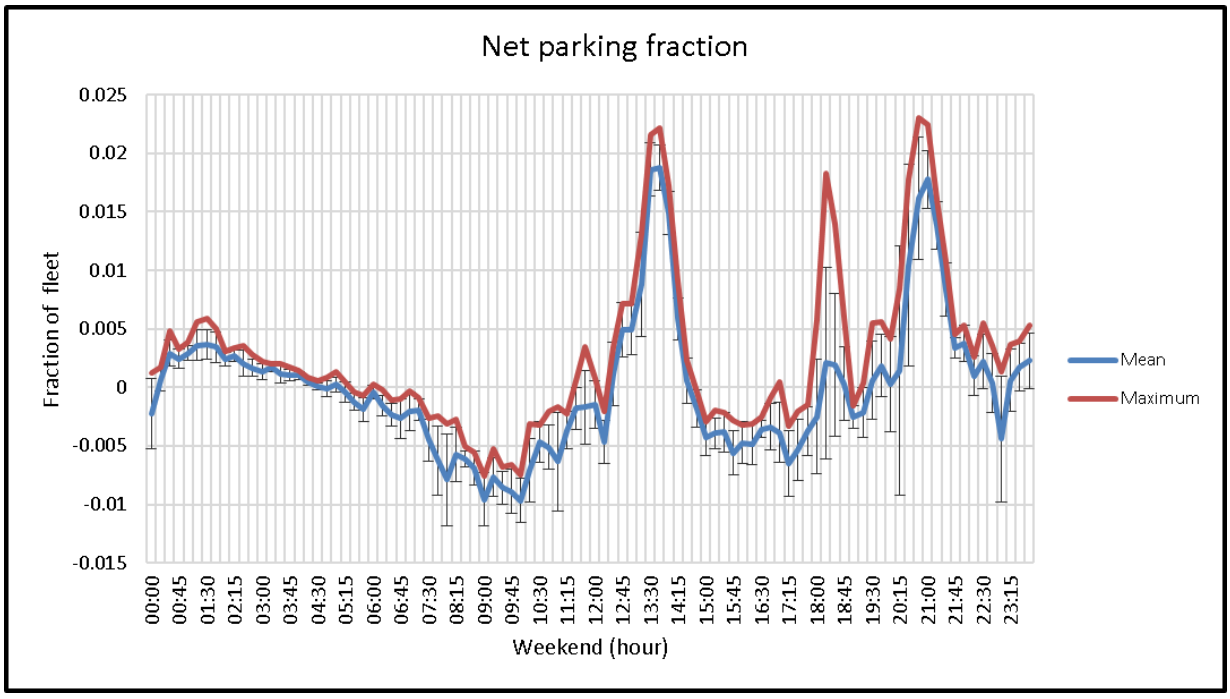

Fig.20 Net parking rate (Weekend)

From these analyses we can deduce that, over 87% of cars are parked at any given hour of the average day, and never in a year are less than 84% parked. Thus, if anytime charging is undesirable due to peak load problems, time of day of charging will need to be managed by intelligent charging controls capable of responding to time of day rates, a real-time price, or other signals.

4.2 Electric energy demand analysis

The ability to rapidly accelerate the take-up of electric vehicles will be determined to a large extend by the capacity of the local electricity industry to generate and transmit the power required to recharge vehicle batteries. The focus for many has been centred on whether the electricity supply infrastructure can cope with EV adoption growth [59]. Over the long term, supply can always be increased to meet a slow demand growth. It is a fast, and perhaps

unforeseen, short-term growth in power demand due to EV penetration that is of concern. Analysing the demand for the electricity is thus a major task that must be done as number of EVs increases. Failure in that will result in a downward spiral in the electric vehicle adoption.

Electric vehicles will represent an additional new load that is very different to other loads. As a new source of demand that proliferated quickly in the residential market in recent decades, the local supply industry faced a few challenges due to the resulting change in the magnitude and time of peak demand [60]. Recharging EVs are a mobile load and where the load impacts the network depends on where a vehicle is parked-whether in suburban region, in shopping centre car parks and in public car parks located in and around the business and industrial centres. The greater the charging rate is, the larger the burden on the local electricity distribution and transmission network, albeit of shorter duration. Understanding the implication of this new potential load will be critical to the management of behaviours and the planning of the electricity generation, transmission, and distribution capacities over coming decades. A new source of recharging, such like EV recharging, is likely to have a pronounced impact on future demand. The extent to which a system can cope with the change depends on whether poor charging habits can develop as well as the rate of adoption, which may be accelerated by government, economic or resource pressures.

It is reasonable to assume that as the EV market matures and battery technologies capable of faster charging are introduced, there will be a demand for higher powered charging equipment in the home and distributed across the metropolitan regions. Using a level 3 recharging system would increase the load accordingly. If a high powered 3 phase charger is used, this load would be equivalent to a number of houses appearing on the network for as little as an hour a day, which has ramifications for peak demand and network utilization.

In this section of the thesis, we thus planned to analyse the electric energy demand for the users of certain localities within the municipality of Rome. From the floating car data that we already have, we did a cluster analysis of the vehicles that are frequent in some areas. Clustering of the data was done by using DBSCAN. We located the users on the map by the time of arrival from work or other places and mapping had been done accordingly. We cluster the vehicles in few areas and did the necessary calculations. The time of arrival of each and every vehicle have been noted. The peak energy period in the metropolitan area is from 17:30 to 20:30. In this analysis, we assume that the vehicle, as soon as they arrive at home will plug in their vehicle to the power grid and charge until they become fully recharge.

In the next few pages, we describe about the DBSCAN we used to extract the vehicles of the locality under our study.

