

EFFECTS OF AMBIENT TEMPERATURE AND DRIVE CYCLE ON
ELECTRIC VEHICLE CHARGING USING PHOTOVOLTAIC SYSTEMS

A THESIS SUBMITTED TO
THE BOARD OF GRADUATE PROGRAMS
OF
MIDDLE EAST TECHNICAL UNIVERSITY NORTHERN CYPRUS CAMPUS



BY

ERİM GÜRER

IN PARTIAL FULFILLMENT OF THE REQUIREMENTS
FOR
THE DEGREE OF MASTER OF SCIENCE
IN
SUSTAINABLE ENVIRONMENT AND ENERGY SYSTEMS PROGRAM

AUGUST 2019

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ABSTRACT

EFFECTS OF AMBIENT TEMPERATURE AND DRIVE CYCLE ON ELECTRIC VEHICLE CHARGING USING PHOTOVOLTAIC SYSTEMS

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August 2019, 116 pages

Global warming and climate change problem can be solved by only decreasing greenhouse gases (GHGs). About 26% of the global GHG emissions are emitted by the transportation sector. Switching from fossil fuel burning vehicles to electric vehicles is one of the most promising solutions. However, 68% of the electricity is generated by using fossil fuels in the world and if a switch to electric vehicles happens without transforming the electricity generation sector, transportation emissions might even increase. Therefore, EVs are only as clean as their energy source. Implementing renewable energy into transportation sector is a crucial step that must be taken to reduce transportation emissions. Wind energy resources have larger spatial and

temporal variations compared to solar energy. In addition, solar energy is much easier to estimate and imply. PV plants can be installed in a decentralized way. Thus, every parking lot can be covered with PV. In this study, a general model is developed to estimate the energy generation from PV-covered parking lot systems and energy demand for electric cars. After the model is developed, case studies are performed using temperature and drive cycle information for Istanbul, Los Angeles and New York City. These locations are compared in terms of PV-EV feasibility considering several aspects. On the energy demand side, the effects of ambient temperature and driving style are considered to have a more accurate model. The results show that PV system can cover the annual demand for all case studies. The annual energy demand of 10 cars in Istanbul case study is about 300 MWh while the energy generation from the modeled 22.5 kW PV system is about 306 MWh. In the comparison of two cities, Los Angeles which represents mild ambient conditions is more favorable than New York City which represents the ambient conditions which include cold winters and hot summers. The results reveal that the ambient and driving conditions can increase the energy demand by 50%. As a result, PV-EV systems decreases the stress on the grid due to EV charging. Scheduled charging can increase the benefit even more.

Keywords: Driving cycle effect, electric vehicle, solar charging, sustainable cities, temperature effect.

ÖZ

SICAKLIK VE SÜRÜŞ ÇEVİRİMİ FAKTÖRLERİNİN FOTOVOLTAİK SİSTEMLER İLE ELEKTRİKLİ ARAÇ SARFI ÜZERİNDEKİ ETKİLERİ

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Ağustos 2019, 116 sayfa

Küresel ısınma ve iklim değişikliği sorunları ancak sera gazları salınımı azaltılarak çözülebilir. Salınan sera gazlarının yaklaşık %14'ü ulaşım sektöründen kaynaklanmaktadır. Fosil yakıt ile çalışan araçlardan elektrikli araçlara geçiş sorunun çözümü için en umut vadeden seçeneklerden biridir. Ancak, üretilen elektriğin yaklaşık olarak %68'i fosil yakıt kullanılarak üretilmektedir. Eğer elektrikli araçlar fosil yakıt kullanan termik santrallerde üretilen elektrik ile şarj edilirse toplam sera gazı salınımında herhangi önemli bir değişim olmayacaktır. Diğer bir değişle elektrikli araçlar sadece şarj için kullanılan elektrik kaynağı ne kadar temiz ise o kadar temiz olabilir. Bu nedenle ulaşım sektörü ile yenilenebilir enerji sistemleri harmanlanmalıdır. Rüzgâr enerjisi ile karşılaştırıldığında, Fotovoltaik (FV) sistemler bu harmanlamaya daha uygundur. Bunun nedeni rüzgâr enerjisinin tahmin edilmesi

daha zor ve konuma göre deęiřimi daha fazla olmasıdır. FV sistemler iletim hatlarından bağımsız olarak her yere kurulabilir dolayısıyla daha düşük yatırım maliyetleri içerir. Bu tez çalışmasında FV sistemden üretilen enerji ile elektrikli araç şarjı için genel bir model oluşturulmuştur. Bu model seçilen bölge için FV sistemden üretilecek enerji tahmini ve elektrikli araçların ihtiyaç duyacağı enerji talebi tahminlerini içermektedir. Daha sonra üretilen enerji ile talep edilen enerji karşılaştırılmıştır. Ardından geliştirilen model vaka analizi olarak İstanbul, Los Angeles ve New York şehirlerine uygulanmıştır. Los Angeles ve New York şehirleri farklı iklim, çevre ve sürüş özelliklerine sahiptir. Los Angeles, ılıman bir iklimi temsil etmek için kullanılan bir şehirken, New York ise kışları soğuk ve yazları sıcak geçen bir iklime sahiptir. Ayrıca bu iki şehirdeki sürüş davranışları da farklıdır. Tez çalışmasında seçilen bu şehirler FV elektrikli araç şarjına uygunluk açısından pek çok noktadan incelenmiştir. Enerji talebi tahmini modeli oluşturulurken tahminlerin gerçeęi en iyi şekilde yansıtmaları için hava sıcaklığının ve sürüş davranışlarının elektrikli araçların enerji tüketimleri üzerindeki etkisi dikkate alınmıştır. Elde edilen sonuçlara göre tasarlanan FV sistemler seçilen üç şehir için de senelik enerji talebini karşılayabilmektedir. İstanbul vaka analizinde varsayılan 10 aracın yıllık enerji talebi yaklaşık 300 MWh olurken, varsayılan otoparka kurulan 22.5 kW kurulu güce sahip FV sistem yılda yaklaşık 306 MWh enerji üretebilmektedir. Los Angeles ve New York şehirlerinin karşılaştırılması sonucunda Los Angeles FV elektrikli araç şarjı konusunda finansal ve enerji verimlilięi olarak daha uygun olduęu saptanmıştır. Ayrıca enerji talebi tahminleri sırasında hava sıcaklığının ve sürüş profilinin enerji talebini %50'ye kadar artırdıęı gözlemlenmiştir. Sonuç olarak, FV temelli elektrikli araç şarjının, elektrikli araçların şebeke üzerinde oluşturduęu fazladan yükü azalttıęı

belirlenmiştir. Şarj zamanlaması yöntemleri kullanılarak şebeke üzerindeki bu yükün daha da azaltılabilir olduğu gözlemlenmiştir.

Anahtar Kelimeler: Sürüş döngüsü etkisi, elektrikli araçlar, güneş enerjisi ile şarj, sürdürülebilir şehirler, sıcaklık etkisi.





To My Family

ACKNOWLEDGEMENTS

I would like to express my deepest gratitude to my supervisor, Asst. Prof. Dr. Onur Taylan and my co-supervisor Asst. Prof. Dr. Tuğçe Yüksel Bediz for their guidance, advice, constructive criticism, encouragement and insight throughout my research.

I would also like to thank my lovely parents Firdevs and Erhan Gürer, for all their support. They were always supportive and wished the best for me. In short, I would like to thank all my family members for always being there for me and supporting me through hard times. I would also like to thank my dear friends for all their help, advice and suggestions throughout my thesis study.

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CHAPTER 1. INTRODUCTION

1.1 Background and Motivation

The world is estimated to have experienced at least 5 major ice-ages. These changes are part of nature, and they do not occur in a short time [1]. However, human activities, especially for the last century, have caused rapid change of the earth. One of the most popular terms in the last two decades is “global warming” which refers to increase in the earth temperature. There are several reasons for global warming. One of these reasons is the Green House Gases (GHGs) which are emitted generally as a by-product of burning fossil fuels. Another reason is the changes in the use of lands, i.e., the decreasing number of forests, green areas, etc. There is a scientific consensus on the direct relationship between the increase in earth temperature and GHGs[2]. The earth has a very dynamic and complex system, so the changes in the earth temperature create new balances on the earth.

An increase of 2°C in the earth temperature is estimated to cause catastrophic results [3]. Other studies claim that the threshold value is 1.5°C rather than 2°C [4]. There are several CO₂ emission scenarios that are applied to estimate future GHG emissions. One of the scenarios estimates that the CO₂ emission in the atmosphere increases to 970 part per million (ppm) from 350 ppm in 2050 [5]. According to Bristow et al. (2004), the CO₂ levels in the atmosphere should be 400 to 450 ppm to substantially reduce climate impacts [5]. If that occurs, the estimated increase in earth temperature is between 1.4 and 5.8°C [6]. The only way to keep earth temperature below the threshold value is to decrease GHG emissions.

According to the IEA (2016), the whole transportation sector is accounted for 26% of the carbon emissions [7] as presented in Figure 1. Road transportation is accounted for about 20% of the whole global CO₂ emissions [8]. Figure 1 shows the sources of energy used in transportations sector and the sub-parts of the sector as well. As presented, the oil is the primary source of energy in the sector. Not only combustion of the fuel but production of a car also has substantial effect on global CO₂ emissions. For example, about 9% of the transportation carbon emissions is due to manufacturing, whereas 15% is accounted for losses in the fuel supply systems including pipelines to gas stations [8]. Only the remaining 76% is accounted for emissions from combustion of fuel in the vehicle. The role of transportation of global warming has been discussed in 1997 Kyoto protocol. One of the targets of the protocol was to decrease the CO₂ emission due to transportation about 5% by 2012 [6].

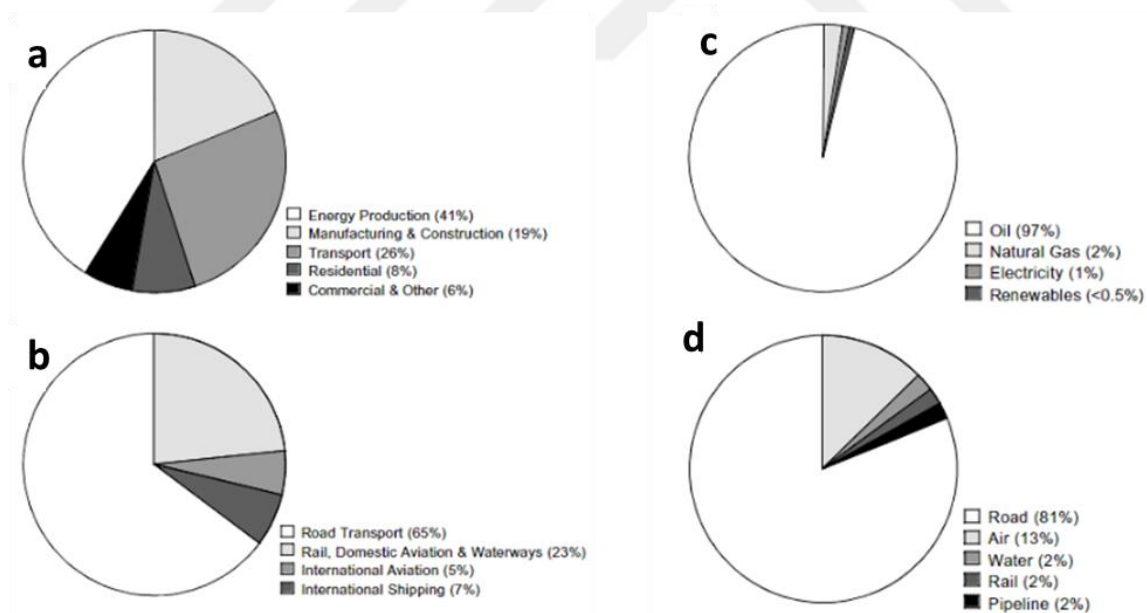


Figure 1. CO₂ emissions per (a) sector, (b) shares of sub-transportation sectors, (c) energy sources used in transportation, (d) shares of sub-transportation sectors [8].

Transportation sector needs more sustainable measures to decrease carbon foot-print i.e., to mitigate the negative impact on global warming. One promising method is switching from fossil fuel-powered vehicles to electric vehicles (EVs). New electric vehicle propulsion systems are considered as a more sustainable alternative in the long-term [9]. They are advertised as “zero-emission vehicles”. When “tank-to-wheel” energy consumption of an average electric, petrol and diesel vehicles are compared, the energy demand for petroleum car is about three times more than electric car. The diesel car has a tank-to-fuel efficiency of 22%. In other words only 22% of the energy contained in the diesel can be used for tractions. On the other hand, the “plug-to-wheel” efficiency of electric vehicle is about 72% with Li-ion batteries [10]. However, electric vehicles are not exactly “zero-emission” vehicles. EV batteries are charged with electricity coming from the grid. Therefore, emission reduction benefits of electric vehicles depend strongly on the grid-mixture. Figure 2 shows the carbon emissions of different vehicle types. As can be seen from the figure, the total carbon-dioxide emissions of the electric vehicle which is powered by coal-based electric are more than the emissions of a gasoline car. Thus, the grid mix is the most important factor in the associated emissions with EVs.

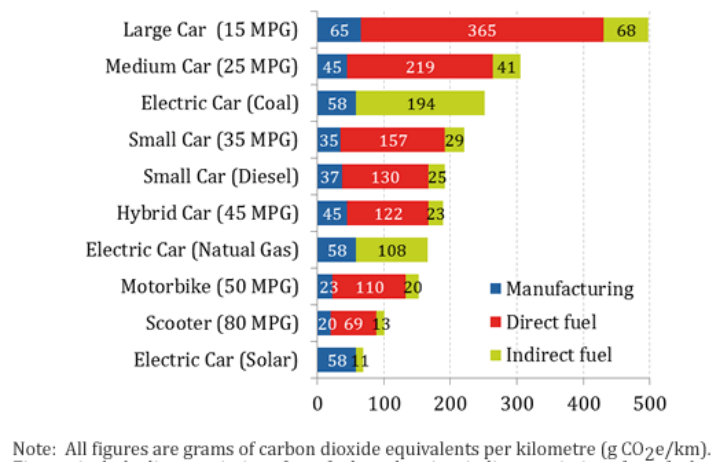


Figure 2. CO₂ emissions from different vehicle types(in gCO₂e/km) [11].

In addition, Figure 3 shows that the grid mix is the main factor affecting the CO₂ emissions of an EV. As can be seen from the figure, the total emissions of an EV in the high carbon grid are pretty close to conventional vehicles. In other words, if an EV is charged by electricity produced by a high-carbon grid, it will not have positive effect on mitigating global warming as expected.

In conclusion, the EVs are as clean as their energy sources. Thus, in order to achieve the GHG emission reduction targets, the EVs should be charged by green energy sources. Solar Photovoltaic (PV) is the most promising technology which provides both clean and cheap energy to users.

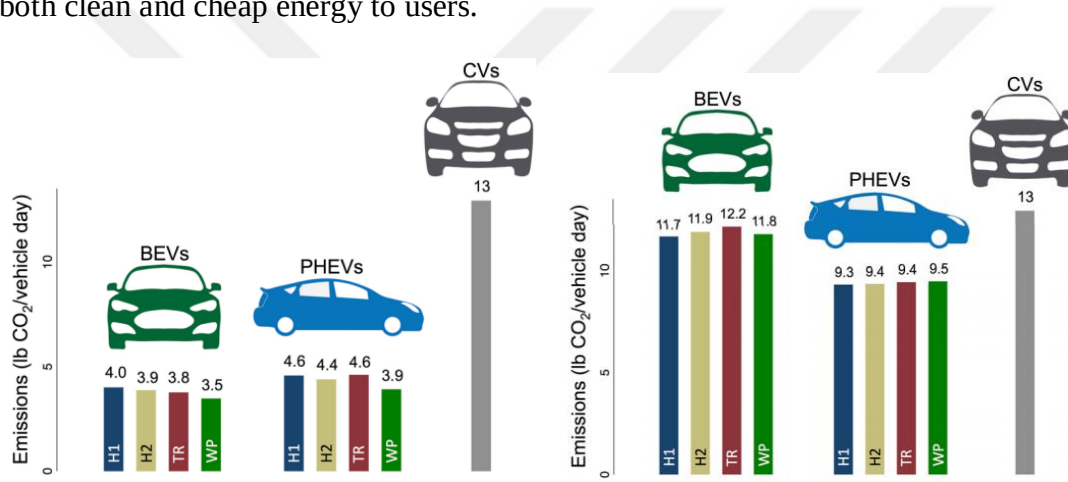


Figure 3. Comparison of total EV, PHEV, and CV emissions for (a) low carbon grid, (b) high carbon grid [7]

1.2 Objective of the Thesis

In this thesis, the main objective is to develop a generic model to design a PV-powered electric vehicle charging station for selected conditions, such as regions and scale of charging station. The main research questions are as follows;

- Are PV powered charging stations feasible? Does the feasibility rate vary by the region and ambient conditions?

- Is it possible to rely entirely on the PV power through the year to meet the daily charging requirements?
- If it is not possible to rely entirely on PV power, then how much demand can be covered by PV to decrease the stress on the grid?

The developed model will be applicable for any selected region by incorporating required parameters into the model. Then, the model is used for several different locations and results will be presented as case studies. In this context, a model is developed to estimate available solar energy through the year and the generated power from customized, designed PV system at the selected region. Moreover, another model is developed to estimate the energy demand by the electrical vehicles at the selected regions and the difference in this demand due to ambient and driving conditions. How much demand will be covered by the PV power system is also investigated in the selected regions.

1.3 Thesis Layout

This thesis study is composed of 5 chapters. In Chapter 1, the background information about the study and motivation of the study is presented. The objectives of the study are also provided. In Chapter 2, the current literature about electric vehicles, PV systems, and PV-EV systems is presented. In addition, contributions of this thesis to literature are provided. Chapter 3 aims to provide relevant theory and methodology used in the study. This chapter is composed of two main parts; solar resource estimation and energy demand estimation. In the solar resource estimation part, the methodology applied to estimate the solar energy generation from a PV system is presented. In the energy demand estimation part, the methodology applied to estimate the energy consumption of a single EV including the effects of ambient temperature

is presented. After that, the methodology applied to estimate the energy demand of a fleet is presented. In addition, methodology for economic analysis of a PV-EV system is given. Chapter 4 includes the results of the case studies where the model is applied to 3 different cities, which are Istanbul, Los Angeles, and New York City. In Chapter 5, the summary of the key results and final remarks are presented.



CHAPTER 2. LITERATURE REVIEW

In this chapter, the literature review is presented. The detailed literature review about electric vehicles, their types, performance measure and how the performance is affected by ambient temperature and driving conditions. Then, the detailed literature review about PV systems and PV-EV systems is presented. Finally, the contribution of this study to the literature is discussed.

2.1 Electric Vehicles

Electric vehicles become more popular recently thanks to their low emissions, higher energy efficiencies and lower cost of operations. They can be categorized into 3 as Hybrid-Electric Vehicles (HEVs), Plug-in Hybrid Vehicles (PHEVs) and Battery Electric Vehicles (BEV). HEVs have both electric motor and Internal Combustion Engine (ICE). Although they have batteries, they cannot be charged from an outsource. HEVs are categorized into series and parallel HEVs. In series HEVs, the Internal Combustion Engine (ICE) is directly connected to generator so that batteries are charged. The vehicle is driven by the electric motor by using the energy from the battery being charged by ICE. On the other hand, in parallel HEVs, the vehicle can be driven by both ICE and electric motors. In other saying, ICE might be both used for electricity generation as well as traction for the vehicle. Figure 4 represents the schematics of parallel and series HEV.

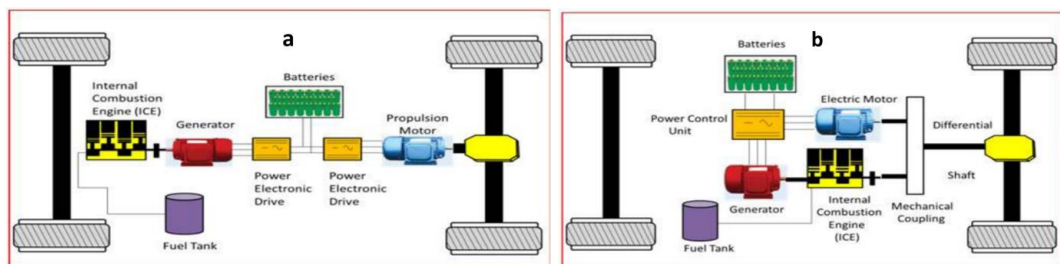


Figure 4. A hybrid electric vehicle with (a) series, (b) parallel hybrid power train [12].

Hybridization factor is introduced to define the rate of hybridization. It is the ratio of electric power of the vehicle to total power (including electrical and mechanical). The HEVs are classified as Micro, Mild and Power hybrids whose hybridization factors are 5-10% 20-25% and greater than 25%, respectively. Honda Civic, Jazz Prius and CR-Z models are several examples for the HEVs. If the hybrid electrical vehicle has option to be charged its battery from the grid, it is called Plug-in Hybrid Vehicle (PHEV). PHEVs have greater battery capacity, and they can be charged both internally and externally. Because of having greater battery capacity, they have higher All-in-Electric Range (AER) compared to HEVs. For example, Ford Fusion Energi can travel about a distance of 21 miles or Chevrolet Bolt can go about 38 miles by electric[13]. Finally, the BEVs are not supported by ICE, i.e., they do not have an ICE. They depend on the stored energy in their batteries which are charged by the power grid. They have longer range compared to PHEV and HEV with an average range of 80 miles [13]. Nissan LEAF, Renault ZOE, Tesla Model S, X are some popular examples of BEV. Figure 5 represents the schematics of PHEV and BEV.

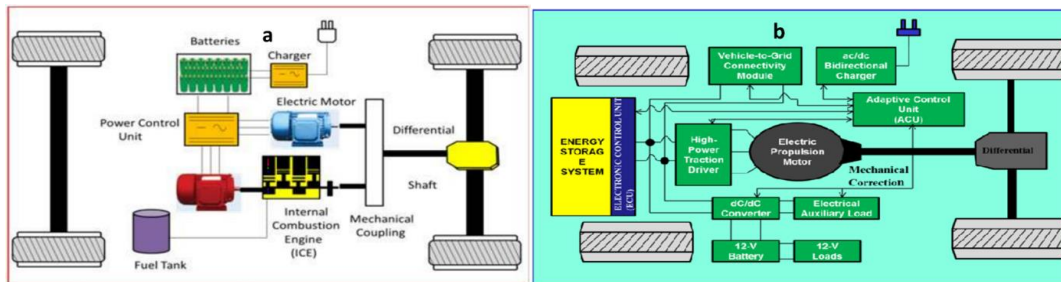


Figure 5. (a) A plug-in hybrid electric vehicle (PHEV), (b) battery electric vehicle (BEV) [12].

2.1.1 Charging Topologies of Electric Vehicles

The infrastructure that is used to deliver electric energy from a grid to an EV charger is called EV Supply Equipment (EVSE). Basically, EVSE is the refueling point for electric vehicles [14]. Each country has its own specific power configuration because

the electrical power grid parameters like frequency, voltage, transmission types vary for countries. The Electric Power Research Institute (EPRI) classifies charging levels as AC Level 1, AC Level 2, Direct Current Fast Charge (DCFC), i.e., Level 3. In Level 1 charging 120 V AC outlets are used. It can provide current from 15 A to 20 A, so the charging occurs at a power of 1.4-1.9 kW. It uses SAE J1772 standards. Due the low charging power, recharge might take 8-20 hours depending on the capacity of the battery. It is the cheapest and common EV charging level. It does not require extra investment for infrastructure. Level 2 charging uses 240 V AC single phase with maximum current of 32 A or 400 V AC with three-phase infrastructures with maximum current of 80 A. Charging powers varies between 7.7 and 25.6 kW. It may take 4 to 10 hours for an EV to be recharged fully. 240 V single-phase AC structure is available most of the homes, especially in Europe. In combination of using same circuit as the other home appliances and decreasing the time required for charging, it is the most favorable level of charging. European Type 2 Mennekes charging plug is generally used. Figure 6 represents the type of plugs for AC charging. On the other hand, Level 3 charging is generally preferred for commercial applications, as it decreases the required time for charging significantly. It takes 10-30 minutes to fill 80% of the battery while charging the remaining 20% takes more time. Therefore, performance of the DC fast charge stations is measured by the time required for 80% battery charge. The conversion from AC to DC generally is handled by the external conversion units while it occurs in the internal conversion units for Level 1 and Level 2 charging. There are two popular charging standards for off-board DC fast charge structures. These are Society of Automotive Engineers (SAE) J1772 “Combo” and Japanese CHAdeMO. SAE recently revises the Direct Current Fast Charge standards,

and it is divided into DC Level 1 and 2 charging whose charging powers are 0-40 and 40-100 kW, respectively. Figure 7 depicts Combo and CHAdeMO plugs.



Figure 6. (a) Charge Plugs for AC charge SAE J1772 Plug, (b) European Type 2 Mennekes [15][16].