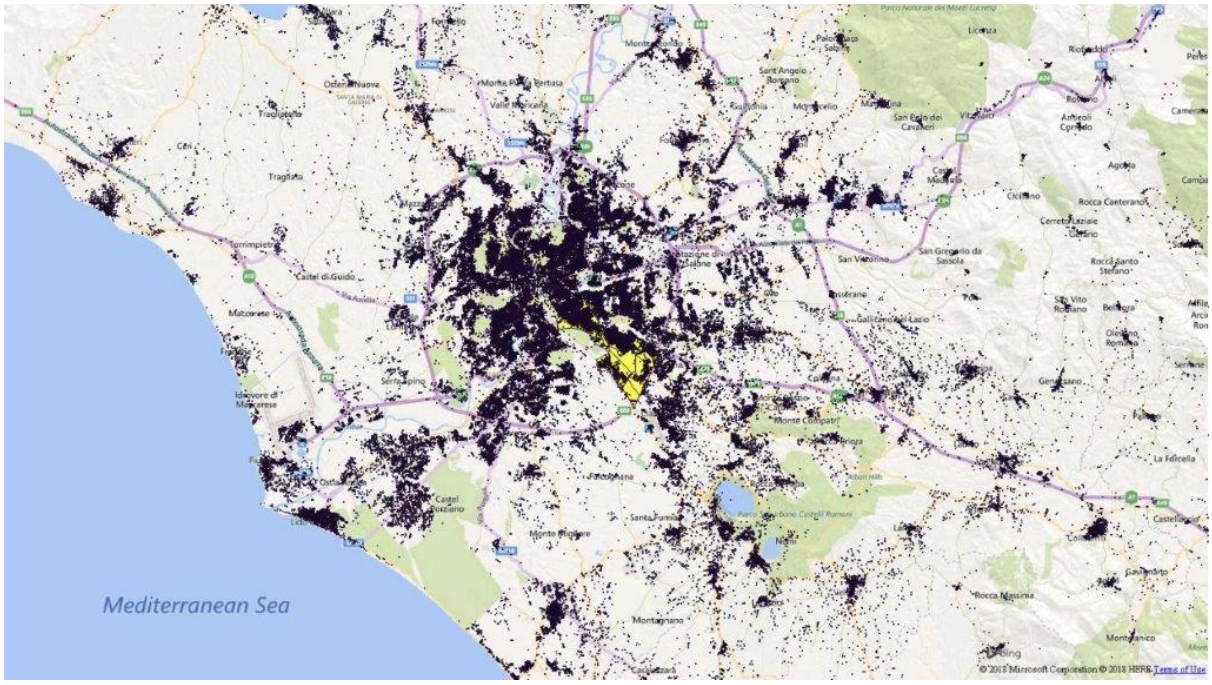

Fig.21 Representation of OBU enabled vehicles in Rome

We monitored all the vehicles in the Tuscolana who start their vehicle in early morning hours and stop their vehicles in late night hours and assumed that those users have residence over that area. We cluster the data by using DBSCAN algorithm and find those who stay in Tuscolana. From the number of inhabitants living in Tuscolana, by calculating 3 members in a family, we found out the total number of families in Tuscolana and Appia. Fig.21 represent the OBU users in our study for Rome and fig.22 represent the users in both Appia and Tuscolana. There are 69700 families in these areas and the energy demand analysis that we did were for those users who live in these areas travelled on 10th of May 2013. It accounts for just 4% of the total fleet in Tuscolana and Appia. Later in our study we will calculate the same energy demand for 30%, 60% and 90% of the car users in the belief that they all will shift from conventional vehicle to electric vehicle. The data that we obtained will compared with the total energy demand for domestic purpose in that area. In fig.22, the yellow area represent the OBU users in Tuscolana and Appia.

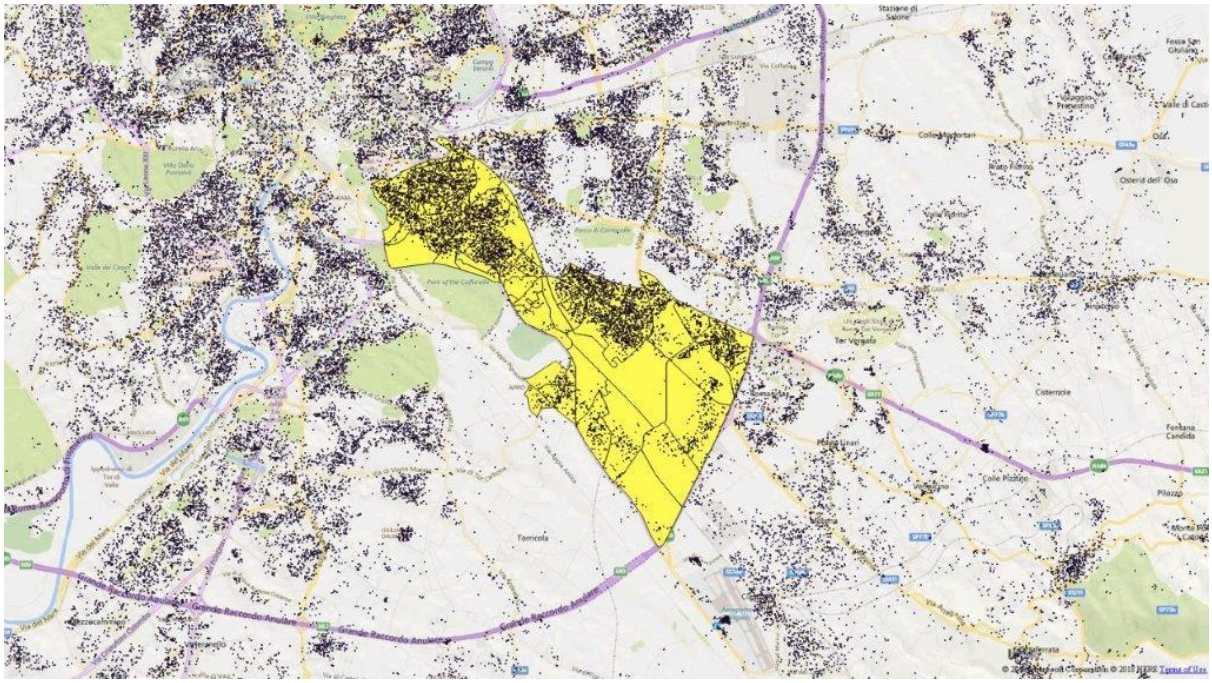

Fig.22 Representation of OBU enabled vehicles in Tuscolana and Appia

4.2.1 DBSCAN

DBSCAN (Density-based spatial clustering of applications with noise) is a density-based clustering algorithm: given a set of points in some space, it groups together points that are closely packed together (points with many nearby neighbours), marking as outliers points that lie alone in low-density regions (whose nearest neighbours are too far away). Consider a set of points in some space to be clustered. For the purpose of DBSCAN clustering, the points are classified as core points, (density)reachable points and outliers, as follows:

- A point p is a core point if at least minPts are within distance ε (ε is the maximum radius of the neighbourhood from p) of it (including p). Those points are said to be directly reachable from p.
- A point q is directly reachable from p if point q is within distance ε from point p and p must be a core point.
- A point q is reachable from p if there is a path p1, ..., pn with p1 = p and pn = q, where each pi+1 is directly reachable from pi (all the points on the path must be core points, except for q).
- All points not reachable from any other point are outliers.