Figure 7. DC Charge Plugs SAE Combo for US (left), Europe (right), CHAdeMO (bottom).

Table 1 summarizes the SAE J1772 charging level standards. As presented in the table, it takes 13 hours to charge a BEV with 24 kWh battery in Level 1 charging, while it takes only 20 minutes for DC Level 2 charging. However, DC Level 2 charging is not

suitable for home or offices. In addition, Table 2 presents the different charging characteristics for several commercially available PHEV and BEVs.

Table 1. SAE J1772 charging levels [14].

Level	Input voltage and current	Charger location	Maximum power (kW)	Battery size (kW h)	Charging time (h)	Typical use
AC Level 1	120 VAC-15 A (12 A useable)	On-board	1.44	24 (energy available 19.2)	10-13	Home or office
	120 VAC-20 A (16 A useable)	1-phase	1.92			
AC Level 2	240 VAC-40 A (32 A useable)	On-board	7.7	24 (energy available 19.2)	1-3	Private or public outlets
	400 VAC-80 A (64 A useable)	1-phase/3-phase	25.6			
DC Level 1	208 VAC-80 A (64 A useable)	Off-board	13.3	24 (energy available 19.2)	0.5-1.44	Public, commercial
	600 VAC-80 A (64 A useable)	3-phase	38.4			
DC Level 2	208 VAC-200A (160 A useable)	Off-board	33.3	24 (energy available 19.2)	0.2-0.58	Public, commercial
	600 VAC-200A (160 A useable)	3-phase	96			

Table 2. Charging data for different commercially available vehicles [14].

Model	Vehicle type	Battery size (kW h)	Energy available (kW h)	Range (km)	Energy consumption (kW h/kW)	AC Level 1		AC Level 2		DC Level 3	
						Demand (kW)	Charge time(h)	Demand (kW)	Charge time(h)	Demand (kW)	Charge time (h)
Nissan Leaf	EV	24	19.2	160	0.12	1.8	11	6.6	2.9	50	0.4
Mitsubishi i-MiEV	EV	16	12.8	150	0.086	1.5	9	3.6	4	50	0.26
Toyota RAV4	EV	41.8	32.18	160	0.20	1.9	17	9.6	3.35	50	0.64
Cooper (BMW)	EV	28	21.5	160	0.13	1.9	11	7.6	2.8	50	0.43
Sabaru Stella	EV	9.2	7.1	80	0.09	1.8	4	3.8	2	47	0.15
Tesla Roadster	EV	53	37.1	340	0.11	1.8	21	16.8	2.2	100	0.37
Chevrolet Volt	PHEV	17.1	13.7	64	0.21	1.4	10	3.6	4	N/A	N/A
Toyota Prius	PHEV	5.2	4.1	25	0.16	1.8	3	3.2	1.5	N/A	N/A
Buick	PHEV	8	6.4	16	0.40	1.4	4.6	3.2	2	N/A	N/A
Frisker karma	PHEV	22	17.6	80	0.22	1.8	10	3.6	5	N/A	N/A

2.2 Solar Photovoltaics (PV) Systems

The world energy demand has grown since the industrial revolution. A huge portion of this energy demand is covered by fossil fuel burning power plants. The increase in greenhouse gases and noticeable effects of global warming leads to increase in renewable energy penetration. Solar energy is one of the popular options due to its enormous potential. The solar energy hits the earth surface which is far more than earth needs [17]. PV market has been growing for last decade. Figure 8 represents the installed PV capacities since 2000. It is clear that installed PV capacity increases every year. Only in 2017, about 100 GW PV system has been installed on the top of already

installed 300 GW [18]. The top main contributor in 2017 is China with 53.1 GW newly established plants [19]. In 2018, PV accounts 6.3% of the global installed capacity, also about 2% of the total energy is generated by PV [19].

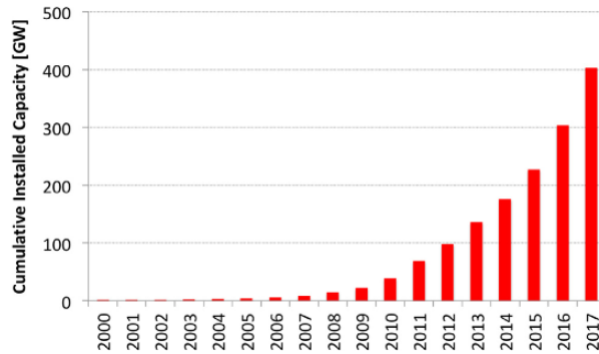


Figure 8. Global installed PV capacity [18].

PV owes its growing popularity to various drivers. One of the drivers of the increasing popularity of PV is reduced cost. The prices which were 4\$/Watt in 2007, decreased up to 0.35\$/Watt in 2017 [18]. Also, the cost of other components of the PV system like inverters, structural elements decreases. These components are called as Balance of the System (BOS). Figure 9 represents the cost of BOS as well as module and labor costs for various years. As it is depicted, not only cost of PV modules but also the total cost decreases.

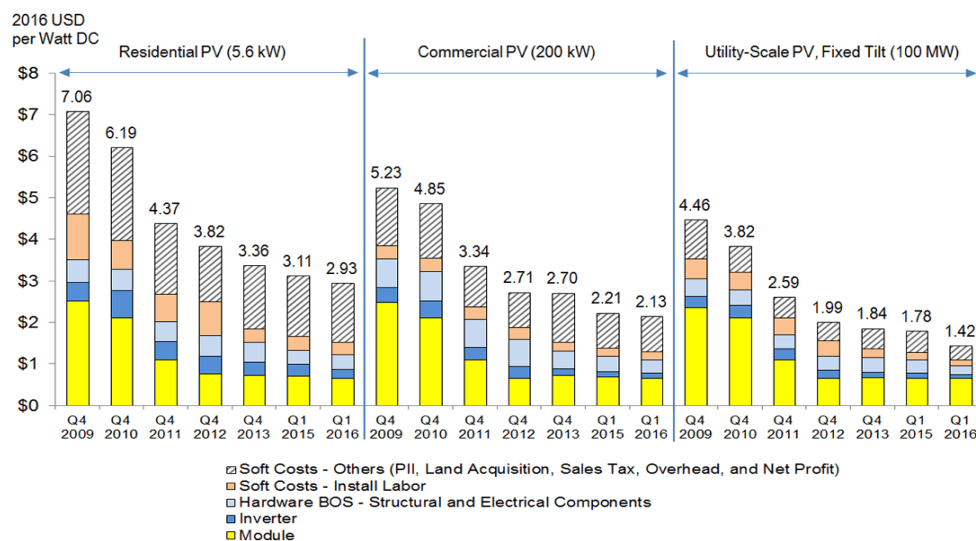


Figure 9. PV power plant components costs [20].

Besides generating clean energy, PV systems are also the most competitive energy generation method in terms of cost among the others. The cost of the unit electricity generated is represented by Levelized Cost of Electricity (LCOE). Comello et al. state that the unit cost of electricity (LCOE) for PV in California in 2017 is 3.19 ¢/kWh while average retail rates are about 14-18 ¢/kWh [18]. Table 3 represents the LCOE of PV for different scales and states in USA. As in California, PV definitely competes against retail prices in Arizona which are about 10-12 ¢ /kWh.

Table 3. LCOE estimates for different scales and countries (¢ /kWh) [18].

	Utility PV	Commercial PV	Residential PV
California	3.2	6.8	11.4
Arizona	3.0	4.9	8.4
Massachusetts	6.0	8.6	15.3

2.3 Electric Vehicle Charging by Solar Photovoltaic-Powered Parking Lots

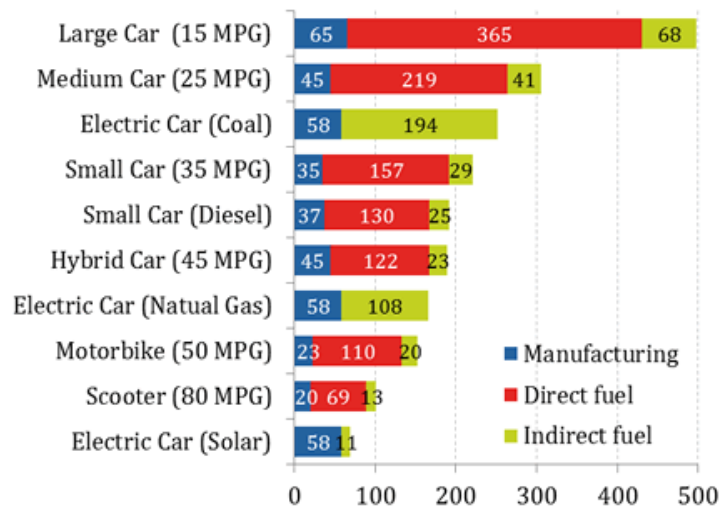
Charging electric vehicles takes time as presented previously in Table 2. In other words, electric vehicles should be in the parking position for several hours to be charged. According to statistics, for 23 hours of the day, the vehicles stay in park position. Moreover, according to National Household Travel Survey, vehicles are parked more than 4 hours for 60% of the commute trips [17]. If the open parking lots are covered by the PV modules, EVs can be charged by solar energy. The most general application is covering two rows of parking space where is occupied by the vehicle as presented in Figure 10. On the other hand, for some cases whole parking lot is cover to increase the yield from the sun. The solar covered parking lots can be established almost everywhere, like supermarkets, offices, university campuses, airports, etc. All the open space parking lots can be converted to solar-charging station without using new lands.



Figure 10. An example of a solar parking lot arrangement [21].

2.3.1 Environmental Benefits

The solar-powered parking lots have several benefits such as environmental and economic. As abovementioned, the carbon footprint of EV highly depends on the source of electricity. Although PV modules emit zero Greenhouse Gases (GHG), they have still footprint because of the manufacturing process. On average, a PV module compensates its emissions within 2 years [22]. At this point, it is required to mention one more time that PV modules have lifetime of about 25 years which means that PV powered parking lots operate as zero-emission charge stations for about 23 years [22]. Moreover, PV modules operate without creating any noise which might disturb the around. On the other hand, wheel-to-wheel CO₂ emission of Solar-Powered Charging is less compared to others. Figure 11 represents the CO₂ emissions per km for different scenarios. It is certain that if an EV is charged by coal-powered power plant, its emission is even higher than petrol vehicles. In addition, the emission of a solar-charged EV is even less than a petroleum-powered scooter.



Note: All figures are grams of carbon dioxide equivalents per kilometre (g CO₂e/km).

Figure 11. Emissions from driving alone [11].

If emissions of the other pollutants, such as SO₂ (sulfur dioxide) or NO_x are compared, emission of an EV charged by solar power is about 95% less than the gasoline-powered vehicles. As a side note, the remaining 5% is due to wear of brake pads and tires.

2.3.2 Grid Benefits

The penetration of EVs increases the total electricity demand. It affects the performance and required rated power on the grid. PV-powered parking lots help to decrease the extra demand on the grid. In other words, PV charging stations minimize the effects of penetration of EVs on grid [25]. There are several studies which investigate the effects of penetration of EVs on the grid and ways to decrease its impacts. Drude et al. studied the effect of a fleet which contains 250 EVs on the grid [26]. Figure 12 represents the total demand of the selected region including fleet. As depicted in the figure, implementation of PV decreases the demand so that the stress on the grid decreases [26].

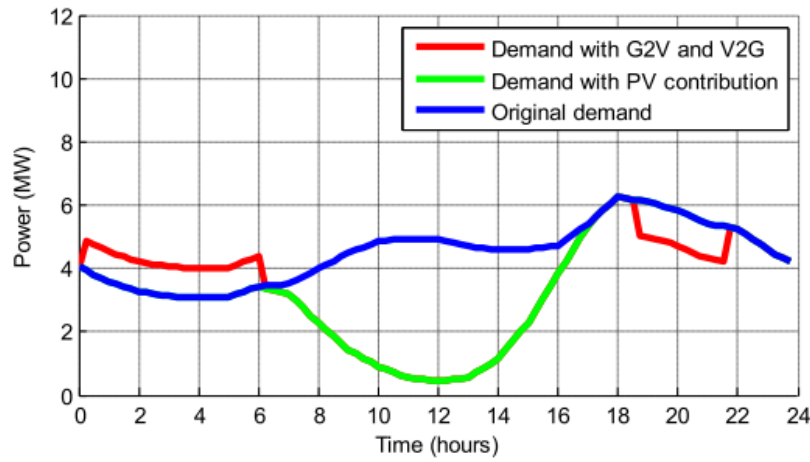


Figure 12. Demand of the selected region including 250 EVs with/without PV [26].

2.3.3 Strategic Benefits

In modern society, energy security is one of the basic needs of countries to grow. There are several primary sectors which demand energy, and transportation is one of them.

Figure 13 represents the energy demand of transportation and the sources of supply. As clearly depicted, almost all of the demand is covered by the oil. The growth of countries which do not depend on foreign energy sources, i.e., “energy secure” will be faster compared to “energy insecure” countries. The foreign energy dependency of Turkey was 68% and 71% in 2015 and 2019, respectively [27]. Being highly dependent on foreign sources has several consequences on the Turkish economy. In 2018, \$12.7 billion worth processed petroleum oil is imported which is almost accounted for 6% of total import [28]. However, large EV penetration and charging them by solar energy together are promising to decrease the energy dependency of the countries because the energy is directly coming from the sun rather than importing from foreign country.

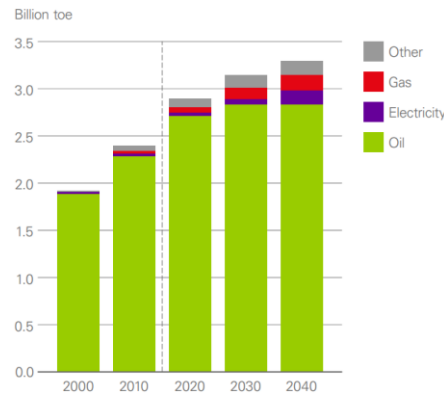


Figure 13. Energy Demand of Transportation and Sources of Supply [29].

2.3.4 Other Benefits

According to several surveys, one of the barriers in front of the adaptation of electric vehicle is lack of charging points [17]. Since every open-space parking lot can be converted into solar-powered EV charging stations, the EV penetration is going to be positively affected by the solar charging stations. On the other hand, most of the populations live in urban areas where there is not enough land to build a solar farm. Therefore, covering parking lots with PV is convenient in terms of land use as well.

The PV-covered parking lots provide also shading for the vehicles. This might decrease the effects of sun exposure of the vehicles, such as interior trim damage, paintwork irregularities, etc. Moreover, the interior temperature of the vehicle will be lower thanks to shading, so that the thermal comfort is improved [17]. In addition, since interior temperature is closer to the comfort level, the use of AC decreases. The less use of AC, the higher range of the EV, because AC consumes power from the battery.

According to EPA, 1 ton of emitted carbon costs \$40 to society [23]. It means a single electric vehicle can provide saving for society about \$5000 from healthcare expenditures compared to regular gasoline vehicles [23]. In the USA alone, there are

263.6 million vehicles [24]. Also, the air quality so as the living standards of the people can be improved.

2.3.5 Operation Configurations of PV-EV systems

Photovoltaic parking lots have several basic components, like PV array, DC-DC converter with Maximum Power Point Tracker (MPPT) and DC Charge controller. Also, there are other several components depending on the configuration of system. There are two main configurations of PV systems to charge EVs which are on-grid and off-grid.

2.3.5.1 On-grid PV-EV

As the name implies, the PV system is connected to the grid in the on-grid configuration. To have a connection between the PV system and the grid, there should be an inverter addition to basic components mentioned above. Figure 14 shows the schematic of on-grid configuration. The inverters are used in on-grid systems can be bi-directional or uni-directional. If the power from PV modules not enough, the inverter can convert AC electricity of the grid into DC to feed the system. On the other hand, it operates as DC-AC converter in the cases which the energy is not needed for charging to deliver electricity to grid [30].

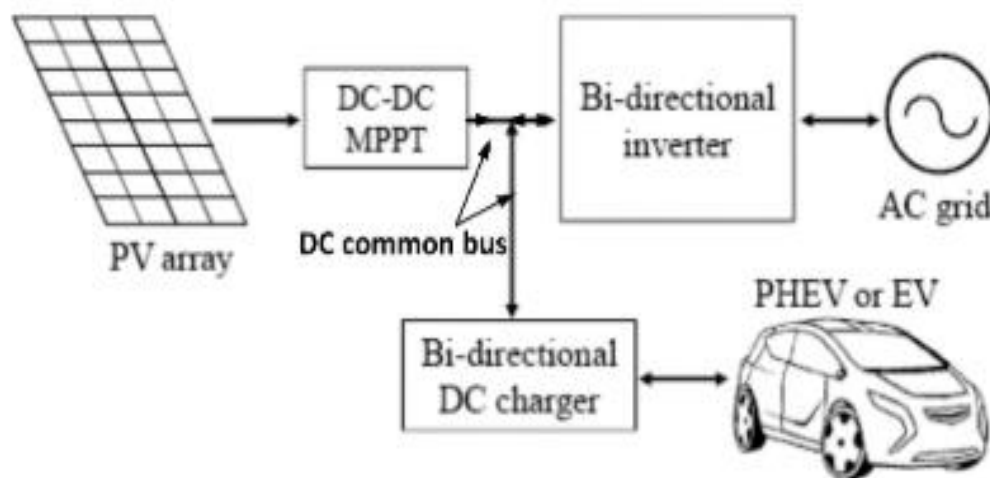


Figure 14. On-grid PV-EV charging station [30].

2.3.5.2 Off-grid PV-EV

An off-grid system is also called as a stand-alone system. In this configuration, only source of energy for charging is the PV power i.e., grid is not connected, unlike the on-grid configuration. Figure 15 presents the schematic of an off-grid system. Since the system is not tied to the grid, the number of conversions is less. Therefore, conversion losses are less. However, since PV power is the only source, the correct size of PV system is more crucial. Furthermore, the energy storage systems can be added to the system, so that the vehicles can be charged even if there is not enough power from the PV system. As presented in Figure 15, charge controller is needed in this configuration. It is a DC-DC converter which is used to tune the voltage for charging. They are generally capable of MPPT which provides maximum power harness from the system [30]. The PV output power is a function of irradiance, cell temperature, battery voltage, etc. MPPT system dynamically calculates the current which maximizes the energy for these parameters by using several algorithms.

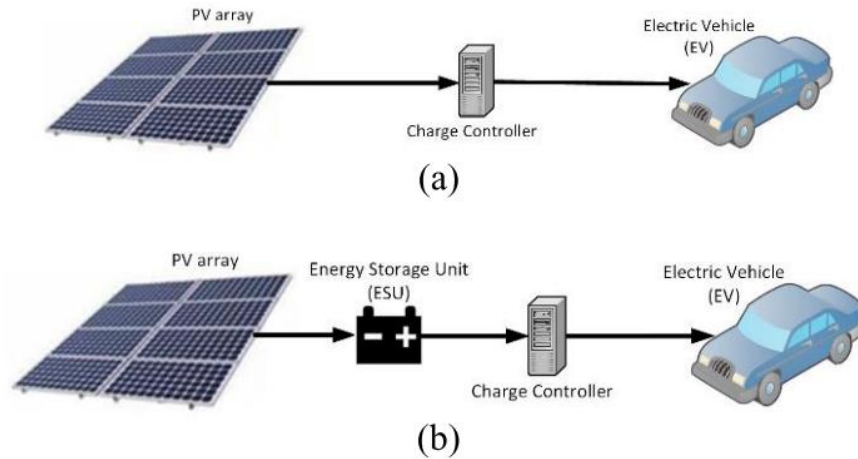


Figure 15. Off-grid charging configuration (a) without battery, (b) with battery [30].

There are four different power flow for on-grid and off-grid PV-EV configurations. Figure 16 summarizes these four modes of power flow. The first power flow (EV-PV Mode 1) is the charging electric vehicle only by the energy from the PV. In general,

this is the main purpose of the PV-EV systems. Both stand-alone and on-grid systems can operate in EV-PV Mode 1. In Mode 2, EV is charged by grid partially/fully. Only on-grid systems can operate in Mode 2. In Mode 3, the energy that battery contains is used to feed the grid. In other saying, the energy is flowing from battery of EV to grid. It is called the Vehicle-to-Grid (V2G) configuration. Finally, in Mode 4, the excess power of PV is used to feed the grid which only can be seen in on-grid configuration [31].

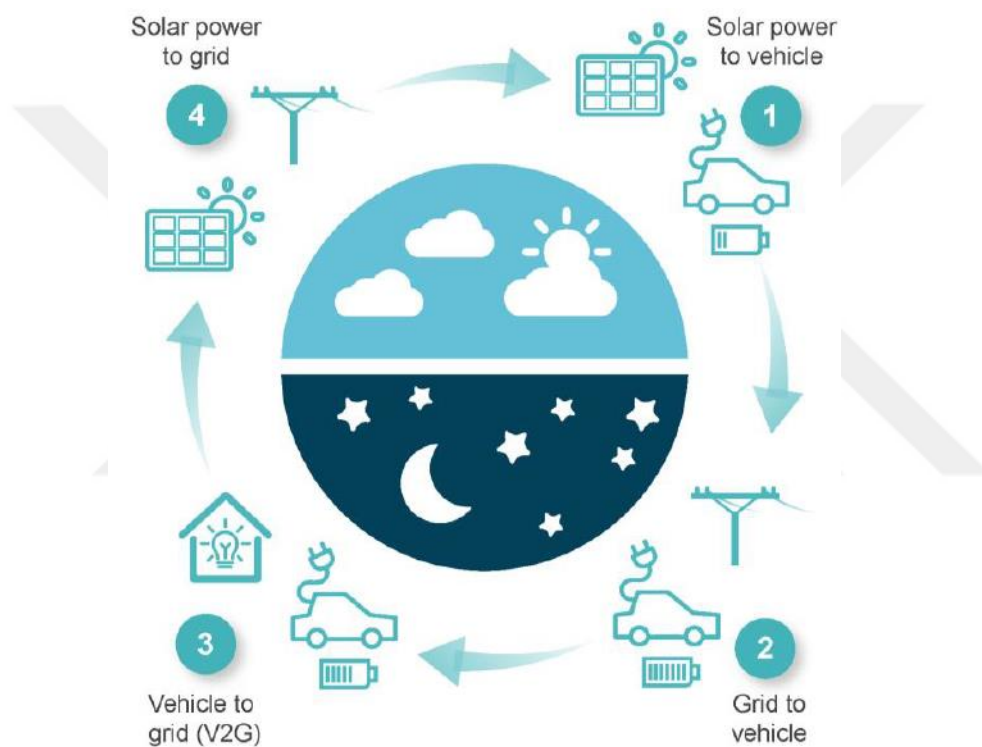


Figure 16. Possible power flows for PV-EV charging stations [31].

2.4 PV-EV Examples from World

There are various applications of PV for EV charging. Nunes et al. claims that the first pilot PV-EV was initiated in California to demonstrate that it is feasible. The rated power was 2.1 kW_p [17]. In another study, Birnie III studied the feasibility of EV charging during daytime rather than changing at late hours when the demand is low [32]. It was suggested that daytime PV-EV charging is very suitable for workplaces

because the vehicles stand at parking position through the day. According to the author, the important factors which play crucial role for applicability of PV-EV are the available solar energy and the energy demand of the EV. In other words, there should be a balance between energy demand and supply to make an applicable PV-EV system. In the same study, a case study for New Jersey (NJ) was presented [32]. A parking space whose area is 15 m² was covered by PV modules. The modules were oriented horizontally and the module efficiency was 14%. Using the Typical Meteorological Year (TMY) data of selected neighbor, the estimated daily energy yield from PV varied from 4 kWh to 13 kWh. The author claimed that it was enough for a typical EV to travel minimum of 13 miles. Also, since 70% of the commute trips are less than 15 miles, PV-EV systems are applicable [17]. Finally, the author suggested that parking lots are more convenient for PV modules than rooftops because rooftops have restrictions for modules to be correctly oriented [32].

As mentioned in the previous paragraph, energy balance between energy demand from EV and energy supply from PV is crucial for PV-EV parking lots. Chukwu and Mahajan studied the effect of a 50 kW PV system on this balance for a parking lot [33]. To demonstrate different energy demand scenarios, different EV models, such as Nissan Leaf, Tesla Roadster were selected. The battery capacities were 24 kWh for Nissan, while it was 53 kWh for Tesla. Authors also studied the impact of vehicle-to-grid (V2G) concept on the net balance of the parking lot. The authors claimed that V2G has several important advantages. The most important advantage is that vehicle batteries are used for energy reserve for grid. In other saying, the reserved energy inside the batteries can be used to regulate the grid. Also, since electricity tariff changes through the day, V2G system enables parking lot owner to sell electricity which is generated by PV to grid when the tariff is high to create extra revenue. The

study concluded that the energy taken from grid decreases by the integration of PV system. In fact, authors claimed that all demand for EVs can be covered when PV power is available. On the demand side, the battery size of the EV directly affects the balance. The 50 kW PV system could cover the entire demand of Nissan Leaf, and there was still surplus energy. On the other hand, it was not able to cover the demand of Tesla Roadster. It was strongly pronounced by authors that integration of PV decreases the stress on the grid [17][33].

Various studies in the literature have focused on on-grid configurations. Goli and Shireen focused to maximize the energy utilization of PV system, i.e., minimizing the energy taken from grid [34]. For this purpose, the authors designed an on-grid PV-EV parking lot with an energy storage system. Due to the storage system, the design could work as an off-grid system. The parking lot could operate in four different methods which were pretty similar what is presented in Figure 16. The rated power of PV system in the design was 5.5 kW_{PV}. In the first mode, the voltage generated by the modules were less than 50 Volts. In that mode, PV power is not used for charging instead the grid energy is used. If the grid demand was peak, in that case the EVs were charged by the storage system. In the second mode, in which PV voltage was between 50-250 V or the power was between 900-4500 W, the PV energy was used to charge the EVs; however, it was not enough to fulfill the demand. The deficit was covered by either storage system or grid depending on the grid load status. In the third mode, the PV module voltage was greater than 350 V, which corresponded to about 5000 W of PV power, the EVs were only charged by the PV modules. Lastly, in the fourth mode, the generated power was greater than demand, so the surplus was either used to charge the storage system or fed the grid. They concluded that implementing smart charging

will decrease the need for upgrading distribution transformers. Authors also validated their results by a small scale experimental setup [17][35].

There are two different charging types which are controlled and uncontrolled charging. In the uncontrolled charging, the vehicle is started to be charged as soon as it is plugged-in. None of the parameters, like instantaneous grid load, PV power, storage system, sufficient State-of-Charge (SoC) of the battery are considered. On the other hand, in controlled charge, all these parameters are considered. Every controlled-charge algorithm has a special objective, like decreasing the cost, maximizing the use of renewable energy, etc. In one of their study, Honarmand et al. focused on a fleet with 500 Chevy Volt whose battery capacity is 16.5 kWh each [36] They proposed a controlled charging algorithm for PV-EV with V2G which maximizes the profit of the fleet owner. Also, wear of the battery was considered. Several statistical methods were applied to estimate the energy demand of the fleet. The arrival and departure times were randomly selected. Furthermore, the duration of the parking of each car was estimated by using probability distribution functions (pdf) presented in Figure 17. There was a desired final SoC by the fleet owner. Since V2G was considered, three possible operations were possible for the selected fleet vehicles, which were being charged, discharged and at idle. The authors considered two different cases. In the first case, the number of charge-discharge cycle of each battery was considered, and charging was planned according to the number of cycles. In the second case, battery cycles were not considered. In the first case, the wear of the battery put a limit to the number of charges. Thus, the total demand was lower compared to the second case. However, authors concluded that use-of life of batteries was improved in the first case. Moreover, they claimed that the controlled charge algorithms were capable of decreasing the energy demand even more with combination of PV-EV systems [36].

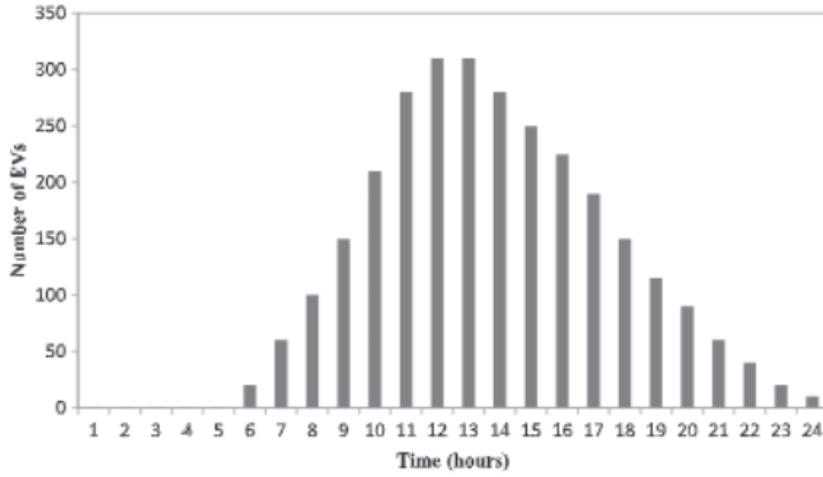


Figure 17. Parking lot usage statistics [36].

Honarmand et al. also studied same parking lot configuration (500 vehicles fleet) but for different objective function [37]. In the study, the aim was not maximizing the profit of the owner of the fleet but maximizing the profit of parking-lot operator. They also added 2 micro-gas turbines (MTs) into the PV-EV system. The information provided by the EV owner and renewable energy yield forecasts were used to schedule the charging of EV, operation of MTs, V2G, etc. with help of linear programming. Several scenarios were considered. In the first case, loads due to EV charging was not considered while scheduling, i.e., it was considered as variable load. Thus, V2G was not considered, and the only source of energy which could feed the grid was from MTs. In the second case, the load due to EVs was considered during scheduling, but V2G was not considered for reverse spinning. In the final case, both loads were due to charging, and V2G potential of EVs was considered for scheduling. In this case, reserve spinning was scheduled considering both MTs and V2G. Figure 18 represents the daily profit for parking lot owner (IPL) and the cost for EV owner. As can be seen from the figure, Case 3 was the best option for both IPL and EV owner [17][38].

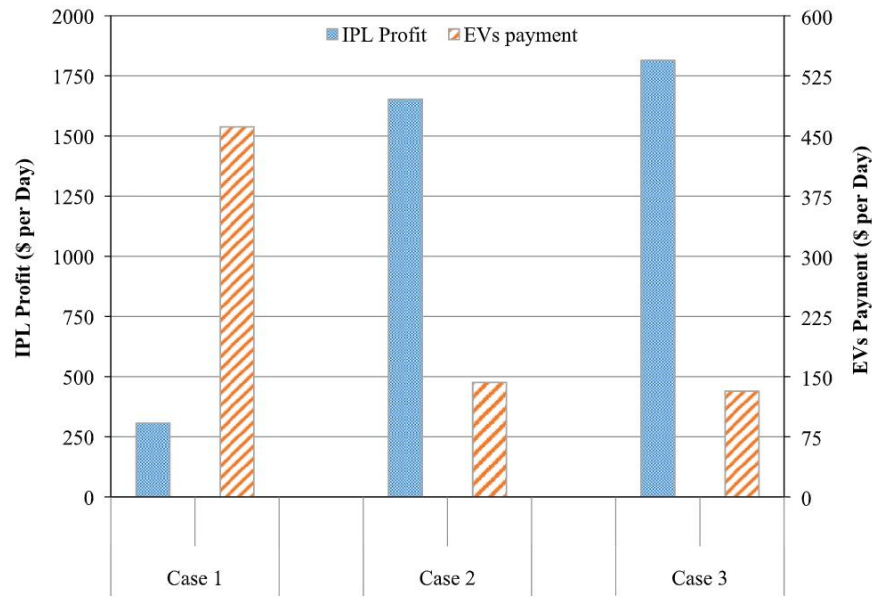


Figure 18. Profit of parking lot owner (IPL) and EV owner [38].

Ma and Mohammed offered controlled charging algorithm for a 75 kW_{pv} PV system with V2G parking lot for Dallas, Texas [39]. TMY for Dallas was used to estimate the energy yield. The parking lot was for a workplace, and its capacity was 350 vehicles [25]. It was assumed that 60% of the parked cars are Plug-in-Hybrids. To estimate the energy demand of the electric vehicles, the authors used the Probability Distributions Functions (pdf) which are presented in Figure 19. The authors compared controlled and uncontrolled charging. They also focused on the effects on the grid peak loads. Their results are presented in Figure 20. As can be seen from the figure, controlled charging provided more evenly distributed energy demand on the grid. It increased the stability of the grid as well as decreased adverse effects of high penetration of PVs on the grid. Also, controlled charging required less energy from the grid during the hours at which grid price was high. A charging prioritization was done based on the parking durations of the vehicles. If the parking duration of a vehicle was longer, the vehicle would not be charged at high grid price hours. In conclusion, controlled

charging has grid stability and economic advantages [25]. The algorithm can even enable of selling electricity from low priority car to grid (V2G) at high energy prices.

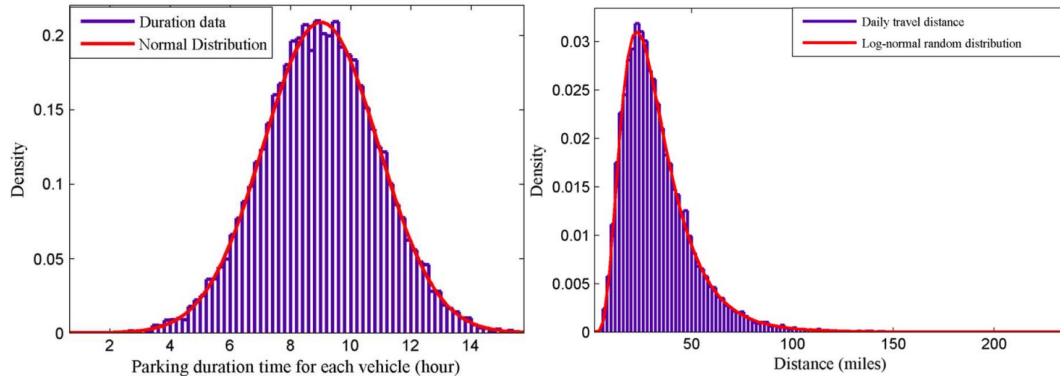


Figure 19. Probability distribution factors for (a) parking duration, (b) travelled distance [39].

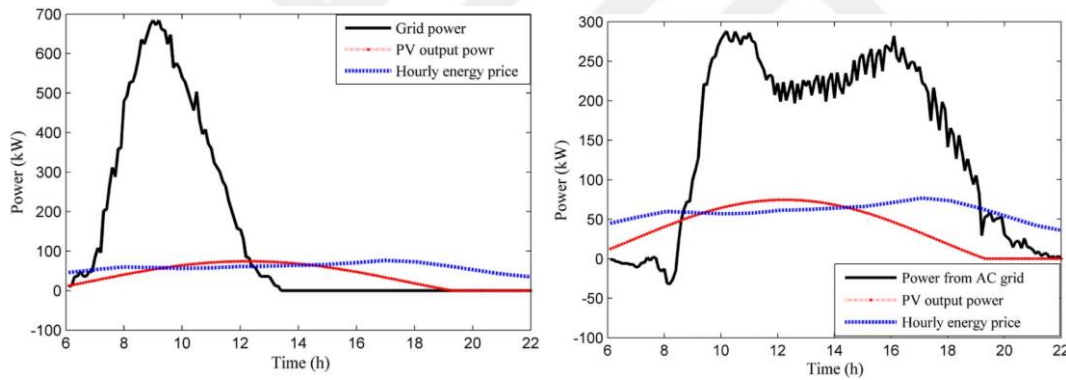


Figure 20. Grid power, PV output power and hourly energy prices for (a) uncontrolled, (b) controlled charging [39].

There are several studies in the literature that studies the PV-wind hybrid electric charging. Li et al. focused on feasibility of both PV and wind for charging [40]. It was concluded that PV system is more suitable than a wind turbine for EV charging. Thus, they further studied on PV-EV charging. The energy demand for a PHEV whose all-in-electric range was 65 km was assumed to be 17 kWh. A PV system for Alberta to cover the demand was designed for different seasons. TMY dataset for Alberta was

used to estimate the energy yield from PV. The PV system was designed for the best and the worst conditions, i.e., for July and December, respectively. PV area of 20 m² was enough for the best case, while the required PV area was 78 m² for the worst case. PV system was either oversized or undersized depending on the area. For example, if the system is oversized, a greater number of EVs can benefit the solar charging but the initial cost is higher. On the other hand, if it is undersized, the demand for all EVs cannot be covered although the initial cost is lower [40].

Moradijoz et al. studied the use of parking lots as an attractive alternative for supporting the grid loads [41]. This study had several objective functions, like maximizing economic benefits of parking lots for grid, minimizing the initial cost, power losses due to conversion and transmission, etc. The main benefit of EVs parking lots for the grid was their V2G capability. Parking lot owners were considered as energy sellers to grid. They offered advantages to owners of EV to promote them for parking their EVs. The authors even considered the compensation for battery degradation to EV owners. Two different cases were studied. In the first case, every objective function mentioned above had the same importance. In the second case, minimizing the initial cost and maximizing the energy reliability had top priority. The results of the first case showed that as energy availability increased, the total benefits decreased. In addition, the availability below 35% resulted in negative total benefits. In the second case, the number of EV vehicles was lowered to increase reliability by compromising the total benefit.

Mouli et al. investigated a parking lot in Holland to decrease the dependency on the grid. A 10 kW PV system was designed [42]. The modules were oriented with 28-degree tilt angle and faced to the south to maximize the energy yields. Authors also considered the solar tracking of modules, but it was concluded that tracking option

was not economically feasible. On the demand side, 3 vehicles were chosen as Nissan Leaf with 10 kWh daily energy demand per vehicle. There were 6 different load profiles assumed; 4 Gaussian, 2 rectangular and 2 constants. The assumed load profiles are presented in Figure 21. Two scenarios were considered in the study [42]. In the first one, 5 days of EV charging was assumed because of being a workplace parking lot. In the second scenario, 7 days of EV charging was assumed. As expected, the fed energy to the grid was more in the first case compared to the second one.

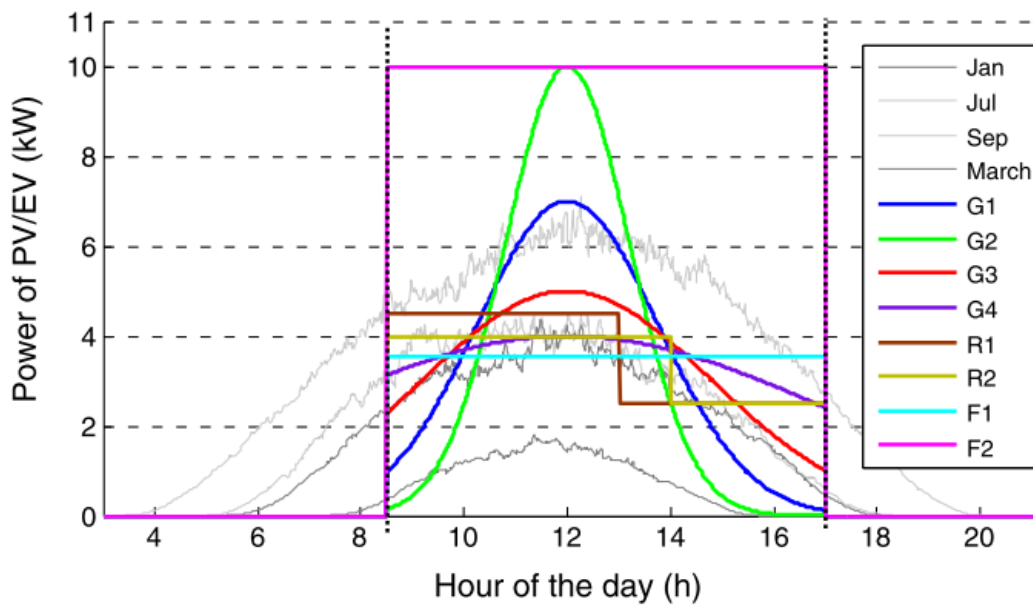


Figure 21. Different load profiles by Mouli et al. [42].

Also, based on different load profiles, a storage system was designed for fully autonomous charging station. The annual energy exchange with the grid for the given two scenarios are represented in Figure 22. It can be seen that a storage system with a capacity of 10 kWh decreased the exchange between the grid of about 25%. Less the grid independency, lower the operation cost and grid impact achieved. The total grid exchange was more for 7-day case compared to 5-day case. However as depicted in the figure, after a certain point, the positive effect of adding storage system decreased. Also, the energy fed to the grid for 5-day scenario was more compared to 7-day

scenario, because in 5-day scenario the generated energy was fed the grid. Finally, as mentioned above, Mouli et al. also studied the effects of adding solar tracker system [42]. Figure 23 represents the comparison of annual energy yield from 10 kW PV in the Netherlands with/without solar tracker systems. As it can be seen from the figure, one axis tracking (only tilt) had the lowest energy generation.

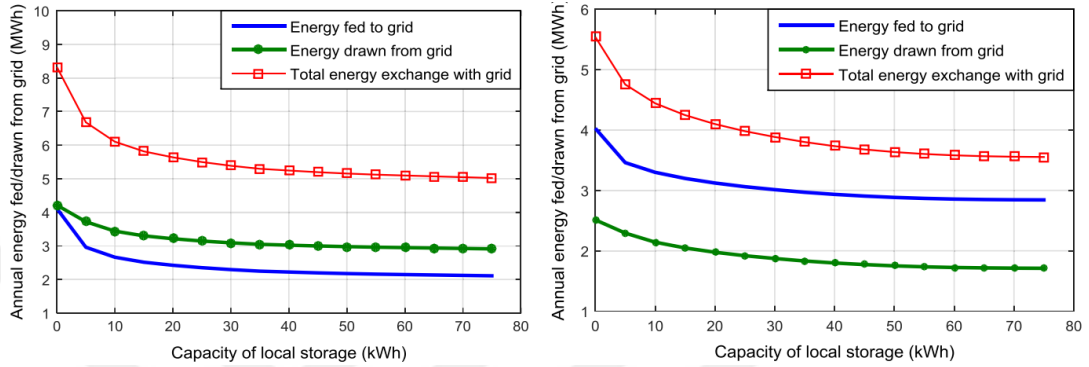


Figure 22. Yearly energy exchange with grid with respect to different storage system capacities for (a) 7 days, (b) 5 days scenario [42].

An optimized, fixed tilt angle which was 28-degree for the selected region provided higher energy output than tilt tracking system. On the other hand, higher energy yield was achieved in 2-axes tracking. However, the difference of energy yield between 2-axes tracking and 1-axis azimuth tracking was quite small. Even though increasing the yield, the authors concluded that tracking systems were not economically feasible.

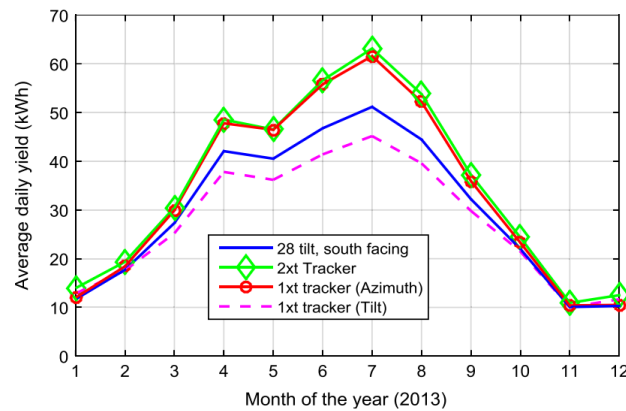


Figure 23. Energy yield from 10 kW PV for different tracking systems [42].

The previous studies represented above considered only a small scale (parking lot scale) implementation of PV-EV. Nonetheless, Neumann et al. studied the potential of PV-EV for utility-scale [43]. They considered all the parking lots in Frauenfeld, Switzerland. In the study, all of the 14,000 vehicles in the town was assumed to be electric, i.e., 100% EV penetration. The total energy demand was 87 GWh for Internal Combustion Engines (ICEs), while it was only 13 GWh for electric vehicles. The study concluded that 29 of the 48 parking lots in Frauenfeld were economically feasible for EV charging. 29 parking lots could annually generate 5 GWh of energy which was enough to cover the about 40% of the demand. Lastly, the authors compared PV system with biogas which is also famous for being environmentally friendly. Based on the comparison, if the energy demand of the fleet was covered by biogas, the total footprint would be 60 times more than PV system.

2.5 Performance of Electric Vehicles

Electrical vehicles have less range than the conventional vehicles which are equipped with internal combustion engines. In addition, the time required to recharge an EV is more than the time takes to refuel the gasoline vehicle. In addition to the limited range, there are several factors which makes the range of the EV even worse. The decreased range negatively affects all the advertised advantages of the EVs such as low running cost. For instance, acceleration and speed characteristics of each trip have a direct effect on power consumption, i.e., range of EV. The maximum range is higher in the smooth driving conditions compared to aggressive driving conditions, because energy required to travel a certain distance is less in smooth driving. Driving cycles are introduced to represent several different acceleration and speed characteristics of travel. In other words, there are driving cycles which can simulate mild, aggressive, normal driving conditions. Besides, temperature plays an upmost important role in the

range of the electrical vehicle. Impact of the temperature on the range of the EV can be divided into two parts. Firstly, the power electronics of the EVs are sensitive to the change in temperature. In low temperatures, the charging is impaired because the resistances in circuitry and cables increase. This leads to reaching maximum allowable battery voltage earlier so that the current which feeds the battery must be decreased. Thus, the charging time increases because of the decreased current. During driving, the minimum allowable battery voltage is reached earlier because of the same reason, since the current is taken from battery as well as power of the EV decrease. Moreover, the regenerative braking capability also decreases in low temperatures. On the other hand, in high temperatures, the internal resistances are much better. However, high temperatures increase the chemical activity in the battery so that the self-discharge rate increases. The other effect of temperature on EV range is air conditioning need inside the cabin. Inside cabin conditioning creates an extra auxiliary load on the battery which decreases the available energy for driving as well as range.

2.6 Factors Affecting EV Performance

2.6.1 Effects of Temperature on EV Performance

Range anxiety is the main barrier for electric vehicles [44]. Range of the electrical vehicle is directly limited by the energy storage capacity of the battery, so it is essential to design a battery which can provide high capacity and performance for broad cell temperature variations. There are several battery types whose chemical compositions are different than each other. Figure 24 represents the various energy storage systems and their specific power. Specific energy represents the driving range while specific power can be translated to instant acceleration. As it can be seen from the figure Li-ion has highest specific energy among the other electrochemical battery systems which means it performs closest as to regular gasoline in terms of specific energy.

This is the most important advantage of Li-ion because weight is an important consideration for the vehicles. Also, a typical Li-ion battery costs around 150 \$/kWh while Ni-MH costs 250 \$/kWh [45]. Also, the charging time for the Li-ion is less than the other battery types. Because of these advantages, Li-ion batteries are generally selected as an energy storage element for the new EVs.

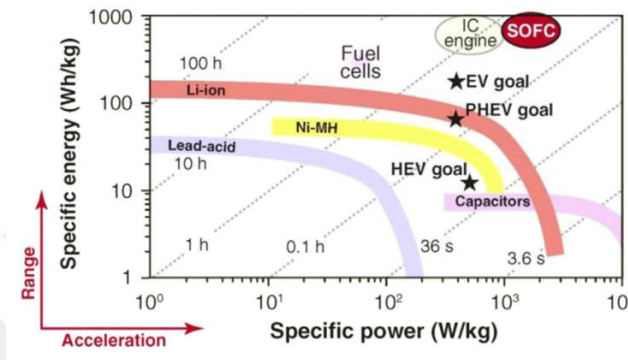


Figure 24. Various energy storage and conversion systems and their specific energies [45].

The working principle of a typical Li-ion battery is illustrated in Figure 25. Li⁺ ions move from positive side to negative side to complete a discharge cycle. For the charge cycle the movement will be vice-versa. During these movements heat is generated and it should be dissipated uniformly[45].

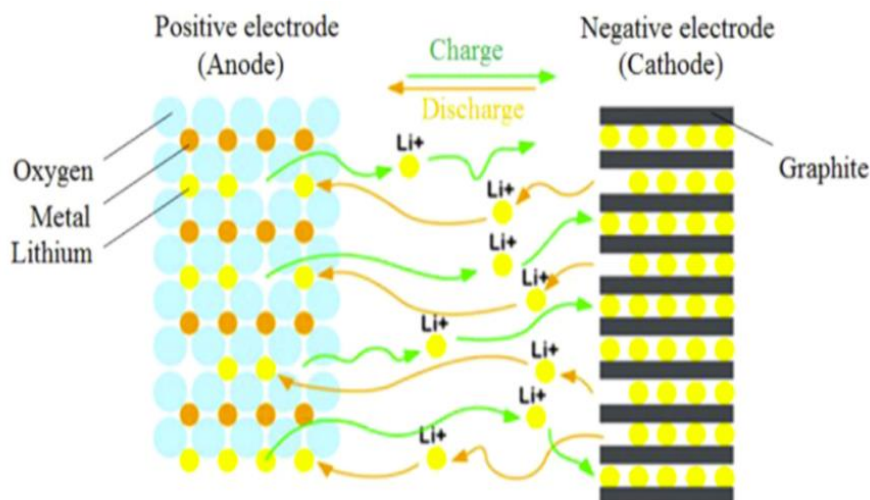


Figure 25. Charge and discharge mechanism of Li-ion batteries [45].