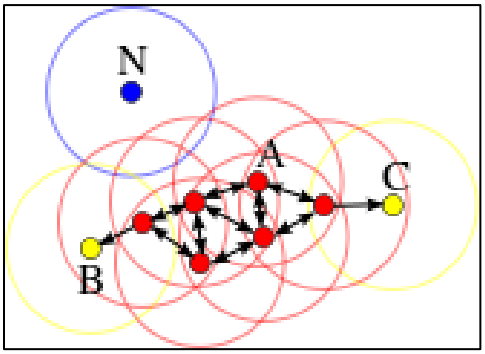

Fig.23 DBSCAN points

Now if p is a core point, then it forms a cluster together with all points (core or non-core) that are reachable from it. Each cluster contains at least one core point; non-core points can be part of a cluster, but they form its edge, since they cannot be used to reach more points.

In this fig.21, minPts = 4. Point A and the other red points are core points, because the area surrounding these points in an ε radius contain at least 4 points (including the point itself). Because they are all reachable from one another, they form a single cluster. Points B and C are not core points but are reachable from A (via other core points) and thus belong to the cluster as well. Point N is a noise point that is neither a core point nor directly-reachable.

Reachability is not a symmetric relation since, by definition, no point may be reachable from a non-core point, regardless of distance (so a non-core point may be reachable, but nothing can be reached from it). Therefore, a further notion of connectedness is needed to formally define the extent of the clusters found by DBSCAN. Two points p and q are density-connected if there is a point 'O' such that both p and q are reachable from 'O'. Density-connectedness is symmetric. A cluster then satisfies two properties:

- All points within the cluster are mutually density-connected.
- If a point is density-reachable from any point of the cluster, it is part of the cluster as well

DBSCAN requires two parameters: ε (eps) and the minimum number of points required to form a dense region (minPts). It starts with an arbitrary starting point that has not been visited. This point's ε-neighbourhood is retrieved, and if it contains sufficiently many points, a cluster is started. Otherwise, the point is labelled as noise. Note that this point might later be found in a sufficiently sized ε-environment of a different point and hence be made part of a cluster.

If a point is found to be a dense part of a cluster, its ε-neighbourhood is also part of that cluster. Hence, all points that are found within the ε-neighbourhood are added, as is their own ε-

neighbourhood when they are also dense. This process continues until the density-connected cluster is completely found. Then, a new unvisited point is retrieved and processed, leading to the discovery of a further cluster or noise.

DBSCAN can be used with any distance function (as well as similarity functions or other predicates). The distance function (dist) can therefore be seen as an additional parameter.

The DBSCAN algorithm can be abstracted into the following steps:

1. Find the ε (eps) neighbours of every point and identify the core points with more than minPts neighbours.
2. Find the connected components of core points on the neighbour graph, ignoring all non-core points.
3. Assign each non-core point to a nearby cluster if the cluster is an ε (eps) neighbour, otherwise assign it to noise.

A naive implementation of this requires storing the neighbourhoods in step 1, thus requiring substantial memory. The original DBSCAN algorithm does not require this by performing these steps for one point at a time.

It has several advantages as follows:

- It does not require one to specify the number of clusters in the data a priori, as opposed to k-means.
- DBSCAN can find arbitrarily shaped clusters. It can even find a cluster surrounded by (but not connected to) a different cluster. Due to the MinPts parameter, the so-called single-link effect (different clusters being connected by a thin line of points) is reduced.
- It has a notion of noise and is robust to outliers.
- DBSCAN requires just two parameters and is mostly insensitive to the ordering of the points in the database. (However, points sitting on the edge of two different clusters might swap cluster membership if the ordering of the points is changed, and the cluster assignment is unique only up to isomorphism.)
- It is designed for use with databases that can accelerate region queries, e.g. using an R* tree.
- The parameters minPts and ε can be set by a domain expert, if the data are well understood.

Every data mining task has the problem of parameters. Every parameter influences the algorithm in specific ways. For DBSCAN, the parameters ε and minPts are needed. The parameters must be specified by the user. Ideally, the value of ε is given by the problem to solve (e.g. a physical distance), and minPts is then the desired minimum cluster size.

MinPts: As a rule of thumb, a minimum minPts can be derived from the number of dimensions D in the data set, as minPts ≥ D + 1. The low value of minPts = 1 does not make sense, as then every point on its own will already be a cluster. With minPts ≤ 2, the result will be the same as of hierarchical clustering with the single link metric, with the dendrogram cut at height ε. Therefore, minPts must be chosen at least 3. However, larger values are usually better for data sets with noise and will yield more significant clusters. As a rule of thumb, minPts = 2·dim can be used, but it may be necessary to choose larger values for very large data, for noisy data or for data that contains many duplicates.

ε: The value for ε can then be chosen by using a k-distance graph, plotting the distance to the k = minPts-1 nearest neighbour ordered from the largest to the smallest value. Good values of ε are where this plot shows an "elbow": if ε is chosen much too small, a large part of the data will not be clustered; whereas for a too high value of ε, clusters will merge, and the majority of objects will be in the same cluster. In general, small values of ε are preferable, and as a rule of thumb only a small fraction of points should be within this distance of each other.

Distance function: The choice of distance function is tightly coupled to the choice of ε and has a major impact on the results. In general, it will be necessary to first identify a reasonable measure of similarity for the data set, before the parameter ε can be chosen. There is no estimation for this parameter, but the distance functions need to be chosen appropriately for the data set. For example, on geographic data, the great-circle distance is often an excellent choice.

4.2.2 State of charge

To know about the state of charge of the vehicles after they come home, we assume that every vehicle travelled on 10th of May 2013 are of same kind. We meant by same kind is that the total battery capacity of all those 1943 vehicles are 30 kWh and the energy consumption is 0.16 kWh/km. The battery state of charge (SoC) is defined as the ratio between the amount of energy currently stored in the battery, and the total battery capacity. As we have conventional vehicles in out disposition, we consider all the vehicle under our inspection as EVs. That is for all the 1943 vehicles out of 2045 vehicles arrived home on 10th May 2013 in the locality of Tuscolana.

Rest of the vehicles either did not travelled on that day or they travelled more distance than the battery can deliver. The formula for finding State of charge was derived from the product of energy consumption (EC) in (kWh/Km) and distance travelled by the vehicle during that day in Kilometres (Km) subtracted from battery capacity (kWh). The result in kWh is then converted to percentage (%) to get the State of charge of the vehicles.

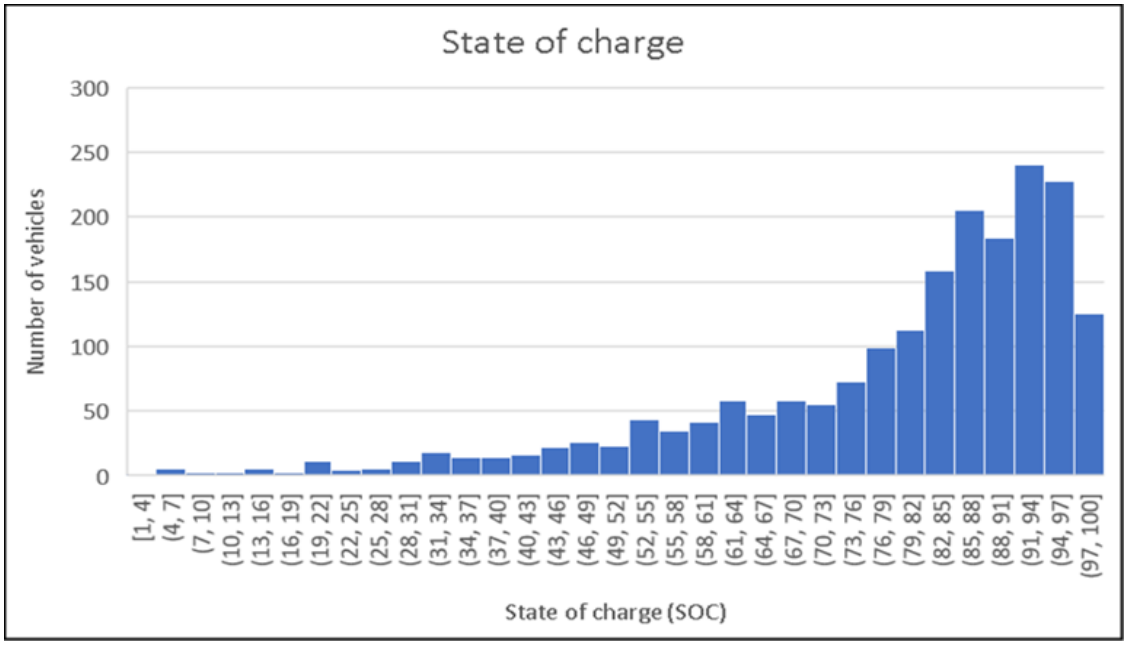

Fig.24 State of charge of vehicles

From this State of charge analysis, we can know how much energy the vehicle used up during the day. Fig.24 shows the state of charge of various vehicles in the locality.

SOC = Battery Capacity (kWh) – Energy consumption (kWh/Km) * distance travelled (Km)

Our result shows that around 37 percentage of the vehicles have more than 90 % of SOC while they reach home in the evening. That means a good percentage of them are not travelling far distances. This is also an ideal condition for EVs. About 240 vehicles have state of charge between 91-94%.

4.2.3 Energy demand profile

Battery electric vehicles are powered by the electric power the receive from home or office while they are being parked. As the percentage of total fleet of EV increases the need for electric energy will also increase. It is necessary to analyse the energy demand required so that we can know how much effect EV has on the electric grid. For the effective management of smart grid, this analysis is essential.

For the electric energy demand analysis, we took a day (Friday 10th of May 2013) and chose a locality. Our chosen locality was Tuscolana, since we found a large agglomeration of vehicles in that locality than other localities. We planned to carry out analysis on the assumption that the vehicle on that region, when they came home, immediately plug their EVs to the electric port until they have fully charged. We started by extracting the vehicles with the details on the distance each vehicle travelled on that day and the time of arrival of each vehicle at home. In order to find the time of arrival, we take the last time point of each vehicle during that day. To know the state of charge of each vehicle and subsequently the time they need to get fully charged, we assume that each and every vehicle have similar battery capacity, energy consumption and of same vehicle class. Here in our analysis we planned to model a car with 30 kWh of battery capacity and 0.16 kWh of energy consumption. As per the current market Nissan Leaf has similar specification. As we know the battery capacity of an EV is defined as the maximum electric charge that vehicle's battery can store. By using the battery capacity, energy consumption and distance travelled by each vehicle, we calculated the SOC. It gives us details on the energy it needed to be fully charged and the time taken for them to get fully charged. The time needed for the vehicle to get fully charge is found out by dividing the electric energy needed for the vehicles and the power used in the home which is 3.7 KW.

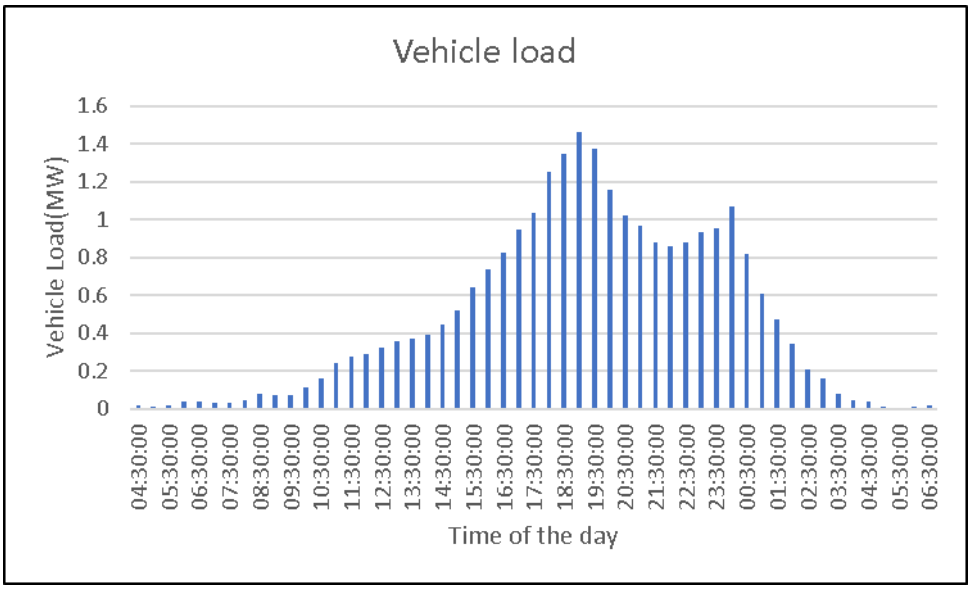

Fig.25 vehicle load profile

We then add the time when each vehicle reached home and the time they needed to get fully charged to obtain the end time of the battery charging. So, we now have the starting time and the end time of the vehicle charging. Our next task was to find the number of vehicles who

charge their EVs every 30 minutes. We take the vehicle count without getting multiple counts for the same vehicle. In order to avoid errors while calculating load profile during mid night, we took values corresponding to the next day also. Fig.25 shows the energy demand/vehicle load profile.