The performance of the Li-ion battery is sensitive to change in the temperatures. As highlighted in Figure 26a, the amount of energy which battery can store varies with temperature. In addition, as illustrated in Figure 26b the energy which can be discharged from Li-ion cell also changes with respect to temperature. These prove that as the temperature decreases the usable energy in the cell decreases [46]. Increase in internal resistances causes reaching to cutoff charge voltage (about 420 V) earlier [47], so lower SOC can be achieved. In addition to fact that Li-ion cannot be 100% charged at low temperatures, it is found that at lower temperatures the charging time also increases for Li-ion cell [48].

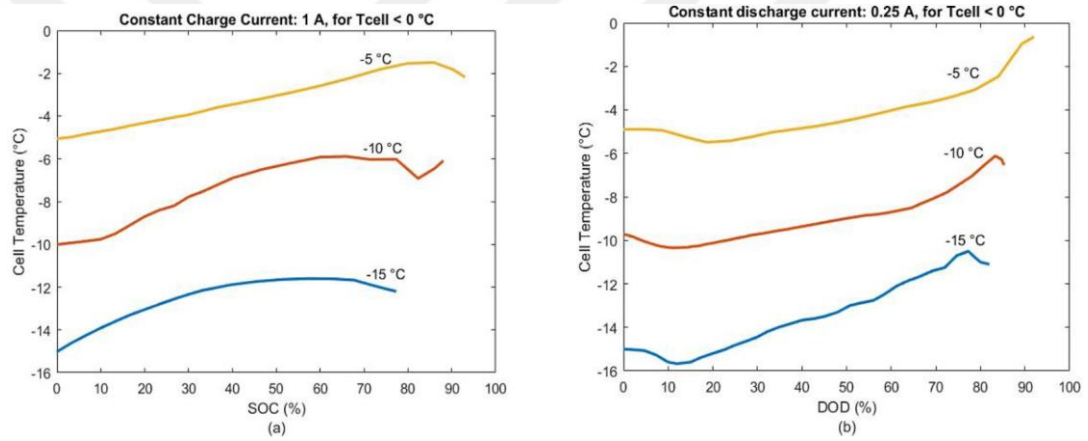


Figure 26. The effect of temperature on a Li-ion cell SOC and DOD when (a) charging, (b) discharging at low temperatures [49].

The decrease in the usable energy limits the available range of the electric vehicle. Shidore and Bohn (2008) studied how the range of Plug-in Hybrid Vehicle (PHEV) changes with respect to temperature and results are presented in Table 4. All Electric Range (AER) decreases about 13% at -7 °C without any AC load because PHEV can supply 5.5 kWh energy at -7 °C while it can supply 6.2 kWh at 20 °C[50].

Table 4. Decrease in the range with decrease in temperature [50].

Initial Battery Temperature	All Electric range from 90% to 30% SOC on the UDDS	% drop in AER
20 degrees C	17.4 miles	0
0 degrees C	15.7	9%
-7 degrees C	15.0	13%

One of the reasons for Li-ions batteries having a poor performance at lower temperatures is at the electrolyte conductivity decreases at lower temperatures as presented in Figure 27. Another reason is slow Li diffusion through the surface layers and through the bulk of active material particles[46] One of the other reasons is the kinetic movement of the charged particles slows down at the lower temperatures which decreases the performance of the Li-ion battery again.

Moreover, the internal resistances inside the Li-ion battery pack increases at the lower temperatures. The basic relation between the voltage resistance and current is represented in Equation (1).

$$V = I \times R \quad (1)$$

Moreover, heat loss due to internal resistance is calculated by using Equation (2).

$$P = I^2 \times R \quad (2)$$

As abovementioned, there is a maximum allowable voltage value for the batteries to protect the battery health. Based on Equation (1), for any constant voltage value, higher resistance in the circuitry leads to decrease in the current. This will affect the total time required for battery to be charged fully. Also, electrical power dissipates as heat through the resistances so internal resistances increases the total loss through the battery.

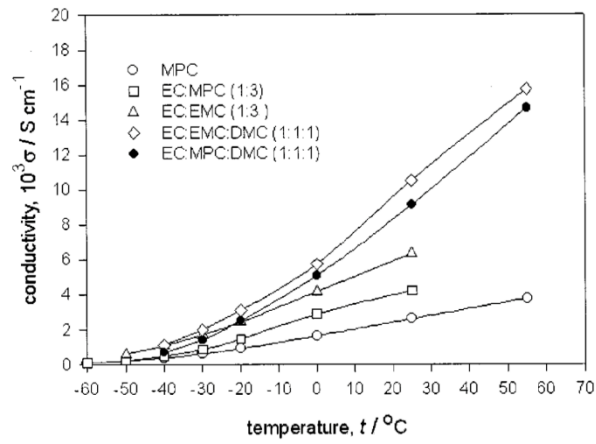


Figure 27. Conductivities of 1 mol/dm³ LiPF₆ electrolyte solutions as a function of temperature [48].

Figure 4 represents the resistances inside the Li-ion battery of a typical EV. As presented in Figure 28, the pack resistance inside the battery at -30 °C is almost 8-10 times higher than the resistance at 30 °C. Furthermore, at low temperatures Li ions diffuse graphite while normally they should diffuse in the electrolyte. An additional problem is that low-temperature operations of Li-ion cells cause irreversible capacity lost [46].

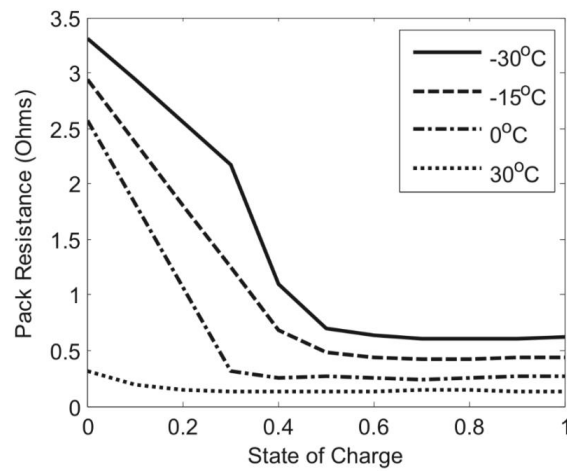


Figure 28. Battery Resistance as a function of temperature and state of charge (SoC) [51].

Shidore and Bohn (2008) also studied the resistance losses for the battery of a PHEV at different temperatures and results are presented in

Table 5. It can be clearly seen that decrease in the temperature substantially increases the resistance losses [50].

Table 5. Resistance losses for various temperatures [50].

	Resistance losses at 20°C = 279 Wh
Resistance losses for the 0°C initial temp case: 320 Wh	$\Delta I^2 R t$ between 20°C and 0°C 320 - 279 = 41 Wh
Resistance losses for the -7°C initial temp case: 364 Wh	$\Delta I^2 R t$ between 20°C and -7°C 364 - 279 = 85 Wh

Performance decrease of the Li-ion batteries at low temperatures are discussed. Batteries are one of the key components of the EV. They play a significant role in EVs performance measures such as the maximum range, power. Therefore, effects of the temperatures should be considered while performance calculations for EVs are being done.

Air conditioning (AC) and heating load should be also considered for EVs. In addition to the negative effect of low temperatures on performance of the Li-ion battery, ambient temperature conditions cause the extra auxiliary load which is HVAC load. Air-conditioning system is one of the important components of an automobile not only because it is responsible for thermal comfort but also it is required for safety. The primary duty of HVAC system is maintaining cabin temperature and humidity level within comfort level. On the other hand, it provides recirculation in order to keep CO₂ level inside the cabin within safe region. It is also used to defog the windshield of a car to keep the vision of driver clean [52].

Auxiliary loads are also depending on the ambient conditions. Figure 29 represents the auxiliary load of Nissan Leaf with respect to temperature. It is apparent from this

figure that the auxiliary load is higher at lower temperatures and minimum at the temperatures between 60-75 °F (15-24°C). These results are not a coincidence because at mild temperatures the HVAC system is not needed. Figure 29 also proves that substantial amount of auxiliary demand is from HVAC and the driver preferences play an important role in the size of the auxiliary load.

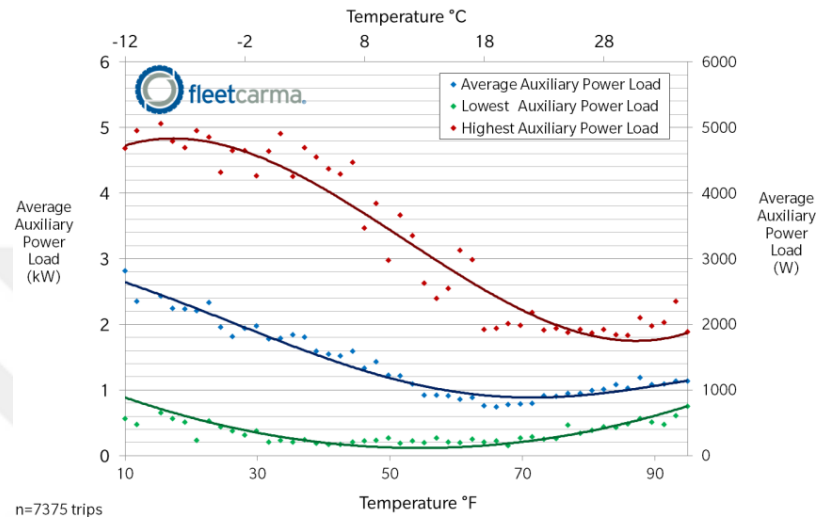


Figure 29. Change in the auxiliary load of Nissan Leaf with temperature [54].

AC system for a compact size EV with a coefficient of performance of 2.33 can consume power up to 3 kW. This means, if AC is operated in the maximum performance it can consume 3 kWh of energy within an hour. Table 6 shows the impact of these AC systems at various power level on the range including driving cycle effects.

The maximum AC load can decrease the maximum range in FUDS (simulates urban driving) about 36%. In addition, a steady-state AC operation that is assumed to consume total auxiliary power of 1500W might decrease range about 16%. As in the previous paragraph, driver preferences affect the size of the auxiliary demand. If driver prefers to operate AC at low load instead of maximum load, he/she can get extra 40 miles.

Table 6. AC simulation results [55].

	500 W	1500 W		2500 W		3500 W	
	Range km (mi)	Range km (mi)	Change from 500 W Case	Range km (mi)	Change from 500 W Case	Range km (mi)	Change from 500 W Case
FUDS	175.9 (109.3)	147.7 (91.8)	-16%	125.5 (78.0)	-29%	108.9 (67.7)	-38%
HWFET	183.6 (114.1)	167.5 (104.1)	-9%	154.0 (95.7)	-16%	142.1 (88.3)	-23%
US06	116.0 (72.1)	107.6 (66.9)	-7%	102.5 (63.7)	-12%	95.3 (59.2)	-18%
SC03	174.3 (108.3)	146.9 (91.3)	-16%	126.8 (78.8)	-27%	111.2 (69.1)	-36%

Mebarki et al. (2013) also investigated the effects of AC load on the power consumption of EV. In the study, several ambient conditions which are presented in Table 7 are assumed and how the power consumption of the vehicle changes in order to keep cabin temperature at 24 °C is investigated [56].

Table 7. Different Climatic Conditions [56].

Phases	Time (s)	Temperature (°C)
Phase 1	0–2	24
Phase 2	2–4	28
Phase 3	4–6	32
Phase 4	6–8	36
Phase 5	8–10	40
Phase 6	10–12	24

Figure 30 represents the battery power consumption simulation results in MATLAB for different AC loads with ambient conditions and without AC load respectively. As can be seen from the figures, as the difference between ambient temperature and desired cabin temperature increases, the consumed battery power increases as well. All these AC loads are assumed to steady-state AC load. The power consumption at 5th phase is about 10% more than the case without AC, which will decrease the maximum range about 10%. The study concludes that the AC load decreases

maximum range of an EV and these auxiliary loads have to be decreased in order to extend the range [56].

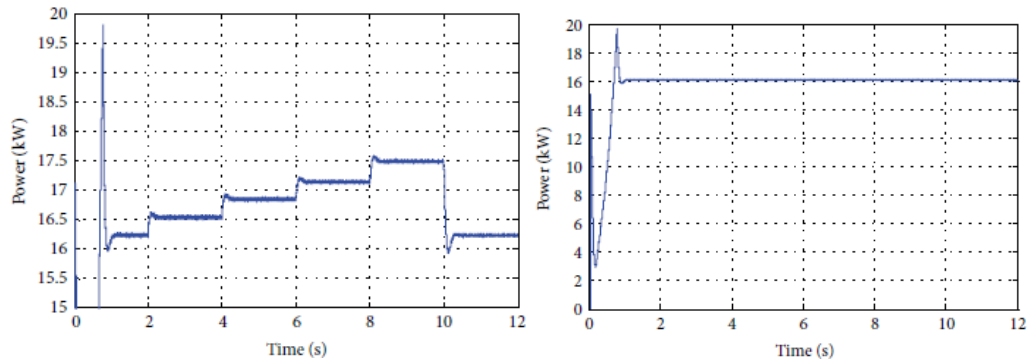


Figure 30. Evolution of Li-Ion battery power for the electric vehicle (a) AC load with different conditions, (b) without AC load [56].

The above MATLAB simulations investigate cooling need inside the cabin for the cases which ambient temperature is higher than the desired cabin temperature. In internal combustion engine, the thermal management of the cabin requires less power when heating of the cabin is required. The waste heat from the engine is used to heat up the cabin. On the other hand, there is not enough waste heat to heat up the environment. Therefore, external heater unit should be used in EV which will put on extra demand on battery on cold days. Argonne Laboratories tests some EV on dynamometer to simulate some conditions including different ambient conditions. represents test results for Ford Focus EV under different climatic conditions, AC loads and drive cycles.

The effects of ambient temperature can be seen easily from . The Focus EV has its maximum range of 112.5 miles at 95°F (35 °C) without any AC load while it has a minimum range of 41 miles at 20°F (-7 °C) with maximum AC load(heating) for UDDS drive cycle. Also, the range of Focus EV for UDDS at 95°F (35 °C) without AC can decrease about 50% if maximum AC load is assumed. Moreover, the range at

20°F (-7 °C) without heating is 100.7 miles while it is 41 miles at with maximum heating load. Thus, heating load decreases range up to 60%. The decrease in range is more than the 95°F, because at lower temperatures performance of Li-ion battery decreases as well which was mentioned before.

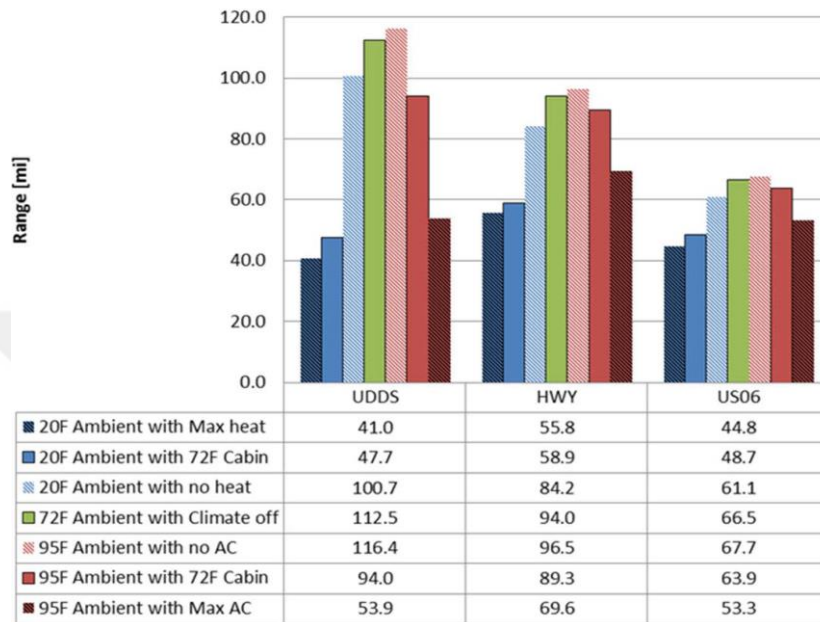


Figure 31. Electric Range of a Ford Focus EDV for various ambient conditions, AC loads, driving cycles [57].

Like any other cars in the traffic EVs should also have some auxiliary devices to obey the standards. The auxiliary devices are such as lights, horn, cabin heating system (defogging) [52].

Moreover, in a brand-new car, there are some luxury devices like power steering, brake assist, heated seats, air conditioning, etc. All of these auxiliary loads are powered by the battery in the EV so they consume the energy which supposed to be used to move the vehicle. Higher the auxiliary load, less range might be achieved. Table 8 represents one of the auxiliary load which is light system in a typical vehicle with their energy consumptions [53].

Table 8. Characteristics of Light System [53].

Light Type	Power of the single lamp, W	Number of lamps	Peak Power, W	Working Time and Conditions
Headlamps	60	2	120	All time, as a daylights
Braking	21	3	63	During Braking
Turning	21	6	126	During turning manoeuvres
Anti-fog Lamps	35	3	105	During fog conditions
Reversing	21	2	42	During Reversing Manoeuvres
Number Plate	5	4	20	All the time
Cabin Lights	20	1	20	All the time
Total:			496	

The energy consumption of light system generally omitted because it is very small compared to other auxiliary systems. For example, if four of the turning signals in a vehicle are assumed to operate 50 seconds per day 0.583 Wh energy is consumed per day and 5.1 kWh energy would be consumed from battery annually. These numbers can be even decreased up to 75% if the bulbs are switched to LED [52].

The effect of temperature is explained in the previous paragraphs. Since the temperature depends on the locations and seasons, the performance of the EV also depends on the locations and seasons. There are several studies which investigate how the performance of an EV changes with location. Neubauer&Wood researched on 3 different locations which are Phoenix, Los Angeles and Minneapolis in USA. These cities are selected to represent the cold, mild and hot ambient temperature conditions. Figure 32 shows the temperature distributions of the selected cities and power consumption of Tesla Model S 60 with/without AC load on these cities. Also, figure includes the comparison of two different HVAC technologies PTC heater and Heat Pump (HP) system. Maximum power consumption is seen in Minneapolis regardless of AC load. It is because of the fact that ambient temperature decreases to below zero which increases resistance losses and AC load. On the other side, in Los Angeles as a representation of mild climate, the power consumption is minimum. One of the reasons is that the annual temperature distribution fluctuates around 20°C and does not drop below zero and increases to high temperatures neither. This minimizes both

internal resistance losses and AC loads. Lastly in the Phoenix, the power consumption is slightly higher than Los Angeles (LA) case because the annual temperatures can be as high as 40°C which results in higher AC loads than LA. Also, the high temperature requires battery thermal management (BTM) which puts extra power demand on battery. In addition, the use of Heat Pump instead of PTC provides considerably less power consumption [51].

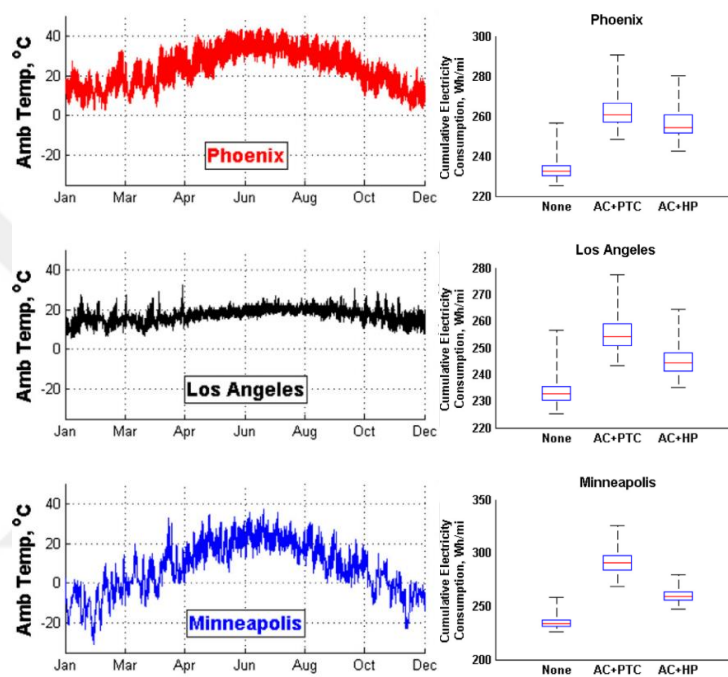


Figure 32. Annual temperature distributions of 3 cities and the effect of climate and cabin HVAC on utility and electricity consumption (Wh/mi) of Tesla Model S 60 [51].

Kambly&Bradley (2015) study show the maximum range of EV car with 24 kWh battery changes for the Phoenix and Los Angeles within the year. Figure 33 illustrates the results of study. Closer inspection of figures shows that range decreases at the mid-day driving because the ambient temperature and solar insolation are higher at the mid-day. The reduction in range is less pronounced in the remaining parts of the day. Furthermore, range reduction is more pronounced in the Phoenix compared to Los Angeles. It is a similar trend as in the case of Tesla Model S explained in the previous

paragraph. It proves that regardless of the model of EV, the temperature effects the power consumption, i.e., the maximum range in the same way.

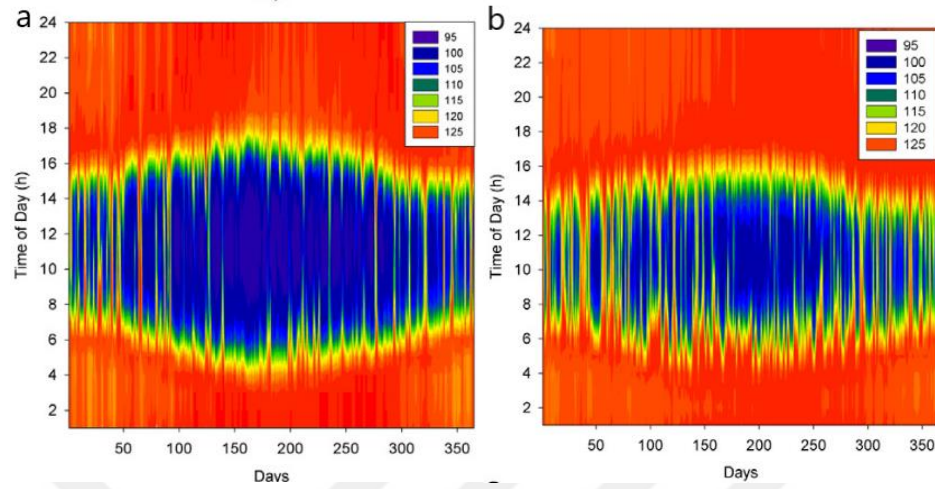


Figure 33. The effect of geographically-realized climatic and environmental conditions on EV range for (a) Phoenix, (b) Los Angeles [58].

Yuksel and Michalek (2015) studied the effects of temperature, region and grid mix on the range of Nissan Leaf and CO₂ emission across the USA. Their findings are represented in Figure 34. It is apparent from Figure 34a that the median range varies with the cities because the average ambient temperatures also vary. For the hot climates like Phoenix, where the daily average temperature reaches up to 40 °C, the median range value of 69 miles can decrease to 49 miles at hot days. On the other hand, in the cold climates like Rochester, the range can decrease about 36% of the median value. From the blue box data, it is apparent that the range of Nissan Leaf has least variation in San Francisco which is mainly resulted by even temperature distribution within the year. Additionally, the map in Figure 34b shows average power consumption of Nissan Leaf for different locations. The power consumption can differ about 15% based on the location again due to temperature variations. In the states where the climate is mild the power consumption is less which results higher range for the electric vehicles [59].

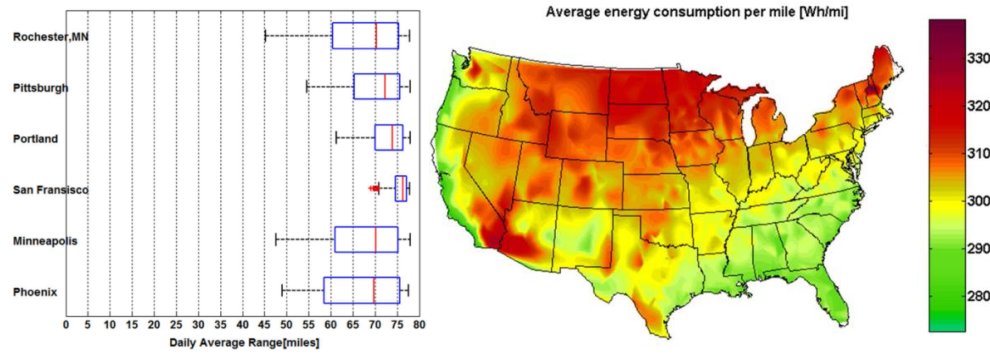


Figure 34. (a) Daily driving range distributions for selected cities [59], (b) Energy consumption per mile averaged across the fleet over a full year (Wh/mi) [59].