Rome is served by an extensive motorway network. The congestion in the city is also notorious. The total area of the city is 1,285 square kms with total population of 2,872,021 inhabitants/square km. So, the population density is 2,088 inhabitants/square km. The car ownership rate is also one of the highest of its kind in entire Europe. There are 696 cars/1000 inhabitants. And the high cars/square km (5500 cars/square km) results in high traffic density within the city boundaries. The total length of the roads is 8827 Kms, out of that 227 Kms are highway.

The locality that we take in to consideration for this particular study are Tuscolana and Appia. It has an area of7.1572 square Kms with 152,704 inhabitants. That is about 21335.71 inhabitants per square Kms. There are about 69700 families in the area Tuscolana. The fig.26 and fig.27 below depicts the average weekday and weekend loads of the area. For the weekday, it shows the peak demand is 1.8 MW of power at around 19.00 and the least demand is on the early morning hours. This result was derived from analysing the weekday out of one whole week. The demand gradually decreases after 23:30 only to increase after 08:00.

For the weekend, the peak demand is stretched between 1.4 and 1.6 MW from 18:30 to 23:30. The peak period is similar in both cases, as in our study where all the vehicles were plug in as soon as they arrive at home. This is an end-of-the-day charging scenario.

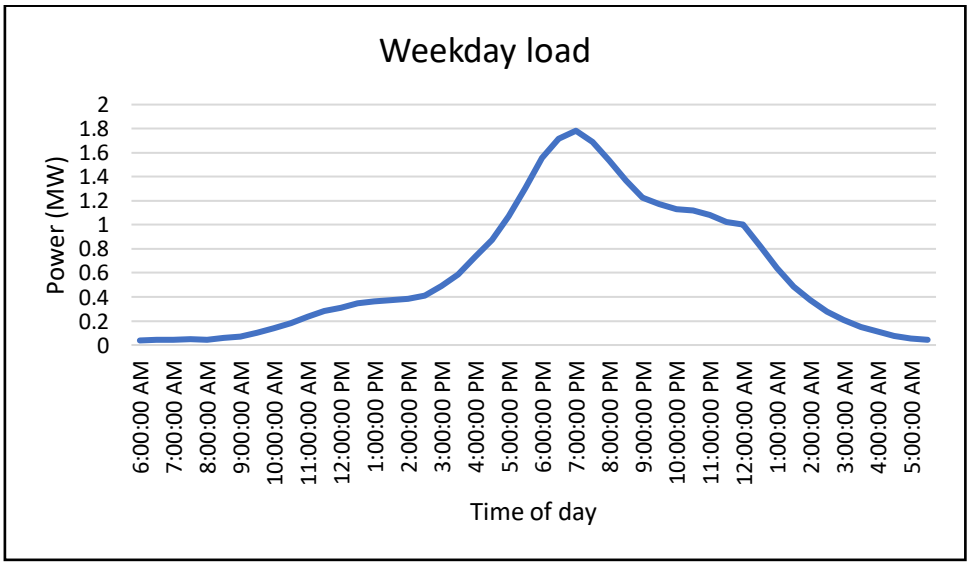

Fig.26 Average weekday load

The percentage of vehicles that were participated for this analysis were only 4% of the total vehicle in Tuscolana and Appia . We also analyse how much the load will be if we increase that to 30%, 60% and 90% of the total fleet in our study area. The Fig.29 below shows the peak demand has raised from 1.4 MW to over 12 MW for 30% of the vehicles.

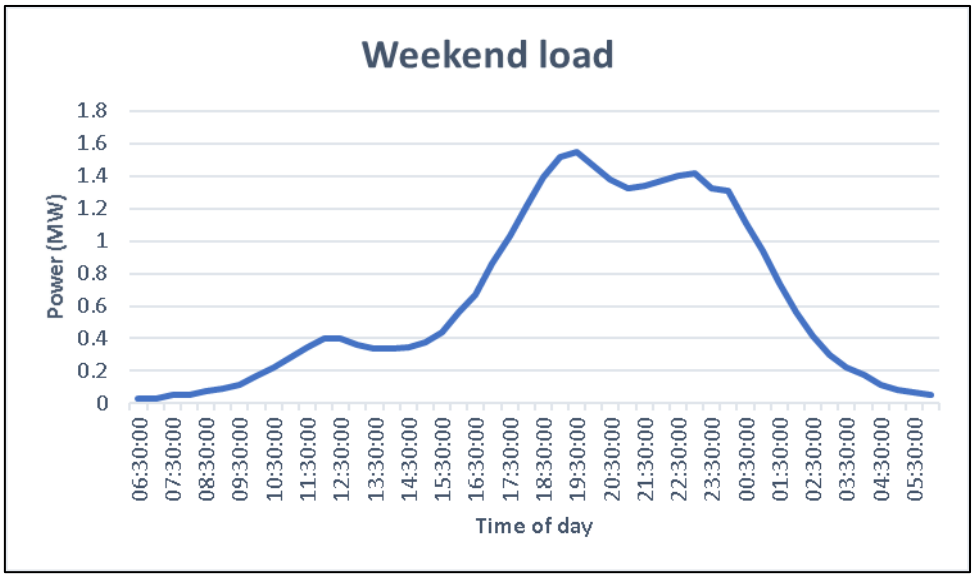

Fig.27 Average weekend load

Fig. 28 shows the energy demand for a week. We can see that the peak hour is almost same all the days.

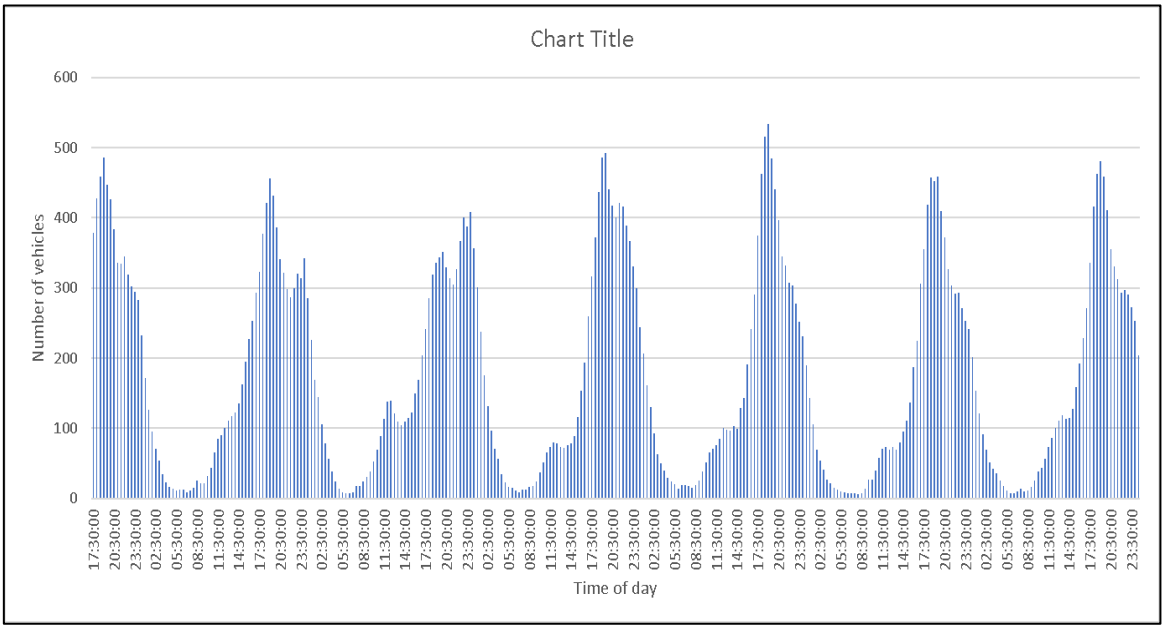

Fig.28 Energy demand for a week

We need to understand that, we can reduce the over population by structuring a controlled charging system here. That is the vehicles should also charge in the off-peak hours so that we can balance them and avoid the scarcity for energy. Fig. 29 shows the energy demand for 30% of the fleet in Tuscolana and Appia.