2.6.2 Effects of Drive Cycle on EV Performance

Correct estimation of fuel/energy consumption of vehicles is crucial [61]. The estimations might be done by assuming the engine works at average conditions based on real-life traffic data. However, the results will not be accurate because the real-life driving conditions include fluctuations, several stops, several aggressive accelerations, etc. The emissions, as well as fuel consumptions, depend on vehicle parameters like type, model, mass, fuel type and operational parameters like acceleration, distance, speed, etc. One of the ways to determine required information for vehicles is direct measurement. However, it is impractical considering there are numerous vehicle models and drive patterns. It is estimated that the direct emission test for a vehicle costs about 10,000 GBP [62]. Therefore, there should be a cost-effective alternative to estimate the fuel consumption and emissions of the vehicles. One cost-effective way is developing a driving pattern to represent the driving characteristics of a vehicle on the road [60]. These established patterns are called drive cycles. Drive cycle enables emission and fuel economy test under reproducible conditions. They are classified based on which drive pattern they are representing like city, highway driving patterns. To test light vehicles chassis dynamometers are used.

The wheels of the car positioned such a way that they are contacting with the roller of dynamometer. The dynamometer simulates the real-life resistance due to friction and aerodynamics of the vehicle [63].

The drive cycles are grouped in two, steady-state and transient drive cycles. The steady-states drive cycles are generally used for testing of heavy vehicles like trucks, marine engines, etc. On the other hand, transient drive cycles are used for light vehicle simulations because light vehicles used under different transient conditions like urban driving. Figure 35 shows the New European Drive Cycle (NEDC) which is specifically designed for light vehicles in Europe. It can be seen from the figure that drive cycle includes both urban and highway drive conditions. However, since NEDC is not created based on real-life traffic data, this drive cycle might underestimate the real driving conditions. On the other hand, Figure 36 shows a drive cycle which is generated based on real-life traffic data. Close inspection of the figure shows, even the speed humps are simulated in the drive cycles so the drive cycle is more realistic [63].

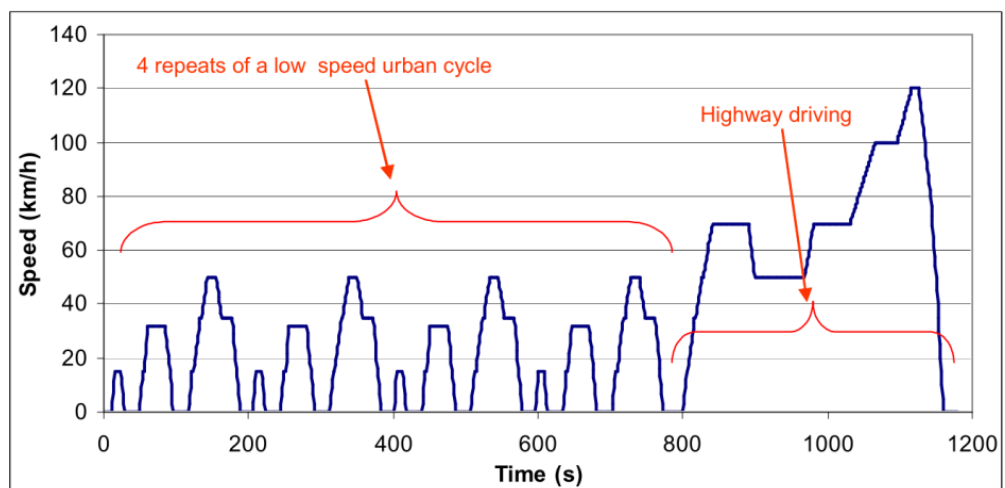


Figure 35. New European Drive Cycle (NEDC) [63].

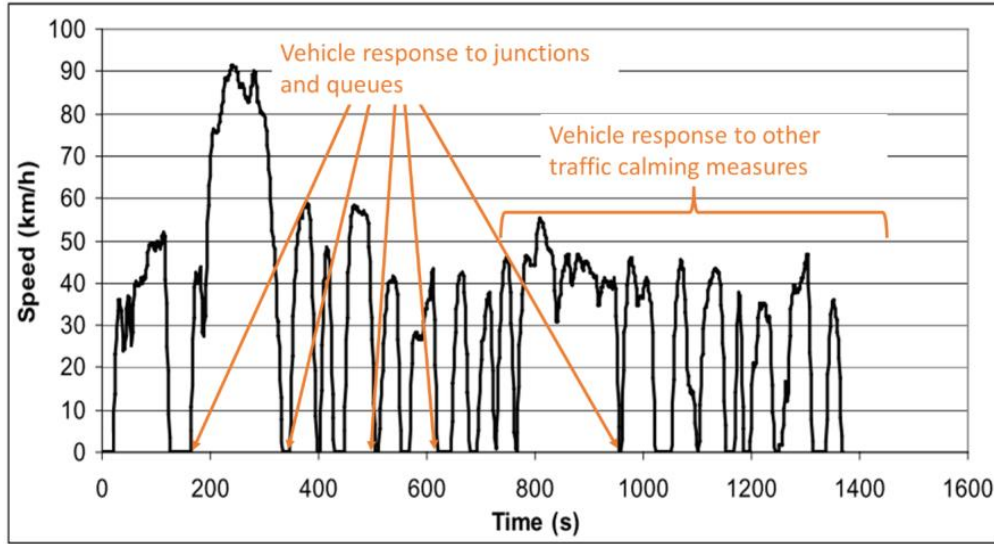


Figure 36. “Urban Dynamometer Driving Schedule (UDDS)” drive cycle as an example of a realistic cycle [63].

A required power on the wheels for the vehicle to travel at specified state is called tractive efforts. Tractive effort on the wheels can be calculated by using Equation (3).

$$P_{wheels} = \left(ma(t) + mg \cdot \cos(\theta) \cdot \frac{C_r}{1000} (c_1 v(t) + c_2) + \frac{1}{2} \rho_{air} A_f C_D v^2(t) + mg \cdot \sin(\theta) \right) \cdot v(t) \quad [64](3)$$

Equation (3) clearly demonstrates that the power consumption of an EV strongly depends on driver aggression and travel speeds. Figure 37 represents the available range of Nissan Leaf for different scenarios with respect the travel speed. As the travel speed increases, range decreases i.e., energy consumption increases. Also, additional mass on the vehicle or headwind toward vehicle leads to decrease in range because they increase the tractive effort. On the other hands, Figure 37 represents the power consumption of electric vehicle for different driving aggressions and trip speeds. It is apparent from this figure that, higher driver aggression results in higher energy consumption for electric vehicles. It is because of the fact that higher driver aggressions demand higher accelerations which increases the tractive effort.

Moreover, as the trip speed increases the power consumption increases as in the case of Figure 37.

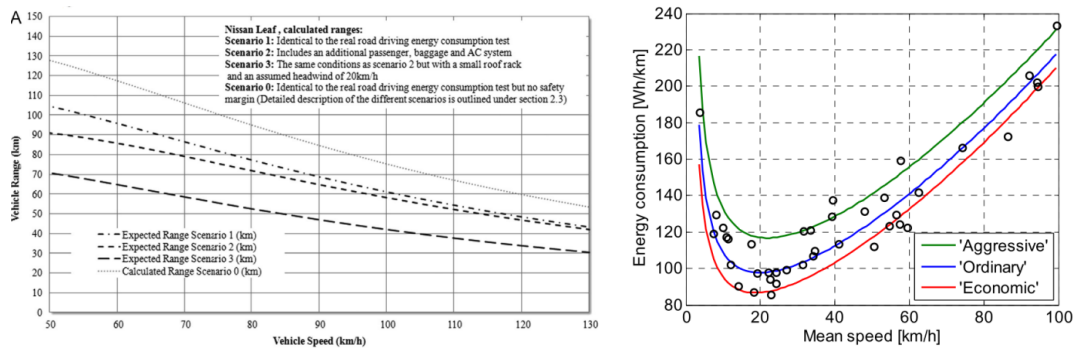


Figure 37. Variation of vehicle range (a) with respect to vehicle speed [65], (b) with respect to vehicle speed and aggression [59].

The energy consumption i.e. range of EV varies by different driving conditions. On the other hand, drive cycles are created for simulating the different driving conditions. Therefore, it is logical to expect that the energy consumption of vehicle varies by the drive cycle. Figure 38a shows a great example of how the range of an EV varies by drive cycle. In addition, Figure 38b represents the comparison of drive cycles in terms of average acceleration, speed and stop frequency. The range differs by drive cycle due to the fact that every drive cycle has different acceleration, deceleration and travel speed pattern as stated before. The range is minimum in the New York city driving cycle (NYCC) because stop frequency is higher. Stop frequency will directly increase the tractive effort for acceleration. On the contrary, the range is maximum for highway drive cycle (HWFET) mainly because of the fact that the average acceleration is lowest among the other cycles which minimize the tractive efforts for accelerations. Although HWFET and Los Angeles drive cycle (LA92) has similar average speeds, the maximum range decreases from 170 miles to 110 since average acceleration in LA92 is higher.

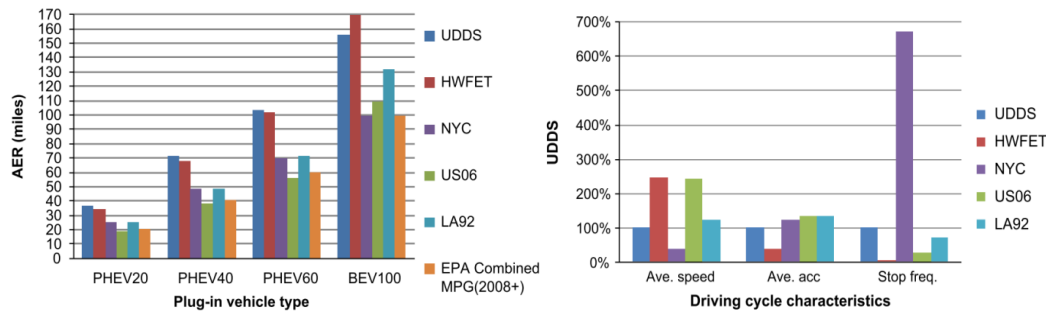


Figure 38. (a) All electric ranges(AER) under different drive cycles [61], (b) Comparison of driving cycle characteristics [54].

Driving aggression in any drive cycle is also an important factor which affects the energy consumption as well. In other words, the combined effects of both driving cycle and driving aggressions should be taken into consideration. Figure 39 represents the energy consumption of an EV for different drive cycles and different average speeds. In the figure, energy consumption varies by average speed for a specific drive cycle. Different average speeds for a specific drive cycle refer to different driving aggressions. For example, higher average speed refers to higher driving aggression. It is apparent from this figure that; higher aggression increases energy consumption. For instance, in Artemis Urban drive cycle, 2 km/h change in average speed increases the energy consumption about 40 kWh. It clearly proves that energy consumption in urban drive cycles is sensitive to driver aggression.

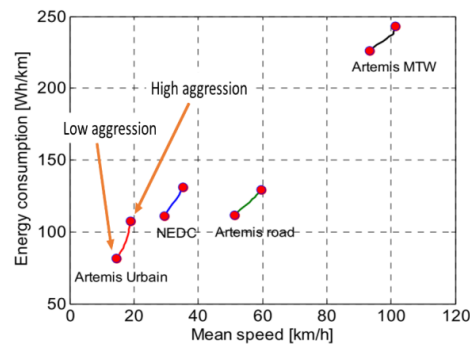


Figure 39. Effects of driver aggression on energy consumption for different drive cycles [66].

CHAPTER 3. THEORY AND METHODOLOGY

In this section, the applied methodology in the study is introduced. The related theory is also presented. Firstly, the general model is presented. The general model is divided into two subsections. These are PV output and electric vehicle energy demand estimations. Methodology for economic analysis is also included in this chapter.

3.1 General Methodology for the Analysis

In this section, a generic model for energy generation from PV covered parking lot system and energy demand for electrical cars is established. Model is composed of two main sections: energy generation and energy demand. First, the location of the PVEV system is decided. Each location has its own unique solar resource, temperature profile, driving conditions and Vehicle Miles Travelled (VMT) data. These are used for estimating both energy demand and energy generation of the PVEV system. Solar resource data enables to estimate the yearly energy generation from PV plant. On the other hand, deciding on the electrical vehicle type (brand, model, etc.), daily mileage and driving conditions are required to estimate the demand side because the energy consumption of an EV highly depends on these parameters. Based on these parameters, the energy consumption of an EV is estimated. After that, the energy demand of the fleet is found by combining this with the VMT data and ambient temperature. After estimating the energy demand and energy generation, energy balance analysis is done. The demand and generation of energy are compared to the output parameters. Figure 40 represents the framework for the analysis. The main aim is to develop this generic model and to apply this developed model into different cities. The model is created by using Matlab software. A diagram showing the framework of the analysis is given in Figure 40.

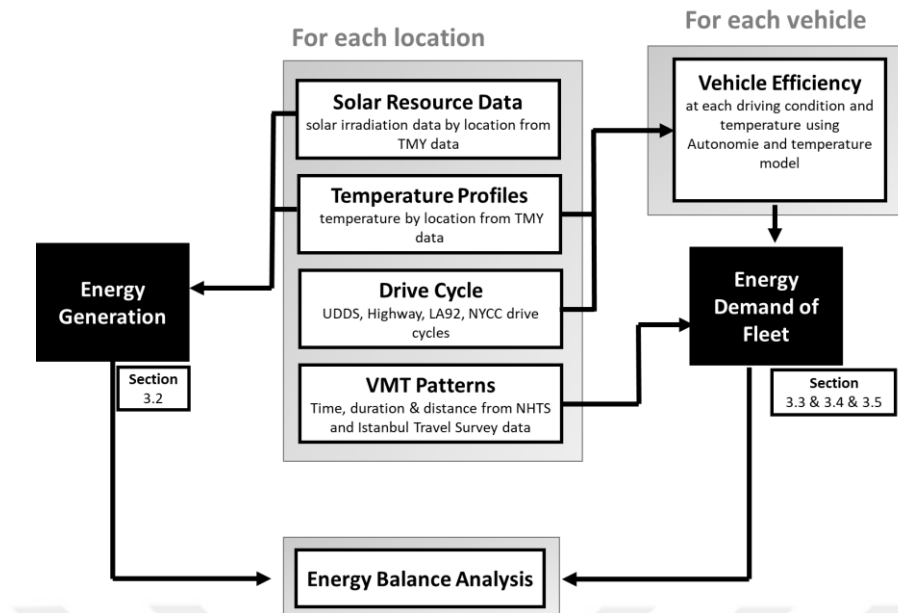


Figure 40. Framework for the analysis

3.2 Estimation of Solar Energy Generation

Electric vehicles require electric energy. In this study, the aim is to cover this demand by electricity produced by PV systems. Therefore, the correct estimation of the available solar energy is crucial. In this section, methodology to estimate solar energy potential is discussed.

3.2.1 Components of Solar Radiation

The electromagnetic radiation that is emitted by the sun is called solar radiation. The incoming solar radiation from the sun travels through several layers of the atmosphere. The different molecules on the atmosphere like carbon dioxide, water vapor and ozone absorb some radiation with certain wavelengths. Also, some portion of the radiation is scattered as it hits these molecules or dust. Some portion of the radiation is reflected back to space as it hits the clouds. The rest reaches the atmosphere without any change. Thus, the solar radiation is divided into three different components; scattered (diffuse), reflected and direct (beam) radiation. Figure 41 shows these components of the solar irradiation.

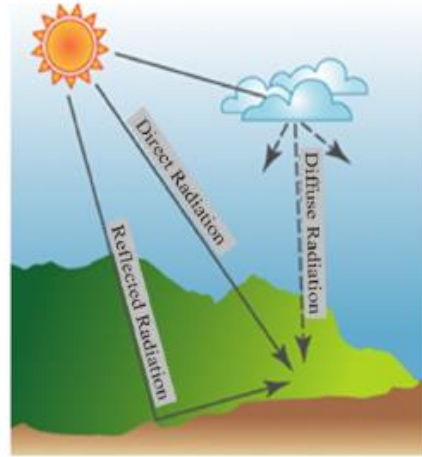


Figure 41. Components of solar irradiation [67].

Direct (beam) radiation is the part of the radiation which reaches the earth surface without any change of direction. It is denoted by letter B . The diffuse part of the radiation is scattered by the atmosphere, so it does not directly come from the direction of the sun. It is denoted by D . Finally, the reflected radiation is denoted by R . The total radiation which hits the earth surface will be a summation of these three components and called global radiation (G). The global radiation is presented as,

$$G = B + D + R \quad (4)$$

Solar irradiance is defined as the radiant power of the sun per unit area. Its unit is generally W/m^2 . The solar irradiance on the outer atmosphere is called solar constant and the magnitude is 1366 W/m^2 [68]. On the other hand, solar irradiation is solar energy intensity per unit area and its unit is Wh/m^2 .

There is a geometric relation between the solar irradiation on the arbitrarily positioned plane surface and solar insolation, so the position of sun relative to arbitrarily positioned plane surface can be related by several angles. These angles are **latitude** (ϕ), **declination** (δ), **tilt** (β), **surface azimuth** (γ), **solar azimuth** (γ_s), **hour** (ω), **zenith** (θ_z) angles and **angle of incidence** (θ). Figure 42 shows some of these angles.

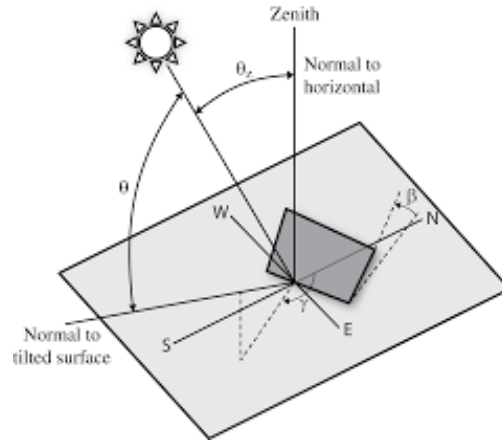


Figure 42. Geometric relation between sun and arbitrary plane [69].

The calculation will be done by using the set of equations based on Duffie & Beckman (2013).

Declination angle (δ) is defined as “angular position of the sun at solar noon”. It can be found using Equation (5).

$$\delta = 23.45 \sin \left(360 \frac{284 + n}{365} \right) \quad (5)$$

where n is an integer which represents the day of the year (1-365). The declination angle varies between $-23.45 \leq \delta \leq 23.45$ within a year.

As previously mentioned, geometric relations depend on time. Solar time is used instead of local time in these calculations. Solar time is a representation of time in terms of movement of the sun. Solar time is 12:00 when the sun is at its highest altitude with respect to the ground plane at a given day. The duration between sunset and solar noon is the same as the time between sunrise and solar noon. Most of the times, local time differs from solar time due to eccentricity of the world's axis with respect to its orbital plane and other effects (daylight saving time). Solar time is calculated using Equation (6).

$$t_s = t_{std} + 4(L_{std} - L_{loc}) + E \quad (6)$$

where t_s is solar time, t_{std} is standard time, L_{st} is the longitude for local time zone, L_{loc} is the longitude for the exact location, and E is the equation of time. E can be calculated by Equation (7).

$$E = 229.2(0.000075 + 0.001868 \cos B - 0.032077 \sin B - 0.014615 \cos 2B - 0.04089 \sin 2B) \quad (7)$$

where B , L_{st} and L_{loc} can be calculated by using Equations (7.1), (7.2) and (7.3), respectively.

$$B = (n - 1) \frac{360}{365} \quad (7.1)$$

$$L_{loc} = \begin{cases} L_{loc} & \text{if location is in West} \\ 360^\circ - L_{loc} & \text{if location is in East} \end{cases} \quad (7.2)$$

$$L_{std} = \begin{cases} 360^\circ - \text{time zone} * 15^\circ & \text{if location is in East} \\ \text{time zone} * (-15)^\circ & \text{if location is in West} \end{cases} \quad (7.3)$$

Hour angle is another geometric relation. It converts solar time into an angle. Hour angle (ω) is less than zero in the morning, equal to zero in the solar noon and greater than zero in the afternoon. Equation of hour angle is presented in Equation (8).

$$\omega = (t_s - 12) * 15^\circ \quad (8)$$

Solar zenith angle (θ_z) is the angle between beam radiation and horizontal normal. It is complimentary with solar altitude angle (α_s). Solar altitude angle is zero when the sun rises. Sum of the zenith angle and altitude angle is 90 degrees. Zenith angle (θ_z) is calculated using Equation (9).

$$\cos \theta_z = \cos \varphi \cos \delta \cos \omega + \sin \varphi \sin \delta \quad (9)$$

Both surface azimuth (γ) and tilt angle (β) are used to describe the orientation of the arbitrary plane surface. Tilt angle is the angle between the tilted surface and horizontal. On the other hand, the surface azimuth angle is the angle between the south direction and surface normal of the plate projected on the horizontal plane.

Solar azimuth angle (γ_s) is the angle between the south and the projection of beam radiation on the horizontal surface. It is less than zero in the morning, equal to zero at the solar noon and greater than zero in the afternoon. In other words, if projection of beam radiation on horizontal surface is on east side the solar azimuth angle is negative (morning). If it is on west side, the angle is positive (afternoon). It can be calculated by Equation (10).

$$\gamma_s = \text{sign}(\omega) * |\cos^{-1}(\gamma'_s)| \quad (10)$$

where (γ'_s) can be calculated by Equation (10.1).

$$\gamma'_s = \frac{\cos(\theta_z) \sin(\varphi) - \sin(\delta)}{\sin(\theta_z) \cos(\varphi)} \quad (10.1)$$

Lastly, the angle of incidence (θ) is an angle between the beam radiation and the surface normal. When θ is zero, sunlight hit the surface perpendicularly, i.e., the angle between surface normal and the sunlight is zero. The angle of incidence strongly depends on the tilt angle (β) and the surface azimuth angle (γ). Therefore, these angles are the parameters that should be arranged such a way that angle of incident is minimum to maximize the incident solar radiation on a surface. The formula of the angle of incident is provided in Equation (11).

$$\cos(\theta) = \cos(\theta_z) \cos(\beta) + \sin(\theta_z) \sin(\beta) \cos(\gamma_s - \gamma) \quad (11)$$

The solar irradiation that hits on an arbitrary plane can be found by using the geometric relations explained above if the solar data for a specific location are available. There are various forms of solar data. It might be composed of instantaneous measurements (irradiance) or integrated over for a specific period (irradiation) like an hour. Generally, solar data include direct and diffuse radiation terms for a horizontal surface. Some solar data sets are obtained statistically to represent typical weather conditions for a specific location over a specific period like 30 years. These datasets are called Typical Meteorological Year (TMY), and they typically include hourly values of

direct ($I_{b,n}$), also called Direct Normal Irradiation (DNI), diffuse (I_d) and global horizontal irradiation (I) on horizontal surface, ambient temperature (T_{amb}), wind speed, relative humidity, etc. TMY data can be used to estimate the long-term performance of solar energy systems, such as PV systems [68]. In this study, TMY is used to conduct performance analysis of PV systems. However, it includes irradiance data on horizontal surface, so irradiance on inclined plane should be estimated by some geometric relations. Total irradiance on tilted surface is represented by Equation (12).

$$G_c = I_c + D_c + D_g \quad (12)$$

where G_c is global tilted irradiance (GTI) that is the sum of direct irradiance (I_c), diffuse irradiance (D_c) and ground reflected (D_g) irradiance on the tilted plane. Please note that D_g is neglected in this study because it is very small compared to the other components of the tilted irradiance. While direct irradiance on tilted plane (I_c) can be deterministically calculated by Equation (13) [70], there are several transposition models in the literature to estimate the diffuse irradiance (D_c) on inclined surface. One of the most popular transposition models is represented in Equation (14)[70].

$$I_c = I_{b,n} \cos(\theta) \quad (13)$$

where $I_{b,n}$ is Direct Normal Irradiance (DNI), and θ is the angle of incidence.

$$D_c = D_h \left(\frac{1 + \cos(\beta)}{2} \right) \quad (14)$$

where D_h and β are diffuse horizontal irradiance (DHI) and tilt angle of the inclined plane, respectively.

Global tilted irradiance (G_c) on a tilted plane can be estimated by using TMY data and the relations explained above. In the next section, the fraction of this incident solar radiation (G_c) that is converted into electrical energy (E_{gen}) by PV systems is discussed.

3.2.2 Estimation of PV System Output

PV modules convert part of the incident solar irradiance that hits on the module surface into electrical power. There are several types of PV modules with different efficiencies but the most commercial ones are mono- and poly-silica ones. Like all the power generation systems, PV panels have also efficiency. A cell efficiency can be described by Equation (15).

$$\eta_{pv} = \frac{\text{Maximum power}}{G_c} \quad (15)$$

This efficiency highly depends on the temperature of the PV module which strongly depends on ambient conditions, like temperature, wind, velocity and solar irradiation, efficiency of the panel also depending on these parameters. Higher cell temperatures result in lower efficiency values. The cell temperature can be estimated by Equation (16).

$$T_{cell} = T_{amb} + (NOCT - T_{ref}) \frac{G_c}{G_{c,ref}} \quad (16)$$

where the $NOCT, T_{ref}, G_{c,ref}, \eta_{pv,ref}, \beta_{ref}$ and A are given parameters by the PV module manufacturer.

The relation between the cell temperature and efficiency can be calculated by using Equation (17).

$$\eta_{pv} = \eta_{pv,ref} [1 - \beta_{ref}(T_{cell} - T_{stc})] \quad (17)$$

where η_{pv} is the module efficiency at T_{cell} . After finding the module efficiency (η_{pv}), the energy generation from the PV system (E_{gen}) can be calculated by Equation (18).

$$E_{gen} = G_c \eta_{pv} A_{pv} N_{pv} \quad (18)$$

where A_{pv} and N_{pv} is the area and number of the modules used in the PV system, respectively.

For this study, energy generation is predicted for AXITEC AC-250P/156-60S type PV modules. This module is selected as it is the one used in the PV power plant at METU NCC. PV module manufacturers provide a reference efficiency under some specified condition. This module has a reference efficiency of 15.37% under the insolation of 1000 W/m^2 , air mass of 1.5 and cell temperature of $25 \text{ }^\circ\text{C}$ [71]. Table 9 presents the values of the module used in this study.

Table 9. PV module specifications given by manufacturer [71].

A_{pv}	$NOCT$	T_{ref}	$G_{c,ref}$	$\eta_{pv,ref}$	β_{ref}	T_{stc}
$1.63 \text{ (m}^2\text{)}$	$45 \text{ (}^\circ\text{C)}$	$20 \text{ (}^\circ\text{C)}$	$800 \left(\frac{\text{W}}{\text{m}^2}\right)$	15.37%	$0.004 \left(\frac{1}{\text{K}}\right)$	$25 \text{ (}^\circ\text{C)}$

3.2.3 Optimization of PV Module Orientation

The orientation of a fixed, i.e., no tracking, PV module is described by its tilt and azimuth angles, which highly affects the annual energy yield. Thus, the modules should be correctly oriented to maximize energy output. However, since the position of the sun changes within the day as well as within the year, the optimization is complicated. For instance, in summer, the solar radiation hits the Northern Hemisphere with smaller solar incident angles, so lower tilt angles provide better energy output. Generally, the orientation of a PV system is optimized to maximize the total annual energy output [72].

The energy yield of the PV system is calculated for every tilt angle so that the angle maximizes the energy output can be found. Figure 43 represents an example of annual energy output from 10 kW PV system in Netherlands for different tilt angles. It is clear that tilt angle of about 30 degrees maximizes the annual energy output. For every selected region similar pattern should be followed to have an optimized orientation of PV modules.

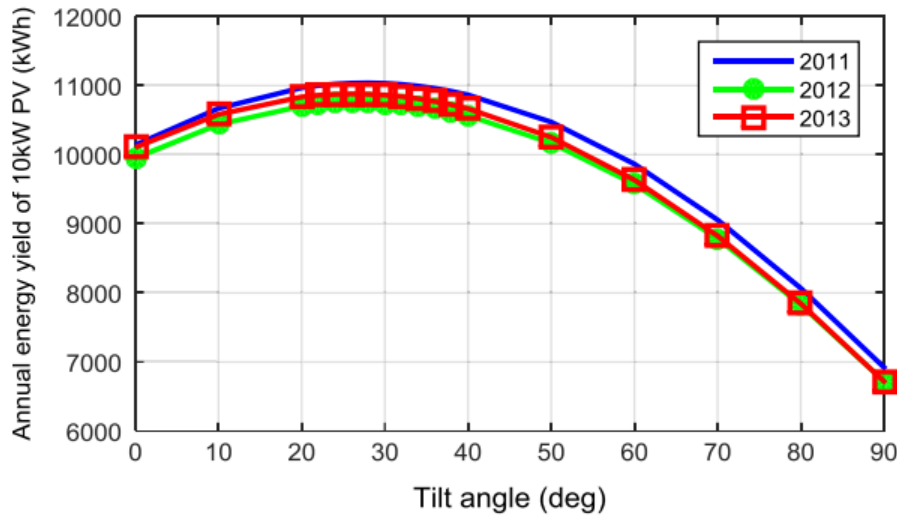


Figure 43. Energy yield from 10 kW PV for different tilt angles [42].

3.3 Estimation of EV Energy Demand

3.3.1 Models for Estimating Energy Consumption of Single EV

It is very crucial to estimate or measure the energy consumption of electric vehicle correctly. There are several methods available. These are energy consumption measurement of an EV on the real-life conditions by driving, chassis dynamometer measurement, estimation by using empirical tractive effort formula and use of simulation software. Real-Life Energy Consumption Measurement requires data collection systems to collect data regarding battery state-of-charge (SoC), voltage and current values as well as velocity, acceleration, etc. These data collection systems are required to be installed on the test vehicle so that the data collection can be operated while the vehicle is driven on the route [73]. Although it provides the most accurate results, it was not applied in this study, as it required several high-tech onboard data loggers as well as EVs. On the other hand, the physical model can be applied to all broad of vehicle and driving conditions with relatively lower accuracy.

In this study chassis dynamometer test results and simulation software are used to estimate the energy consumption of an EV.

3.3.1.1 Using Chassis Dynamometer Test Results

Chassis dynamometer testing method has been used for performance measurement of conventional vehicles. It is used to measure emissions, the fuel consumption of the vehicle on the simulated road conditions, etc. It is also applicable for EVs. It can be used to test components of the EV such as storage system, electrical motor, battery management system, regenerative braking system [74]. Apart from estimating the energy consumption of EV, chassis dynamometer tests can be also used for life cycle test for batteries, as batteries have limited serving duration.

There are several institutes which perform chassis dynamometer tests for electrical vehicles for different load and ambient conditions. For example, Argonne National Laboratory provides energy consumption data for several EV models. As an example, Figure 44 represents the energy consumption of Nissan Leaf under different load conditions (city driving, highway driving, different ambient temperatures, etc.). The accuracy of the data may be slightly lower than onboard measurement method but these data are highly utilized. As it is depicted in the figure, the EV was tested only for selected drive cycles [75]. In this thesis, Chassis Dynamometer Test results are used to estimate the energy consumption of single EV including temperature effect for generic drive cycles such as Highway, UDDS, etc.

Test ID (#)	Cycle	Cold start (CS) hot start (Hst)	Date	Test Cell Temp (F)	Test Cell RH (%)	Test Cell Batc (kWh)	Vehicle cooling fan speed: Speed Match (SM) or constant speed (CS)	Solar Lamp (W/m ²)	Vehicle Climate Control settings	Hood Position (Up) or (Closed)	Window Position (Closed) or (Down)	Cycle Distance (mi)	Cycle Fuel economy (mpg) (Full scale)	Cycle HV battery integrated net current (DC Ah)	Cycle HV battery Average Zero crossing Voltage (V)	Cycle HV battery Net Energy (DC Wh)	Cycle HV battery Net Energy Consumption (DC Wh/mi)
Test sequence purpose: Standard testing																	
61203025	UDDS CS	CSH	03/07/12	20	9.67	29.26	SM	Off	72 °F	Closed	Closed	7.44	-	8.332	379.191	3109	418
61203026	Highway	HSL	03/07/12	20	11.91	29.24	SM	Off	72 °F	Closed	Closed	10.25	-	9.275	374.008	3368	320
61203027	UDDS HS	HSL	03/07/12	20	12.73	29.23	SM	Off	72 °F	Closed	Closed	7.44	-	7.602	367.981	2750	371
61203028	US06	HSL	03/07/12	20	13.24	29.23	SM	Off	72 °F	Closed	Closed	7.99	-	9.821	359.965	3396	421
61203029	US06	HSL	03/07/12	20	13.64	29.22	SM	Off	72 °F	Closed	Closed	7.99	-	10.114	345.800	3344	419
61203030	*Partial UDDS HS	HSL	03/07/12	20	14.61	29.22	SM	Off	72 °F	Closed	Closed	4.63	-	5.439	305.200	1659	358

Figure 44. Example Results of Chassis Dynamometer Test for Nissan Leaf by Argonne National Laboratory [75].

3.3.1.2 Using a Simulation Software

There is several simulation software used to estimate the energy consumption of EVs. For example, ADVISOR (ADvanced VehIcle SimulatOR) is released by National Renewable Energy Laboratory to provide a modeling tool for assessment of the efficiency of vehicles like hybrids, EVs, etc. Several components of the subparts of the EVs, like batteries, power trains are modeled in the vehicle. By changing vehicle specifications, several vehicles can be simulated. In addition, different vehicles can be tested under different load condition easily without requiring expensive test benches. ADVISOR is based on Matlab software [76]. Recently a more powerful simulation software, called “Autonomie”, is provided by Argonne National Laboratory (ANL) in collaboration with General Motor (GM). It includes model of three main systems which affect the response of a vehicle. These are environment, driver and vehicle propulsion systems. Since it considers many vehicle parameters, it provides very accurate results.

Chassis Dynamometer Testing provide results for generic drive cycles. In this thesis, Autonomie is used to estimate the energy consumption of an EV for specific drive cycles like LA92, NYC which are not provided in the Chassis Dynamometer Testing.

3.3.2 Modeling the Effects of Temperature on Energy Consumption of an EV

The energy consumption of an EV is affected by ambient conditions, like temperature. One of the reasons is that the internal resistances in the circuitry and battery pack vary with temperature. As the ambient temperature drops, especially below 0°C, the internal resistances increase dramatically [49]. Another reason is that the need of cabin conditioning. If the ambient temperature is low, the need of heating the cabin exists. Since there is not any waste heat resource as in the case of an internal combustion

engine, the heating requirement is covered by the PTC heaters. PTC heaters consume energy directly from the battery [77]. On the other side, if the ambient temperature is high, the need of cooling the cabin exists which puts extra energy demand on battery again. Thus, correct modeling the sensitivity of energy efficiency of EVs respect to ambient temperature is crucial. Normally, the effect of temperature is modeled for several drive cycles by the Argonne National Laboratory. However, for the other drive cycles which are not included in the database of the Argonne National Laboratory, a proper model is required. In the literature, there are various studies which investigate the effects of ambient temperature on the energy consumption of EVs. Yuksel and Michalek (2006) provided well-established information about how the efficiency of the EV changes with respect to ambient temperature [59]. Figure 45 represents the results of the study. The minimum energy consumption occurs at an ambient temperature of 70 °F (20-22 °C) [59].

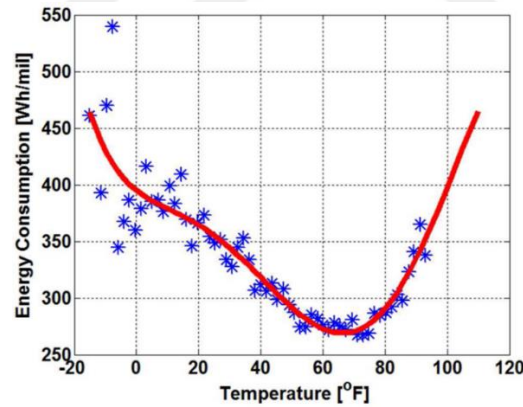


Figure 45. Nissan Leaf energy consumption per mile versus ambient temperature [59].

The effects of ambient temperature on the energy consumption of Nissan Leaf can be generalized for others EVs. In this study, it is assumed that temperature has the same effects on energy consumption of any EV as the Nissan Leaf. In other words, if the energy consumption of Nissan Leaf at 32°F is 25% higher than the minimum energy consumption (at about 70°F) of Nissan Leaf in Figure 45, the power consumption of

any other EV at 32°F will be 25% greater than its corresponding minimum energy consumption. This assumption is represented in Equation (19). Using Equation (19), the energy consumption of any EV at a given temperature can be estimated with reasonable accuracy. As TMY includes hourly temperature data for the selected region, combining TMY with Equation (19) enable to estimate the energy consumption of any EV for each hour of any day within a year.

$$c_{ev}(T(d, h)) = \frac{c_{Leaf}(T(d, h))}{c_{Leaf,min}} * c_{ev,min} \quad (19)$$

where $c_{ev}(T(d, h)) \left[\frac{Wh}{mile} \right]$ is the average energy consumption of a selected EV at an ambient temperature of $T(d, h)$ at h^{th} hour of the day and d^{th} day of the year, $c_{Leaf}(T)$ is the energy consumption of Nissan Leaf at a given temperature picked from Figure 45, $c_{Leaf,min}$ is the minimum energy consumption of Nissan Leaf picked from Figure 45, and finally, $c_{ev,min}$ is the energy consumption of the selected EV without considering the temperature effects.

The results of simulations in Autonomie provide $c_{ev,min}$ values for the selected EV model and drive cycles. Thus, the effects of temperature and driving conditions can be combined.

3.4 Fleet Energy Demand Estimation

3.4.1 Fleet Energy Demand Estimation for Istanbul Case Study

There are three important parameters which affect the energy demand of an EV fleet. These are Vehicle Miles Travelled (VMT) patterns, driving conditions and temperature profiles.

The daily average traveled distance varies by the region. Table 10 represents the daily average traveled distance by transportation type for 2009 and 2023 in Istanbul. In 2023, the average travelled distance with passenger cars will be estimated to be 25 km

per journey. This means a person will travel about 50 km to commute work and back. Therefore, it is assumed that average traveled distance as 50 km for demand estimation of EVs. In this study, it is assumed that EVs are charged during parking like usual, so it is important to estimate to average parking time for Istanbul. It is also important because charging process requires a certain time, and whether energy to travel 25 km (one-way trip) can be provided to the EV during the parking period becomes an important question.

Table 10. Daily average traveled distance (per journey) [78].

		Automobile	Shuttle	Public Trans.
	Year	[km]	[km]	[km]
Current	2009	14	15.91	15.32
Future	2023	25	24.11	26.52

Figure 46 represents trip distribution by the time of the day. As can be seen from the figure, during the hours between 9:00 and 17:00, the majority of the vehicles are parked which would enable EVs to be charged during those times. Therefore, it can be assumed that EVs are connected to charge port at 9:00, and they can be charged until 17:00. This ensures that the EVs will be stay parked for about 8 hours in the weekdays.

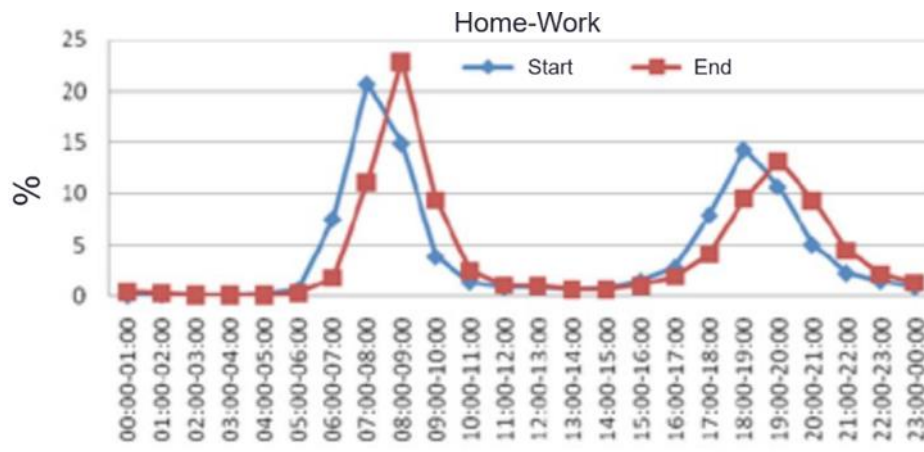


Figure 46. Trip distribution during a typical day in Istanbul [79].

The effects of temperature on the maximum range of vehicle were abovementioned. There are a few EV car models, which are officially imported to Turkey. Among these models, the BMW i3 is selected for this study, because there is enough and necessary information to model its energy consumption. Table 11 presents the assumed energy consumption of BMW i3 under different driving conditions and ambient temperatures taken from Downloadable Dynamometer Database by Argonne National Laboratory [75]. For this study, the power consumption is assumed to form a step function. In other words, between some pre-determined temperature values, which represent different ambient conditions (cold, mild, hot), the power consumption is assumed to be constant. These temperature ranges developed from the Downloadable Dynamometer Database [75].

Figure 46 is also used for determining the time which an EV is being driven. According to Figure 46, most of the cars are on the road from 7:00 to 9:00 in the mornings. The TMY data include the hourly temperature data for Istanbul. These temperature values are used to determine the exact hourly energy consumption of BMW i3 by combining the data from Figure 46 and Table 11.

Table 11. Energy consumption of BMW i3 under different ambient conditions and driving cycles [75].

Electrical Vehicle	Daily trip (km)	$-10^{\circ}\text{C} < T_{\text{amb}} < -1^{\circ}\text{C}$		$-1^{\circ}\text{C} < T_{\text{amb}} < 15^{\circ}\text{C}$		$15^{\circ}\text{C} < T_{\text{amb}} < 30^{\circ}\text{C}$		$30^{\circ}\text{C} < T_{\text{amb}} < \infty^{\circ}\text{C}$	
		UDDC	Highway	UDDC	Highway	UDDC	Highway	UDDC	Highway
		(Wh/mile)							
BMW i3	50	420.6	276.49	368.2	246.1	267.44	186.31	204.32	188.89

3.4.2 Fleet Energy Estimation for New York City and LA 92 Drive Cycles

There are two different chassis dynamometer cycles developed by the United States Environmental Protection Agency (EPA) to represent driving conditions in New York City and Los Angeles. New York City Cycle (NYCC) is represented in Figure 47. As

it is depicted, NYCC represents a “low-speed stop-and-go traffic conditions” and has more idle times. The average speed in the NYCC is only 7.1 mph (11.4 km/h). Moreover, LA92 drive cycle is represented in Figure 48. Compared to NYCC, LA92 has less stop-and-goes as well as idle times. Moreover, the top speeds in the LA92 are higher than the ones in the NYCC. The average speed in the LA92 is 24.61 mph (39.61 km/h). It can be concluded that the energy consumption for the same vehicle in the NYCC will be more than the one in the LA92 due to fact that NYCC represents urban driving conditions with more stop-and-goes.

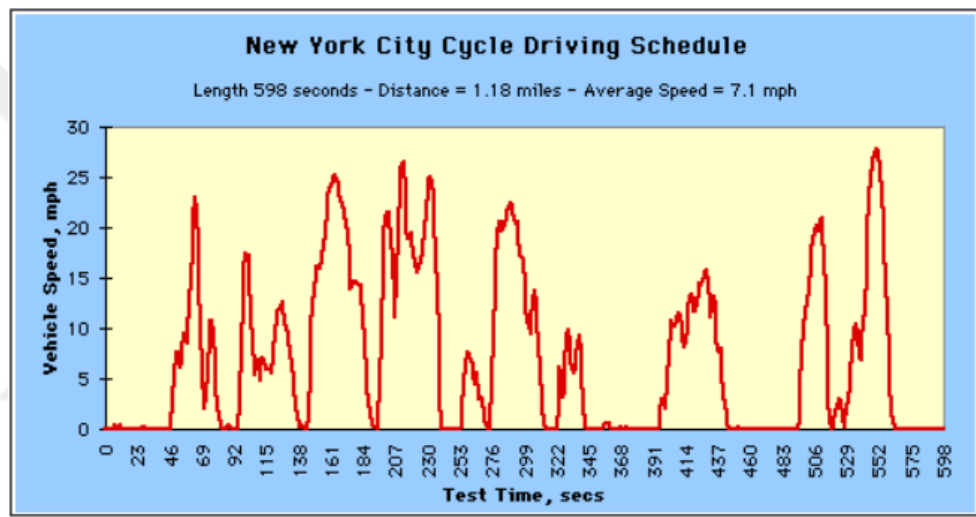


Figure 47. New York City drive cycle (NYCC) [80].

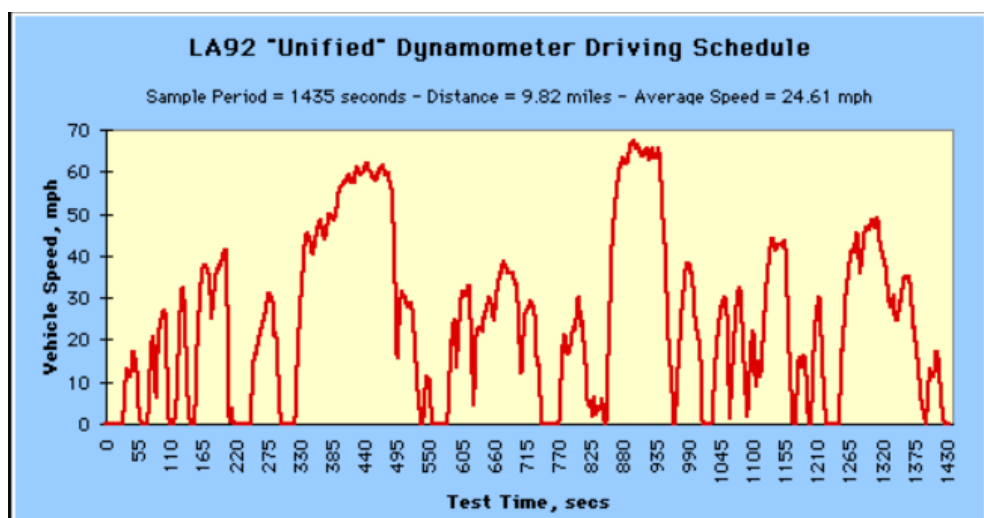


Figure 48. Los Angeles drive cycle (LA92) [80].

For this case study, Nissan Leaf is selected because it is the widespread EV available in the U.S. The Nissan Leaf is simulated for NYCC and LA92 drive cycles by using Autonomie Software.

3.4.3 Travel Behavior Estimation for Los Angeles and New York City Case Studies

The National Household Travel Survey (NHTS) is the source which includes the Vehicle Miles Travelled (VMT) information about citizens of the U.S. in all states. NHTS contains information regarding the mode of travel such as public transportation, private transportation, the purpose of travels such as commerce, recreation. Additionally, it contains information about daily traveled distance for different mode and purpose of travels [81]. Thus, it can be used to estimate travel behavior. In this case study, energy demand is modeled by using the inventory of NHTS to have more realistic results.

The NHTS data are filtered for New York and California states to estimate the energy demand. After the filtration, there are 8409 different trip information in NY and 11465 different trip information in CA. Each trip information includes several data, such as daily mileage, start-end time of the trips, etc. Using the start-end time of the trips, duration of the trip in every hour of the day can be found. For example, if the trip starts at 10:15 and ends at 11:30, the vehicle is used for 45 minutes between 10-11 am and 30 minutes between 11 am-12 pm. This discretization is done for all the trips for NY and CA. The result will be a matrix whose dimensions are (number of trips x 24). Table 12 shows the example of the result obtained for NY. For instance, in trip 2, the vehicle is used only 10 minutes between 20-21 pm.

Table 12. Driving duration (in minutes) by each hour of the day [82].

Trip	hour																							
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
1	0	0	0	0	0	0	0	0	0	0	40	0	0	0	30	0	0	0	0	0	0	0	0	0
2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	10	0	0	0
3	0	0	0	0	0	0	0	0	5	0	0	5	8	0	0	8	0	0	0	0	0	0	0	0
....	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
8409	0	0	0	0	0	0	0	0	0	12	0	0	0	0	0	0	0	12	0	0	0	0	0	0

As mentioned before, the energy consumption of an EV highly depends on the ambient temperature. The energy consumption of Nissan Leaf for different ambient conditions might be estimated using TMY data which include hourly temperature data for 365 days. Combining the hourly temperature values from TMY and the average energy consumption estimation for a specific ambient temperature, the average energy consumption for each hour of the day is found by Equation (19) in Section 3.3.2.

The result can be represented with a [365 x 24] matrix. In Table 12, the data of how many minutes vehicles are driving for each hour is provided. Also, the ambient temperature for each hour is known from the TMY data. Fortunately, the average energy consumption with respect to ambient temperature for each hour of 365 can be found by Equation (19). By combining these, the average energy consumption per mile for the selected state for each hour of the day and each day of the week can be found by Equation (20).

$$c_{ave}(t, d) = \frac{\sum_{h=1}^{24} usage(t, h) * c(T(d, h))}{\sum_{h=1}^{24} usage(t, h)} \quad (20)$$

where $c_{ave}(t, d)$ is the daily average energy consumption per mile for t^{th} trip input and d^{th} day. d and h represent the day of the year and hours of the day respectively. t is the number of the trip and $usage(t, h)$ is used to call the values of hourly driving duration from Table 12.

Next, the daily average energy consumption per mile for the chosen state and chosen day can be found by Equation (21).

$$c_{day}(d) = \frac{\sum_1^t c_{ave}(t, d)}{\text{total number of trip inputs}} \quad (21)$$

where $c_{state}(d)$ represent the average energy consumption per mile for d^{th} day of the chosen state. NHTS data include the daily mileage data for each trip input. However, each trip input represents only 1 day of the year. In this study, it is assumed that each trip input is same for all the days through the year. The total daily energy demand for all the trip inputs for chosen state can be found by Equation (22).

$$E_{demand_day}(d) = \sum_{t=1}^{\# \text{ of trip input}} c_{day}(d) * u(t) \quad (22)$$

where $u(t)$ represents the daily mileage for t^{th} trip input.