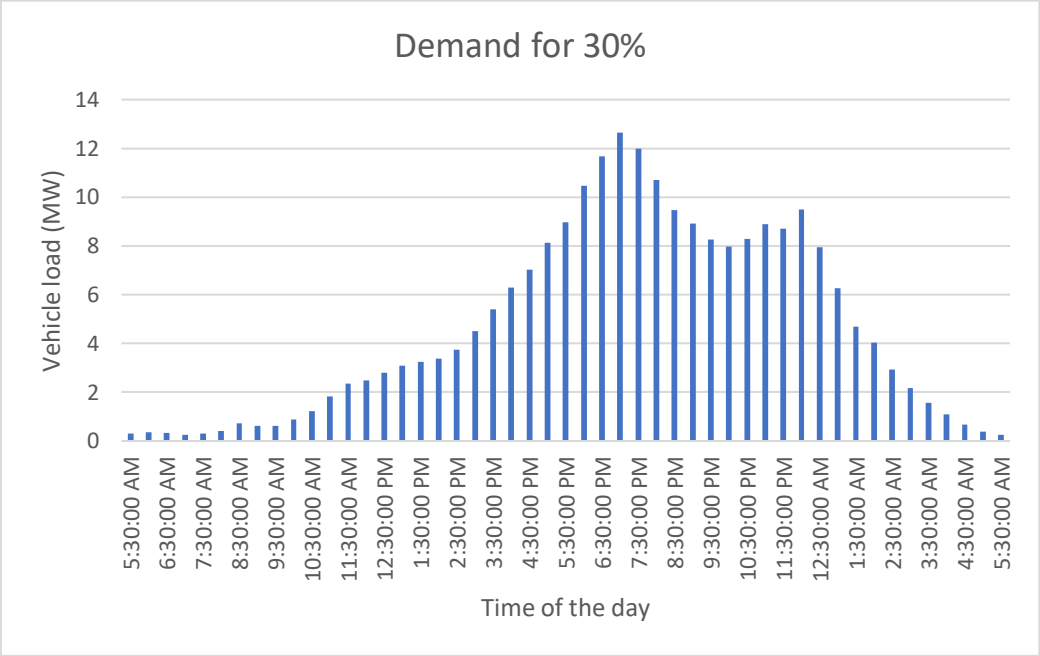

Fig.29 Energy demand for 30% of total vehicles

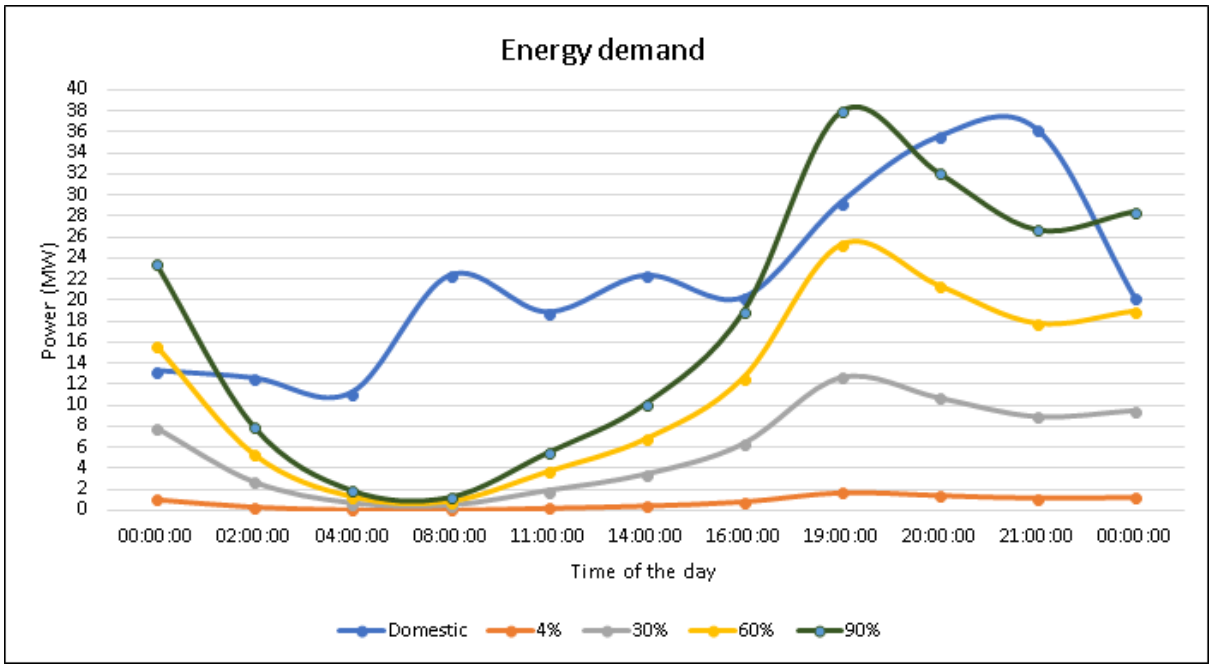

Fig.30 Energy demand for all the families

The fig.30 below shows the energy demand for 4%, 30%, 60% and 90% of the total vehicle and compared that with the energy demand for all the families in the Tuscolana and Appia. The blue line shows the domestic power demand for all the families in the locality. The power demand occurs due to the major electrical appliances other than electric vehicle like refrigerator, Air conditioner, Iron box, heater etcetera. The orange line shows the demand due to electric vehicles. And the grey line shows the combined demand for domestic and EV usage.

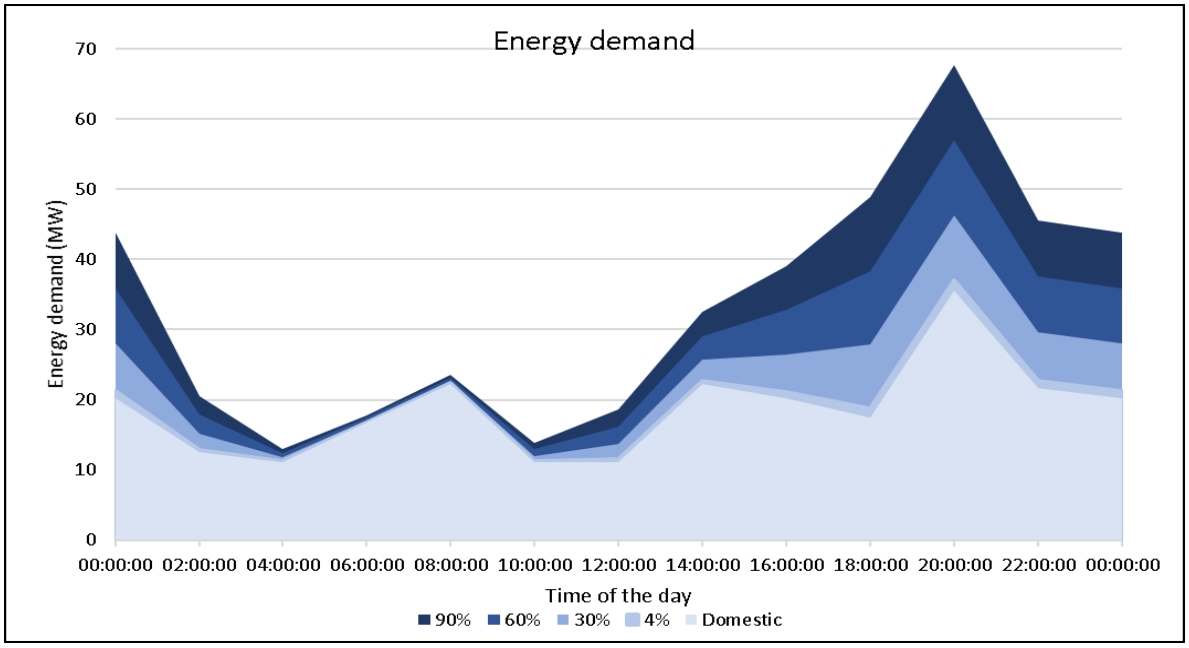

Fig.31 Aggregate energy demand

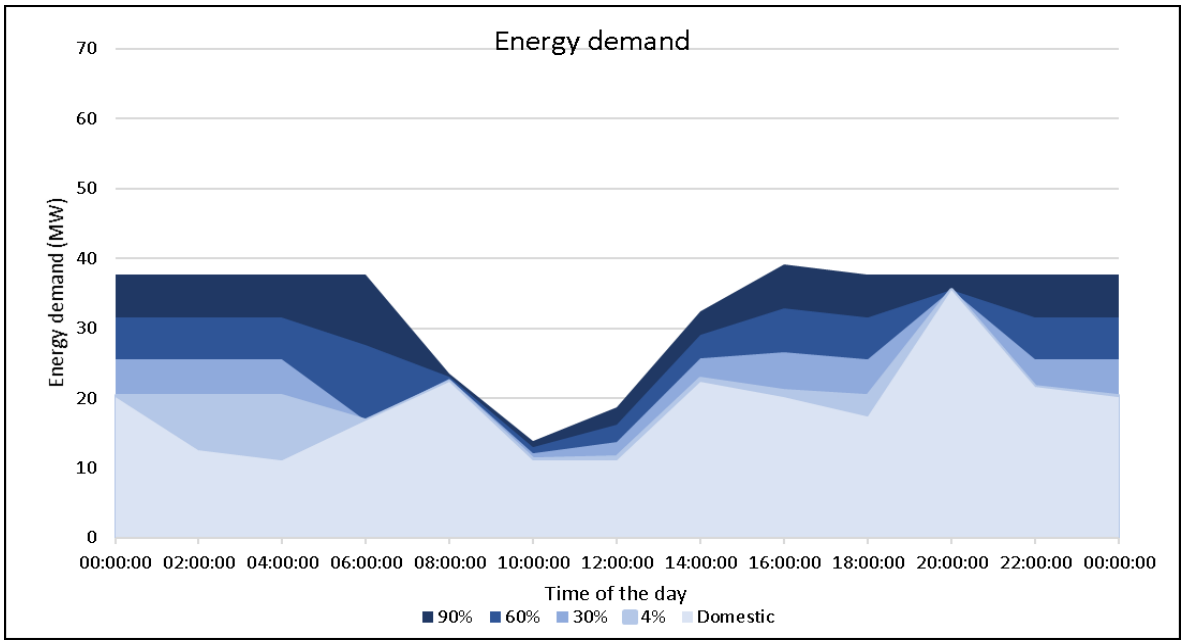

Fig.32 Energy demand under controlled charging scenario

The demand is higher for domestic appliances than EVs. The peak demand for them is 37 MW between 20:00 and 21:00. That is almost same for the 90% of the EV users in Tuscolana and Appia at 19:00. Since the demand will change according to the season, it should be noted that is figure is only for the Spring. From the graph above, we can know the estimate electric demand if 4%, 30%, 60% and 90% of the vehicle users change in to electric vehicle.

Conclusion

Electric mobility relates to electrification of the automotive powertrain – there are several powertrain alternatives under development, with different storage solutions and various sources of propulsion. In the past few years, Europe has gone through the initial adoption phase of electric mobility. After a turbulent period of excitement and promise as well as disappointment, it is now possible to formulate a clearer view on the development of electric mobility to date and its drivers going forward. Although global and European sales figures are still small (below 1% of new car registrations), we see that in some pockets, growth has picked up speed – driven by government support, an improved offering of EVs by the automotive industry, and a growing familiarity and willingness to buy on the side of the consumer. The gradually increasing momentum behind EV adoption – both from the side of the consumer and the automotive industry – suggests that electrified powertrains will play a key role in Europe's mobility going forward. The next few years will be a period of further maturation of the EV industry, nurtured by government support. In the longer run, because of EU regulation, automotive powertrains are likely to further diversify, resulting in a portfolio of powertrains, with electrified alternatives to the traditional combustion engine. The rate of adoption of electric powertrains will depend on several factors in addition to fleet emission regulation, and range of the EVs such as fuel price, battery pack price development.

Many technologies have been emerging in the electric mobility industry to increase the rate of widespread EV adaptation. New battery technologies such as Lithium polymer battery and Metal-Air battery promise much longer mileages. At the same time increasing the total number of batteries in an EV is also helpful to increase range. DC fast charging will enable us to recharge our electric cars much faster than the AC supply. As compared to the 24 Kms of range from one-hour charging (3.7 kW) for AC supply, DC supply can provide 100 Kms of range with 30 minutes of charging (50-70 kW). Smart Grid, a next-generation electricity network equipped with communications and control systems, whose added controls make it possible to efficiently and dynamically manage energy supply and demand. The key is to be able to fine-tune how much energy is generated, and how much energy is needed at any given moment. An electric vehicle is critical because it can communicate with the grid and respond to calls for storing and discharging energy. The aggregation of the EVs as a single controllable distributed energy source can participate in energy market for supporting electric grid in regulation and system management.

In this thesis we concentrated on the potential market penetration of electric mobility and the electric energy demand rising from such a penetration. We analyse the driving patterns of the conventional vehicles travelled in the city of Rome in the year 2013. The outcome of our analysis gives more reasons to buy an EV hence increased penetration in the market. Out of the 1865 vehicles that we analysed, 26% of the fleet travelled between 31- 45 Kms on an average in a year and majority of vehicles travel below 100 Kms (average distance). Highest fraction of users (about 15%) travel between 300-330 days in the year with the average distance travelled among them is 46 Kms. Majority of the users travelled more than 270 days in that year. The daily maximum distance travelled by majority of the users (about 12% of the fleet) is between 100- 150 Kms. In the CDF analysis we found that 25% of the total fleet travel less than 150 Kms a day. When they are ready to make some adjustment such as charging during the day, shifting extra distances to another day, using conventional vehicles etcetera, that percentage will scale up even higher depending upon how many days out of a year they are ready to do these adjustments. If they are ready to adjust for only 2 days, 6 days and 18 days in a year, the population of vehicle that travel below 150 Kms a day will increase to 40%, 61% and 88% respectively. In order to understand how the vehicle is parked during a day, we analyse the number of vehicles that were parked at any given time for a period of one month. We took the month of May for this calculation. The results show that almost 95% of all the vehicles were parked between 00:00-07:00 and 21:00-23:00 on an average. Over 87% of the fleet were parked at any given time during the month. We can assume that this will be the case for all the year. We analyse both weekday and weekend period and both show almost comparable results in the number of vehicle parked.

As the number of EVs are increasing, we must also be aware about the electric charge needed for charging them. In our analysis, by taking in to account the electric energy needed for the residence of Tuscolana and Appia in Rome for a day, over 1.5 MW power is necessary for that locality alone if we consider the energy demand for 4% of the fleet in that locality. When we convert those value to 30% of the total fleet we saw an increase of 11 MW of energy demand. That is a total of 12.5 MW of energy is needed during the peak hours for only 30% of the entire fleet in Tuscolana and Appia. Addressing them as the next priority and channelling more electricity from renewable resources is vital for the sustainable electric mobility in the future. State-of-charge of the vehicle arriving home is also plotted and it shows that 37% of the fleet arriving home has 90% of more charge remaining in their battery, which made our previous results much stronger. We then compared the results of energy demand for 69700 families,

which is the total number of families in Tuscolana and Appia, on both domestic electrical usage and electric vehicle. As we expected, the demand for EVs are much lower than that of domestic usage. But when we compared the domestic demand with that of 90% of the fleet in Tuscolana and Appia, the peak demand is about 38MW. We consider this analysis for an entire week and the resulting curves were almost the same with slight changes in the peak hour values. The analysis that we carried out in this thesis is the end-of-the-day charging scenario. So that the users charge readily after they arrive at home. If the charging is controlled in such a way that the much of the peak hour charging is shifted to off peak hour, we can reduce the electric demand needed to charge the vehicle. Smart charging is technology which optimize the charging infrastructure by creating and distributing the available power in an efficient and flexible manner. With Smart Charging, not only would one can avoid unnecessary costs such as overcapacity fees, but you'll also get the most out of your charging stations in case of limited power capacity, anytime, anyplace.

In general, the possible market penetration analysis shows that even with limited range, electric vehicles could satisfy a large fraction of conventional vehicle users. When a driver has the ability to adjust on a few days per year, by substituting alternative transportation or charging during the day, even short-range electric vehicles can be satisfactory for a significant fraction of the population. Thus, understanding the customer's needs, and correctly segmenting vehicle buyers by range needs, appears to be a more cost-effective way to introduce electric vehicles than assuming that all buyers, and all drivers, need currently-expensive large batteries or liquid-fuel range extenders.

It is obvious from our study that, there is no need for the customers to be anxious about the lack of mileage EVs can give. Many entry-level BEVs out there in the market can give enough mileage for most of the users. From the previous studies that has been done on the similar topic also proves that the range anxiety is just out of question as new more potent EV with long distance mileage are entering the market. The need to track the energy demand is more necessary than ever as the EV intakes are increasing. There should be controlled coordination of energy supply sufficient enough to charge all the electric vehicles. It will be a guiding force to more electric vehicle market penetration.

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