Equation (22) is used to estimate the daily total energy demand for the chosen state. However, since the numbers of trip inputs are not the same, daily average energy demand per vehicle might be more useful for comparison of states in term of demand, which can be found by Equation (23).

$$E_{demand_day_vehicle}(d) = \frac{E_{demand_day}(d)}{\# \text{ of trip input}} \quad (23)$$

3.5 Economic Analysis

Charging the electric vehicles with the energy directly comes from the sun has no carbon footprint. It is one of the reasons why EVs should be charged by solar energy. On the other hand, the cost is an important aspect while considering feasibility of any design. In this part, cost analysis will be introduced. The economic feasibility of the PV systems can be measured by using various metrics [83]. The most popular ones are Levelized Cost of Electricity (LCOE) and Net Present Value (NPV).

3.5.1 Levelized Cost of Electricity (LCOE)

LCOE is the lifetime cost of the power plant divided by the total energy generation of the plant during its lifetime. The resulting number has a unit of value per kWh energy generated such as kWh/\$. It is generally used to compare different energy generation technologies like fossil burning power plants, wind, PV, biomass, etc. It can be calculated by using Equation (24).

$$LCOE = \frac{\sum_{t=0}^T (I_t + O\&M_t)/(1+r)^t}{\sum_{t=0}^T S_t(1-d)^t/(1+r)^t} \quad [83](24)$$

where $I_t \left[\frac{\$}{kW} \right]$ is the initial investment cost which includes construction, modules, inverters, labor, etc. $O\&M_t \left[\frac{\$}{kW} \right]$ is the operating and maintenance costs at year t . $S_t \left[\frac{kWh}{year} \right]$ is the yearly generated energy. Annual degradation of the PV system is represented with d , and r represents the discount rate. The parameters for the last quarter of 2018 is represented in Table 13

Table 13. Parameters used in LCOE calculation[84].

2018 USD per Watt DC	2010	2011	2012	2013	2014	2015	2016	2017	2018
Benchmark report									
Installed cost (\$/W)	5.43	5.04	3.47	2.82	2.80	2.30	2.20	1.88	1.83
System size (kW-DC)	200	200	200	200	200	200	200	200	200
Inverter loading ratio	1.10	1.11	1.12	1.13	1.13	1.14	1.15	1.15	1.15
Ongoing NREL benchmarking									
Annual degradation (%)	1.00%	0.95%	0.90%	0.85%	0.80%	0.75%	0.75%	0.75%	0.70%
O&M expenses (\$/kW-yr)	33	30	28	25	22	19	19	18	18
Pre-inverter derate (%)	90.5%	90.5%	90.5%	90.5%	90.5%	90.5%	90.5%	90.5%	90.5%
Inverter efficiency (%)	95.0%	95.6%	96.2%	96.8%	97.4%	98.0%	98.0%	98.0%	98.0%
Equity discount rate (real)	9.0%	8.6%	8.3%	7.9%	7.6%	7.3%	6.9%	6.9%	6.9%
Inflation rate	2.5%	2.5%	2.5%	2.5%	2.5%	2.5%	2.5%	2.5%	2.5%
Debt interest rate	5.5%	5.4%	5.3%	5.2%	5.0%	4.9%	4.8%	4.8%	4.8%
Debt fraction	34.2%	35.2%	36.1%	37.1%	38.1%	39.0%	40.0%	40.0%	40%

3.5.2 Net Present Value (NPV)

In the projects, there will be positive and negative cash flows during its lifetime. These cash flows are discounted to present to see the value of the project and called Net Present Value (NPV). It includes revenues, initial investments, etc. It is used to measure the value of the projects, ventures. If NPV is negative, it means the investment is not profitable [85]. NPV is calculated using Equation (25).

$$NPV_{xyz} = \frac{Z_1}{1+r} + \frac{Z_2}{(1+r)^2} + \dots + \frac{Z_i}{(1+r)^i} - X_0 \quad [85](25)$$

where Z_1 is the cash flow in the time 1, Z_2 is the cash flow in the time 2 and Z_i is the cash flow in the time i . r is the discount rate, and X_0 is the initial investment.

CHAPTER 4. RESULTS AND DISCUSSION

In this chapter, the results of the case studies are represented. Firstly, the parameters of the designed PV system are represented for each case study. Then, the estimated energy demand for each case study is presented. Finally, energy demand and generation are compared, and the feasibility of the system is discussed.

4.1 Istanbul Case Study

4.1.1 PV Output Estimation in Istanbul

One of the important parameters that affect the utilization of PV modules is the orientation of the modules, i.e., surface azimuth and tilt angles. As a common application, the PV modules are faced towards South to maximize the daily total insolation and average the morning and afternoon insolation. Tilt angle is the angle between the PV module and the horizontal surface. The optimum tilt angle varies by climatic condition, geographic position of the location and period. Thus, every location has an optimum tilt angle for optimum PV utilization. The geographical information about Istanbul is presented in Table 14.

Table 14. Geographical information about Istanbul [86].

Location	Longitude (E)	Latitude(N)	Elevation (m)
Istanbul	29.05	40.58	39

As expressed in Section 3.2, global horizontal irradiance varies by location. In order to estimate the solar irradiation on the PV module in Istanbul, Typical Meteorological Year (TMY) data for Istanbul are used.

The TMY data has following data for a complete year with 5 minutes interval;

- Global Horizontal Irradiation (I)
- Direct Normal Irradiation (DNI & $I_{b,n}$)
- Diffuse Irradiation (I_d)
- Ambient Temperature (T)
- Clearness Index (K_T)

The average daily global horizontal irradiation, diffuse irradiation and clearness index for Istanbul are presented in Table 15.

Table 15. Daily Average Solar Irradiation for Istanbul (MJ/m².day) [86].

Location	Months	I	DNI	K_T
Istanbul	Jan.	5.00	3.08	0.34
	Feb.	7.75	4.36	0.39
	Mar.	11.82	5.95	0.44
	Apr.	15.76	7.53	0.46
	May	20.44	8.41	0.52
	Jun.	22.92	8.56	0.55
	Jul.	22.69	8.23	0.56
	Aug.	19.15	7.65	0.53
	Sep.	15.79	6.23	0.54
	Oct.	10.17	4.86	0.46
	Nov.	6.16	3.47	0.39
	Dec.	4.20	2.70	0.32

The optimum tilt angle is determined for Istanbul, and Figure 49 represents the monthly averaged daily solar irradiances for corresponding tilt angles for Istanbul. As it is depicted, the tilt angle that maximizes the energy generation for winter period will be different than for summer because of the relative movement between the Sun and the Earth. The tilt angle for winter months is greater than summer months because the zenith angle of the solar irradiation increases in the winter. In other words, in the summer period, solar radiation hits the horizontal surface more perpendicularly. The resulting optimum tilt angles for winter, spring, summer, autumn as well as year is presented in Table 16.

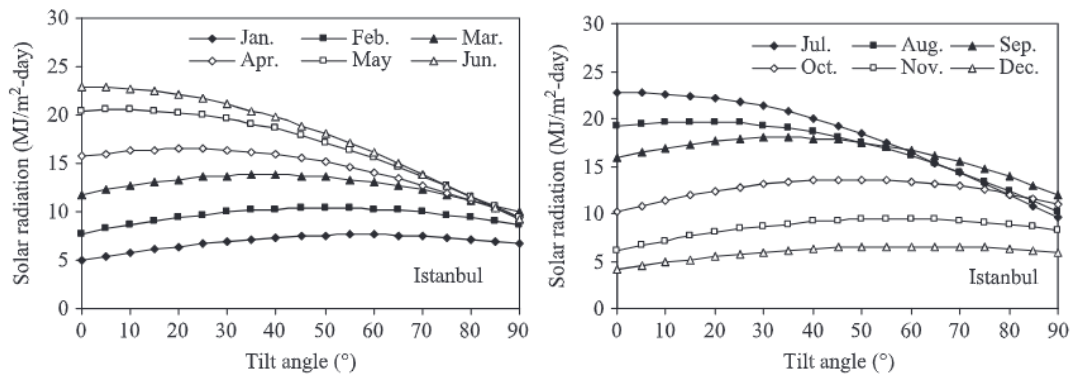


Figure 49. Solar irradiation for different tilt angles for Istanbul [86].

Table 16. Optimum tilt angles for different periods for Istanbul.

Location	Spring	Summer	Autumn	Winter	Yearly average
Istanbul	22.00 °	6.33 °	46.33 °	55.67 °	32.6 °

Since EVs are to be used for 365 days, tilt angle that maximizes the annual energy generation is used in this study. For Istanbul, this tilt angle is rounded to 30°. However, if it is desired the optimize energy generation for another specific period such as winter season, presented tilt angles may be used.

4.1.2 Effects of Ambient Temperature and Drive Cycle on Energy Balance in Istanbul Case Study

In this case study, the PV-EV parking lot is designed for 10 vehicles capacity. A vehicle occupies about 15 m² space so the total available area to be covered by PV modules is 150 m². 90 PV modules whose specifications are given in Table 9 in Section 3.2.2 can be fitted and rated power of the PV system is 22.5 kW. Figure 50 represents the daily energy generation from a 22.5-kW PV system. As can be seen from Figure 50, energy production is higher in the spring and summer seasons compared to winter and autumn seasons. Figure 50 also shows the daily demand for UDDS and highway driving cycles reflecting the effects of ambient temperature.

Moreover, the average energy consumption for combined driving conditions, which is presented as 200 Wh/mile in the technical data sheet of the BMW i3 [87], is presented in Figure 50. However, assuming a constant demand, i.e., ignoring the effects of temperature and driving profile on energy consumption will not give accurate results as compared in Figure 50. Constant demand case underestimates the energy consumption about 30%-50% in winter compared to cases where the temperature effects are included. Regardless of the temperature change, the energy consumption for UDDS is always higher than highway cycle as expected because UDDS represents the aggressive driving while highway cycle represents mild driving. For example, the daily peak energy consumption for UDDS is 160 kWh while it is 100 kWh for the highway cycle, which means that energy consumption of BMW i3 under city drive conditions is about 50% higher than the highway conditions.

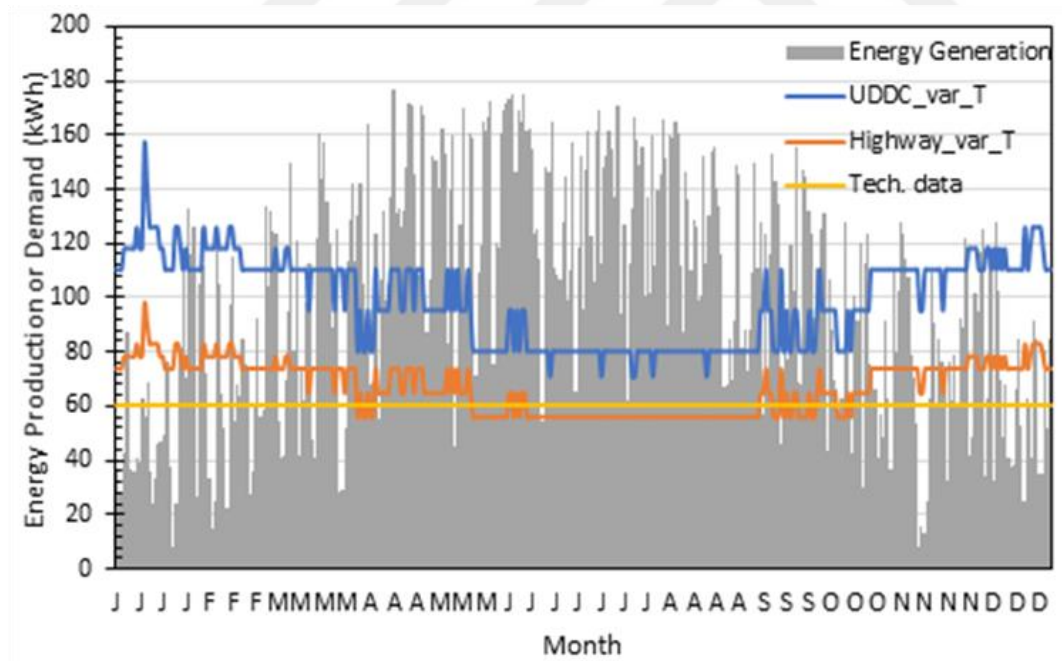


Figure 50. Energy generation from 22.5 kW PV system in Istanbul.

In addition, as the weather gets warmer, energy consumption decreases for both driving cycles as expected. Figure 51 and Figure 52 represent the amount of demand covered by solar energy for UDDS and highway cycles, respectively. For UDDS, solar

energy that is generated from the PV system can cover full demand for about 198 days which is more than half of the year. On the other hand, the generated solar energy can cover full demand for about 268 days for the highway cycle. The difference between the number of days which demand is covered for two cycles cannot be neglected as previously stated. On the other hand, as presented in Figure 50, the energy generation increases as the weather gets warmer while energy consumption for both cycles decreases. This effect can be seen in Figure 51 and Figure 52 clearly, as the weather gets warmer the amount of demand covered by solar energy increases. Although the PV system is assumed as an off-grid system, the effects of the connecting system to grid is also investigated. represents the monthly demand for UDDS and where the demand is covered. As can be seen from , the grid can supply the energy deficit from the PV system and the whole demand can be covered. Additionally, the yearly total energy generation from the PV plant is about 36.7 MWh, while the total yearly demand is about 36 MWh.

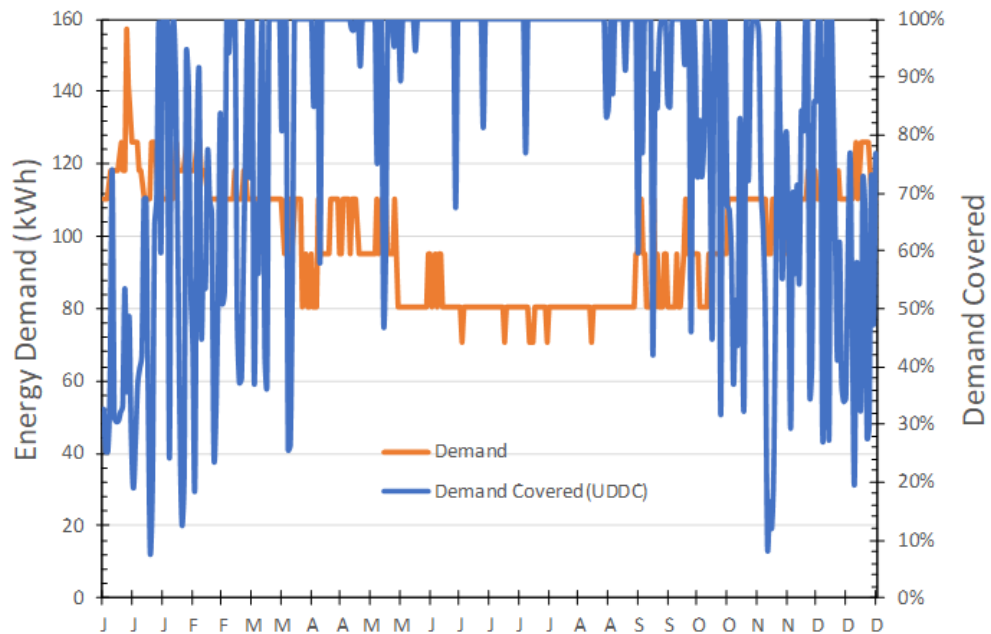


Figure 51. Demand covered for UDDS drive cycle.

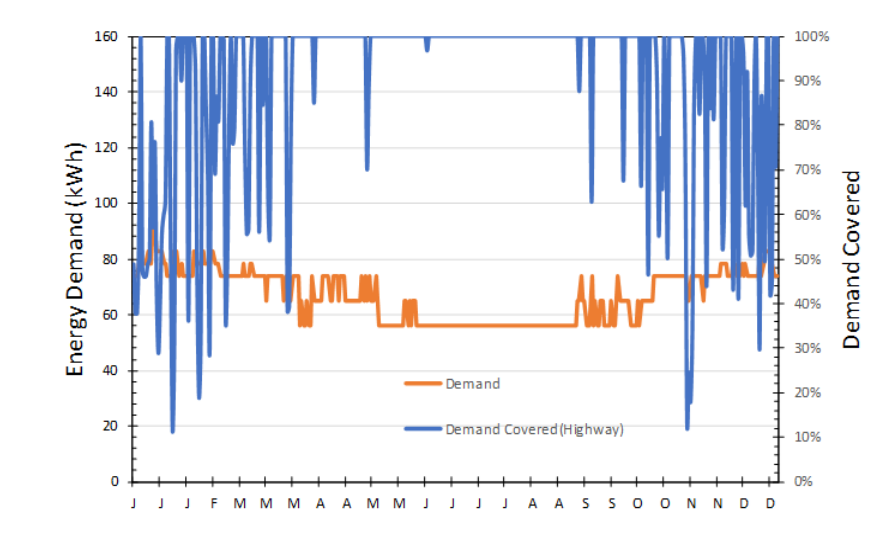


Figure 52. Demand covered for Highway drive cycle.

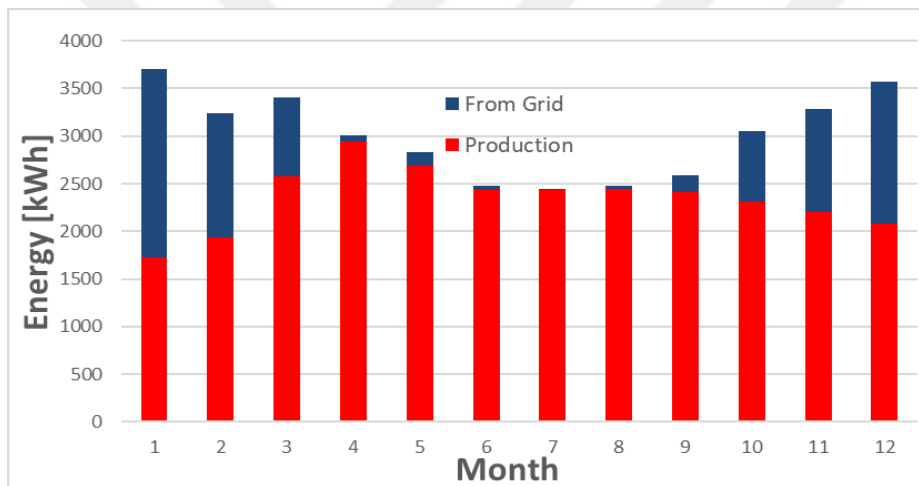


Figure 53. Total demand for UDDS and coverage of demand by source.

On some of the days, PV system generates energy higher than required, and on some of the days generated energy is lower than required as presented in Figure 50. If excess energy is given to grid and re-taken from grid when it is needed, the whole demand can be covered by solar energy which will lead to zero-emission of the EVs. Furthermore, storage systems like batteries might be implemented to the PV system so that stored excess energy can be used to charge EV when there is an energy deficit. However, including energy storage system might increase the cost. In addition, if constant demand was assumed as in the previous studies in literature, the total annual

demand would be about 22 MWh. In that case, designed PV system can cover demand for 15 cars instead of 10, which emphasizes that ignoring temperature and driving conditions effects and assuming constant demand underestimates the energy consumption about 50%.

4.1.3 New York and Los Angeles Case Studies

New York City (NYC, NY, USA) and Los Angeles (LA, CA, USA) have different ambient conditions due to their locations. Thus, the total energy generation from the modeled PV system is different. Moreover, the driving profiles are different for these two locations. In this case study, these two different locations will be compared in terms of PV-EV feasibility.

LA has mild ambient conditions through the year, while the ambient temperatures drop below zero in winter in NYC. Therefore, they can be used to represent different climates conditions. Figure 54 represents the daily average temperatures for LA and NYC through the year. As the figure illustrates, the annual temperature variation in NYC is greater than the one in LA.

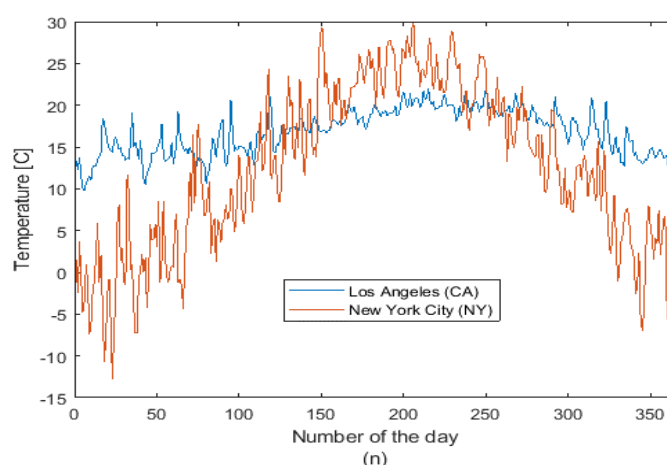


Figure 54. Daily Average Temperatures.

Since the geographic locations of NYC and LA are different, the solar irradiation that hits the surface will also differ. The geographical information about NYC and LA is

presented in Table 17. In addition, monthly average Global Horizontal Irradiation, Direct Normal Irradiation and Diffused Irradiation for NYC and LA are presented in Table 18.

Table 17. Geographic Information of New York City and Los Angeles.

Location	Longitude (E)	Latitude(N)	Elevation (m)
New York City (NY)	40.73	-73.94	7
Los Angeles (CA)	34.05	-118.24	87

Table 18. Monthly average Global Horizontal Irradiation (GHI, I) Direct Normal Irradiation (DNI) and Diffuse Irradiation (I_d) for New York City and Los Angeles.

Location	Month	I [Wh/m ²]	DNI [Wh/m ²]	I_d [Wh/m ²]
New York	January	93.32	83.15	58.70
	February	131.83	104.21	79.76
	March	185.99	143.15	98.88
	April	229.64	144.73	129.31
	May	256.03	150.77	145.72
	June	291.05	194.73	143.20
	July	300.54	229.26	126.76
	August	260.58	190.41	123.24
	September	212.70	167.86	103.06
	October	155.89	149.12	72.68
	November	107.30	103.90	61.54
	December	82.64	75.84	52.38
Los Angeles	January	195.27	146.38	48.89
	February	214.02	152.39	61.63
	March	273.02	195.52	77.49
	April	309.40	215.42	93.99
	May	320.82	203.82	117.00
	June	345.57	225.31	120.26
	July	361.88	258.27	103.60
	August	349.50	247.84	101.66
	September	300.27	221.06	79.21
	October	256.01	191.97	64.04
	November	234.61	186.12	48.49
	December	209.83	165.13	44.70

As presented in Table 18, the GHI in LA is more than GHI in NYC due to location as well as the geographic location of the cities. Thus, the annual energy generation from the modeled PV modules in LA will be more compared to NYC. Additionally, annual variation of GHI for NYC is greater than LA. It may be required to design system as oversized for NYC to cover the demand where the months GHI is lower. On the other hand, since GHI variation is less in LA, the required size of the PV system will be smaller than the one in NYC.

4.1.4 PV Output and Energy Demand

Simulations were performed for the same PV module specifications for NYC and LA to investigate the differences between the daily energy generation from the modeled PV systems in these cities. The PV module specifications are assumed to be same, but the orientation of PV modules is optimized for NYC and LA to maximize the yearly energy generations. The orientation of the PV modules which maximizes annual energy generation for selected locations is shown in Table 19. In addition, Figure 55 represents the daily energy generation per PV module for LA and NYC. The total annual energy generations per PV module are 381 kWh and 457 kWh in NYC and LA, respectively. This means that if the same PV system is built in NYC and LA, the specific annual energy yield per rated power will be 1524.4 Wh/W and 1826.7 Wh/W in NYC and LA, respectively. It can be said that the solar potential is higher in LA compared to NYC.

Table 19. Orientation of modules which maximizes annual energy generation for NYC and LA

	NYC	LA
	(Degrees)	(Degrees)
Surface Azimuth (γ)	0	10
Surface Tilt (β)	27	25

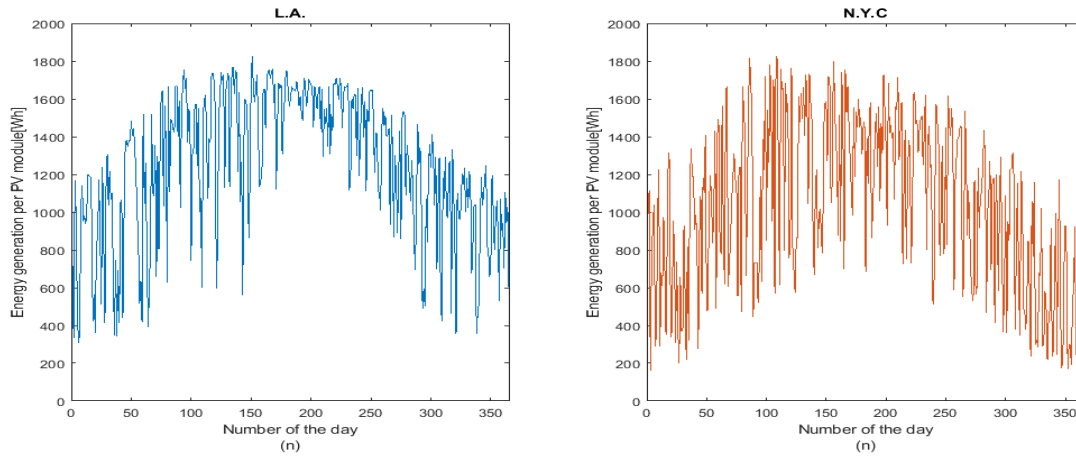


Figure 55. Daily energy generation per PV module for LA and NYC.

The resulting energy consumption values are represented in Table 20. As expected, the average energy consumption in the LA92 is about 16.6% lower than NYCC, since NYCC represents urban driving conditions with more stop-and-goes than LA92. In Table 20, the average energy consumption for UDDS is also given. If the driving conditions in NYC represented by using UDDS, the energy demand of the EVs will be underestimated about 30%. Thus, the drive cycle effect should be considered to obtain a precise energy demand profile.

Table 20. Average energy consumption for Autonomie Simulations for different drive cycles.

	UDDS	LA92 Drive Cycle	N.Y. Drive Cycle
Energy Consumption [Wh/km]	314.91	352.73	422.89

The methodology presented in Section 3.3.2 is used to estimate the energy consumption at other ambient temperatures.

4.1.5 Effects of Ambient Temperature and Drive Cycle on Energy Balance in New York and Los Angeles Case Studies

The energy consumption of an electric vehicle varies with the ambient temperature, and represent the daily average energy consumption per vehicle and daily average ambient temperatures for NYC and LA, respectively.

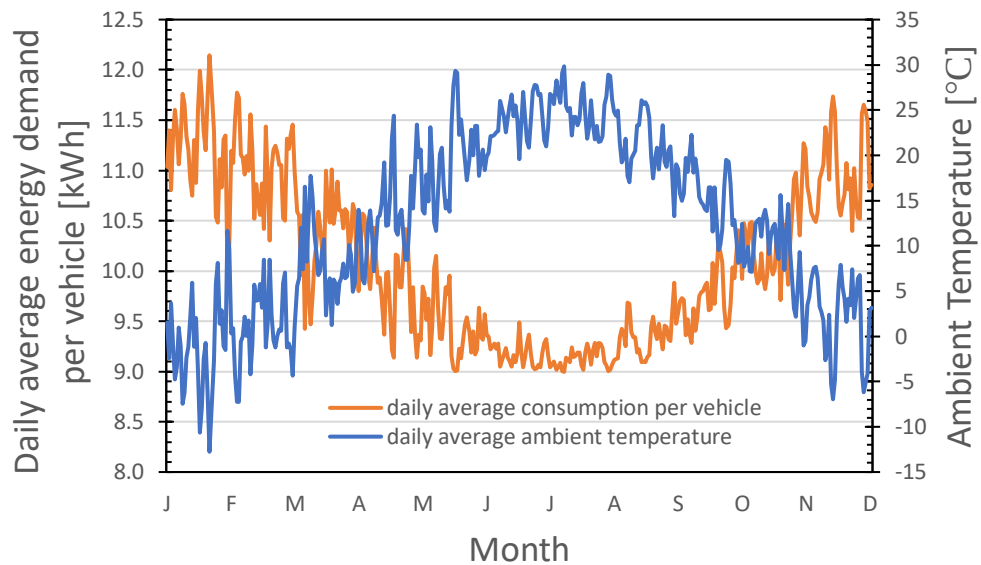


Figure 56. Daily average demand and ambient temperature for NYC.

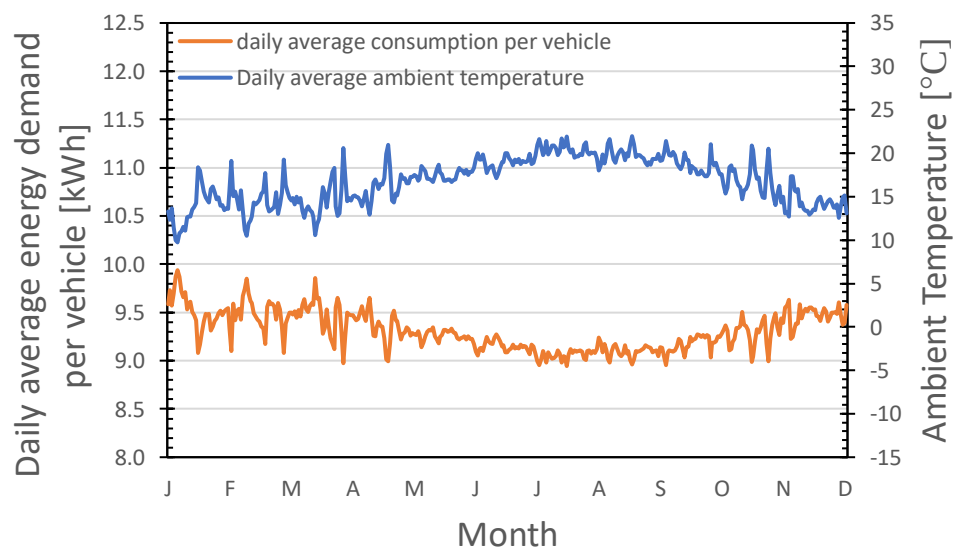


Figure 57. Daily average demand and ambient temperature for LA.

These figures show that the daily average consumption per vehicle fluctuates between 9 to 12 kWh for NYC and 9.8 to 8.9 kWh for LA within the year. Since the daily mileage values are assumed to be constant through the year for both states, the only reason for fluctuations is the effects of temperature. As the temperature increases, the energy consumption decreases in both cities as expected. The fluctuations in the daily average energy consumption are more pronounced in NYC because the annual temperature varies between -12 to 30°C in NYC while it varies between 9 to 22°C in LA. In mild conditions, the energy demand variation due to temperature effect is less. Figure 58 represents the daily total energy demand for all trip inputs in LA and NYC. It is clear that the daily total energy demand for LA is more than NYC. However, as presented in Figure 58(b), the daily average energy demand per vehicle for LA is lower than NYC. Normally, the total daily demand would be lower in LA compared to NYC, if the travel inputs sizes were same. However, there are 11465 and 8409 trip inputs in LA and NYC, respectively. Due to the extra number of trip inputs, the total daily energy demand in LA is higher, although the average energy consumption per vehicle in LA is less. For example, minimum daily energy demand for LA is about 76 MWh, while it is about 104 MWh for NYC. As the next step, PV systems are designed to cover the energy demand in both cities. The PV systems are sized such a way that the annual energy generation from the system is equal to the total energy demand in each city. The annual total energy demand for all trip inputs in LA is 3.89×10^7 kWh, while it is 3.09×10^7 kWh for NYC. The size parameters of the corresponding PV system which covers the annual demand for selected state are presented in Table 21. The energy generated per rated power of PV in LA is 1826.7 kWh/kW, while it is 1524.4 kWh/kW for NYC. Thus, LA has more solar energy potential than NYC.

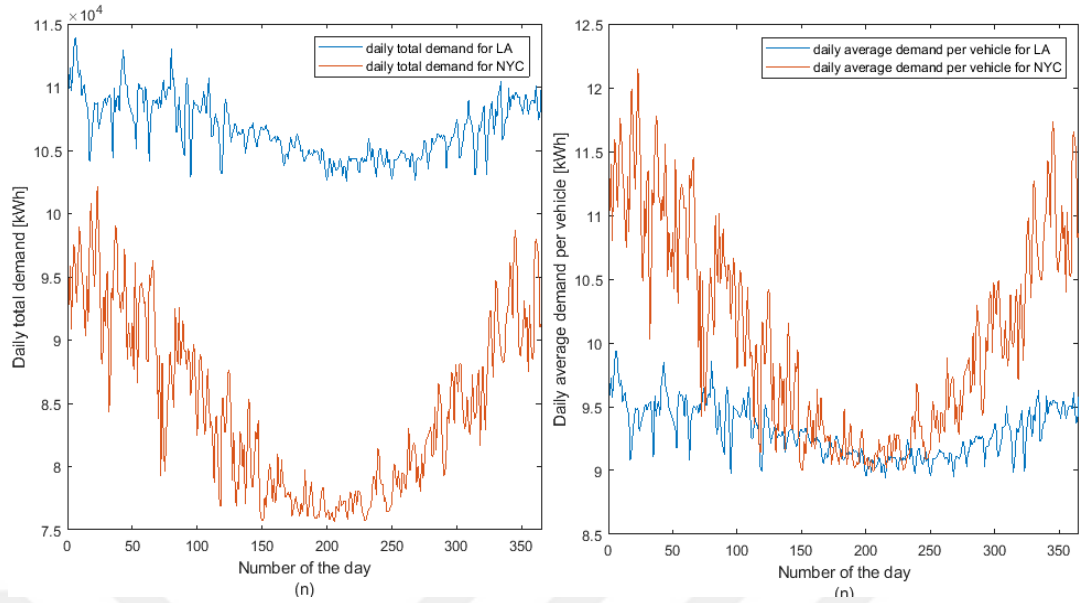


Figure 58. (a) Daily total energy demand, and (b) Daily average energy demand per vehicle for LA and NYC.

Table 21. Size of the PV system for selected states.

Region	Rated Power	Number of modules	Generated Energy	Energy generated per rated power
	[kW]		[MWh]	[kWh/kW]
L.A	213.15	85,262	38.9×10^3	1826.7
N.Y.C	202.74	81,097	30.9×10^3	1524.4

The daily energy generations and energy demands for LA and NYC are represented in Figure 59. In this study, the PV system is sized to cover the annual demand. Also, the PV system is assumed to standalone i.e., off-grid. As can be seen from Figure 59 for various days, the daily demand cannot be completely covered by the PV system, although the annual total demand is covered. On the other hand, the energy generation is higher than the energy demand in summer. Moreover, the energy generation increases due to increase in the insolation that hits the surface while energy demand decreases due to increased ambient temperatures in summer, especially in NYC.

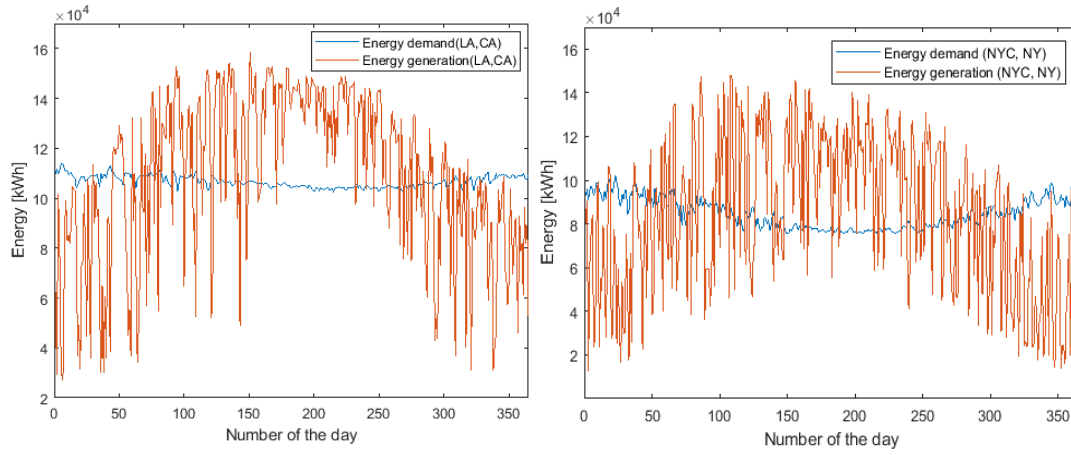


Figure 59. Daily energy generation and energy demand for (a) LA (CA), (b) NYC (NY).

Since the number of the trip inputs are different for NYC and LA, the comparison of PV performance for NYC and LA using total energy demand will not be correct. To eliminate the effects of the number of trip inputs on the demand, daily demand per vehicle is used in this study. The next section elaborates this effect in detail as parametric studies.

4.1.6 Effects of Ambient Temperature and Drive Cycle on PV-EV Charging

There are several parametric studies to assess the performance of the PV system. One of the parametric studies is changing the rated power and finding how many vehicle's demands can be covered for each rated power. Figure 60 represents the number of demand for vehicles covered for each rated power from 0 to 1000 kW. Since the daily average demand per vehicle is less in LA, the number of vehicles whose demand is covered is higher in LA compared to NYC. For example, if the rated power is 1000 kW, the number of covered vehicles in LA is 30% more than NYC. This means that if there were same numbers of vehicle in LA and NYC, the PV system size in NYC would have been 30% more than number for CA. This will increase the total cost of

system about 30% because the main expense of PV system is the PV module. On the other hand, if the size of the PV system is the same for LA and NYC, the avoided CO₂ would be less in NYC because lower number of EVs would be charged from renewable energy.

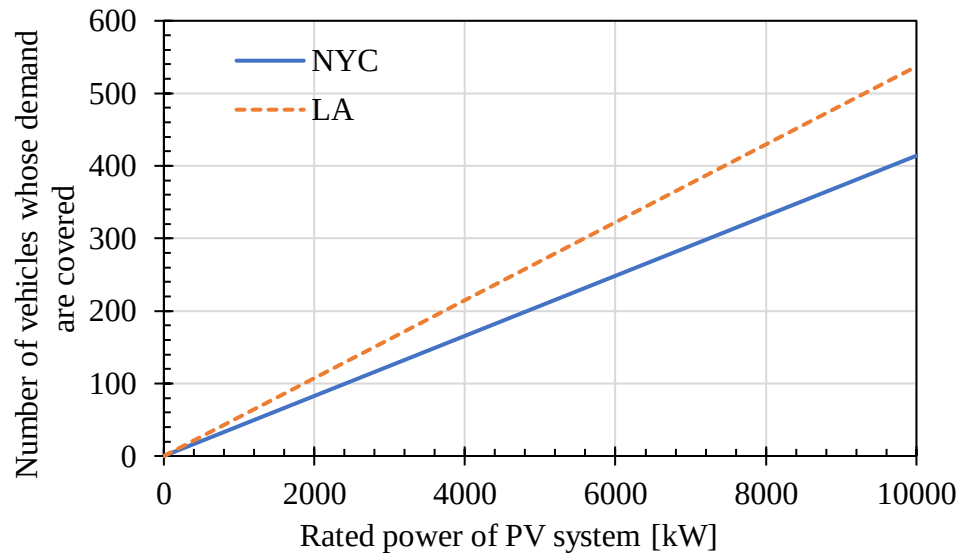


Figure 60. Number of covered vehicle demand for each rated power.

Another aspect of assessing the performance of the PV system is finding the percent demand covered for each rated power. In that case, the total daily demand rather than daily average demand per vehicle is considered. Figure 61 represents the percent demand covered for each rated power for LA and NYC. Since the total daily demand in LA is higher than the one in NYC, the percent demand covered for each rated power will be lower in LA compared to NYC. Although the number of travel inputs is 36% more in LA than NYC, there is no significant difference between percent covered demands for each rated power. In other saying, for the same PV system size, more vehicle can be charged from renewable energy in LA compared to NYC. The number of trip inputs in NHTS is different for LA and NYC because the number of people who participated in survey is different.

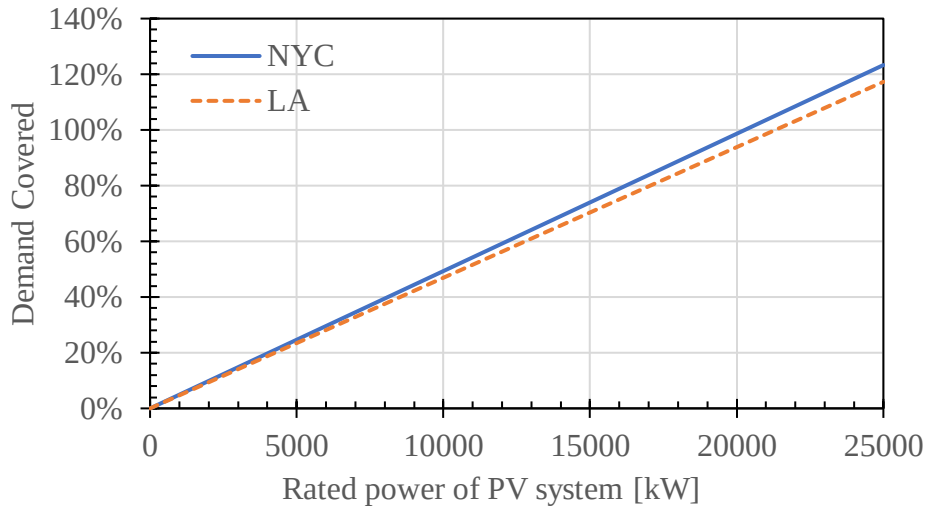


Figure 61. Percent demand covered for each rated power.

The greater number of input leads to an increase in energy demand and affects the fair comparison of two cities. Therefore, the following parametric study is divided into two subsections. The first subsection includes the exact number of trip inputs. The second subsection assumes that the number of cars is the same for both cities.

4.1.6.1 Effects of Ambient Temperature and Drive Cycle Considering the Same Number of Trip Inputs in New York City and Los Angeles

Power consumption of the EVs varies by ambient temperature as abovementioned. Also, different driving conditions which are represented by drive cycles affect the power consumption of EVs. A parametric study is performed to see how these factors affect the total energy demand. The factors which are taken into consideration and the ones which are neglected are presented in

Table 22.

Table 22. Parametric study summary.

Study No.	Temperature Effect	Drive Cycle Effect
1	considered	considered
2	considered	neglected
3	neglected	considered
4	neglected	neglected

The annual energy demand is calculated to clarify the effects of each factor on energy demand. Figure 62 and Figure 63 present the resulting energy demand for all 4 studies for LA and NYC. Figure 62 presents the results of the parametric studies for LA, while Figure 63 represents the results of parametric studies for NYC. As can be seen from these figures, if the drive cycle effect is taken into consideration, the energy demand increases. In Figure 62(a), the energy demand without temperature effect is about 117 MWh for LA. On the contrary, in Figure 62(b), the energy demand without temperature effect is about 131 MWh for LA. The difference is about 12% and resulting from drive cycle effect. On the other side, in NY, the difference is about 30%. The average energy consumption of selected EV in LA92, NYCC and UDDS are 352.73, 422.89 and 314.91 Wh/km, respectively, as presented in Table 20 in Section 4.1.4. Average energy consumption in NYCC drive cycle is higher than UDDS as well as LA92, so the effect of considering drive cycle effect is more pronounced. Annual energy demand values for all studies are compared to clearly pronounce the effect of ambient condition on the energy consumption of EV. Table 23 represents the energy demand differences for Studies #1 and #3. Thus, the only parameter that changes is the effect of temperature because effect of drive cycle is included for Studies #1 and #3. As can be seen from the table, neglecting temperature leads to underestimation of energy demand about 3.0% for LA. On the other hand, it leads to underestimation of 10.4% for NYC. Moreover, the peak difference between daily energy demand for temperature effect considered and neglected cases is 6.5% for LA and 31.9% for NYC. The reason why NYC has higher peak difference is that ambient temperature variation is higher. In other words, the temperature drops below 0°C as well as rises above 35°C as it is presented in Figure 54. It can be said that neglecting the effect of temperature on EV for LA will still provide an accurate result,

even if the daily energy generation and demand were compared. However, for the climates which have similar climate like NYC the effects of ambient temperature on energy demand should not be neglected.

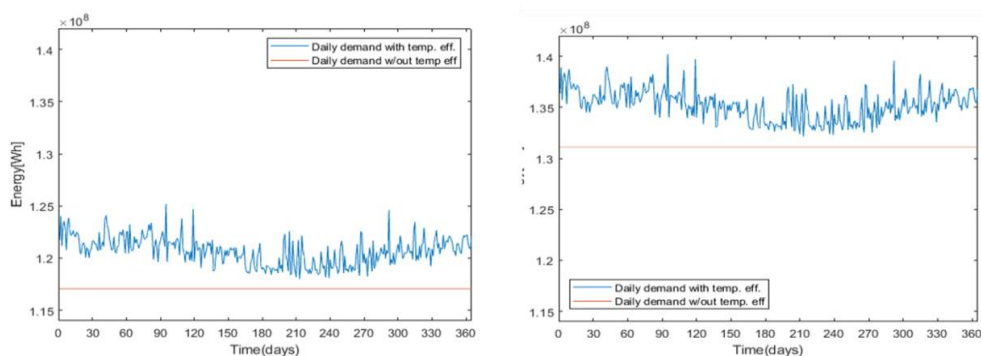


Figure 62. Energy demand for LA (a) (Drive cycle effect neglected) (Studies #2 and #4), (b) (Drive cycle effect considered) (Studies #1 and #3).

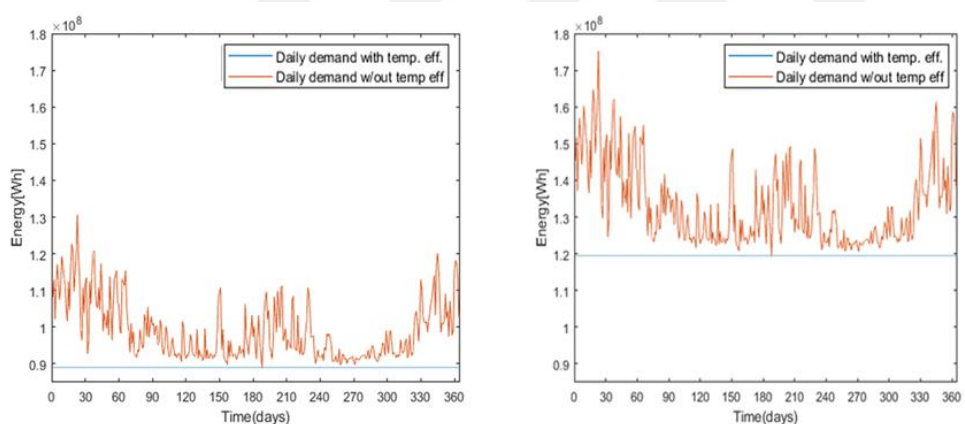


Figure 63. Energy demand for NYC (a) (Drive cycle effect neglected) (Studies #2 and #4), (b) (Drive cycle effect considered) (Studies #1 and #3).

Table 23. Effect of ambient temperature on annual demand for LA and NYC considering the drive cycle effects.

*Drive cycle effect is considered	LA				NYC			
	Demand $\times 10^{10}$ [Wh]		Diff [%]	Peak Diff [%]	Demand $\times 10^{10}$ [Wh]		Diff [%]	Peak Diff [%]
Temp Eff.	Neglected	Considered			Neglected	Considered		
Energy	4.8	4.9	3.0	6.5	4.4	4.9	10.4	31.9

4.1.6.2 Effects of Ambient Temperature and Drive Cycle Considering Equal Number of Vehicles in Fleet in New York City and Los Angeles

NHTS dataset includes a different number of trip inputs for different states, which leads to unfair comparison between the states or cities. Since the number of inputs is different, the total number of vehicles whose demands are considered is different. The total number of vehicles in NHTS for CA and NY are 11465 and 8409, respectively. To have a better comparison for LA and NYC, the same number of vehicles is assumed in both cities. It is assumed that there are 10,000 vehicles in both cities. The purpose is to investigate the effects of traveled distance, drive cycle and temperature in more detail by omitting the difference of vehicle numbers. The probability which the vehicle to be used in specific hour of the day is calculated for both cities, and these probabilities are used to estimate the energy demand of 10,000 vehicles. This estimation is important because the time when vehicles are used in the day should be known to see the effect of ambient temperature on energy demand. Figure 64(a) represents the energy demand for LA and NYC for the case of neglected effects of drive cycles and temperature. The demands are quite close to each other. Although the number of vehicles and average energy consumption per mile are same for both cities, there is small difference between energy demand of LA and NYC. The reason is that there is a small difference between the daily average miles as presented in Table 24.

Table 24. Daily average traveled distances in NYC and LA.

City	Distance [miles]	Distance [km]
NYC	33.57	54.03
LA	32.43	52.19

In Figure 64(b), the gap between energy demand of LA and NYC increases, because the per-mile energy consumption for NYC drive cycle is higher compared to LA as listed in . Figure 65 represents the energy demand of LA and NYC for the case that effects of temperature are considered. Since drive cycle is not considered, in Figure 65(a) the energy demands are quite close to each other, but in Figure 65(b) the gap between energy demands increases as expected. In Figure 65, the daily fluctuations in energy demand are more pronounced for NYC, as the temperature variation in NYC is more. On the other hand, energy demand for LA follows smaller variations due to its even ambient temperature distribution within a year compared to NYC. Effect of temperature is strongly pronounced in these figures. Table 25 summarizes the results in Figure 64 and Figure 65 to provide a better understanding of the effect of temperature on the annual energy demand. The comparison in Table 25 drive cycle effect is neglected. As it is presented, considering the temperature effect leads to 2.9% increase in the annual demand in LA, while the increase is about 10.4% increase for the NYC.

On the other hand, Figure 64(a) and Figure 65(b) are compared to see the combined effects of temperature and drive cycle. In Figure 64(a), none of the effects is included, while in Figure 65(b) both effects are included. As a result of this comparison, total energy demand in Figure 65(b) is about 13.3% and 33.3% higher in LA and NYC, respectively, than the corresponding total energy demand values in Figure 64(a). It proves that drive cycle and temperature effects are more pronounced in NYC, as the annual temperature variation and average energy consumption are higher.

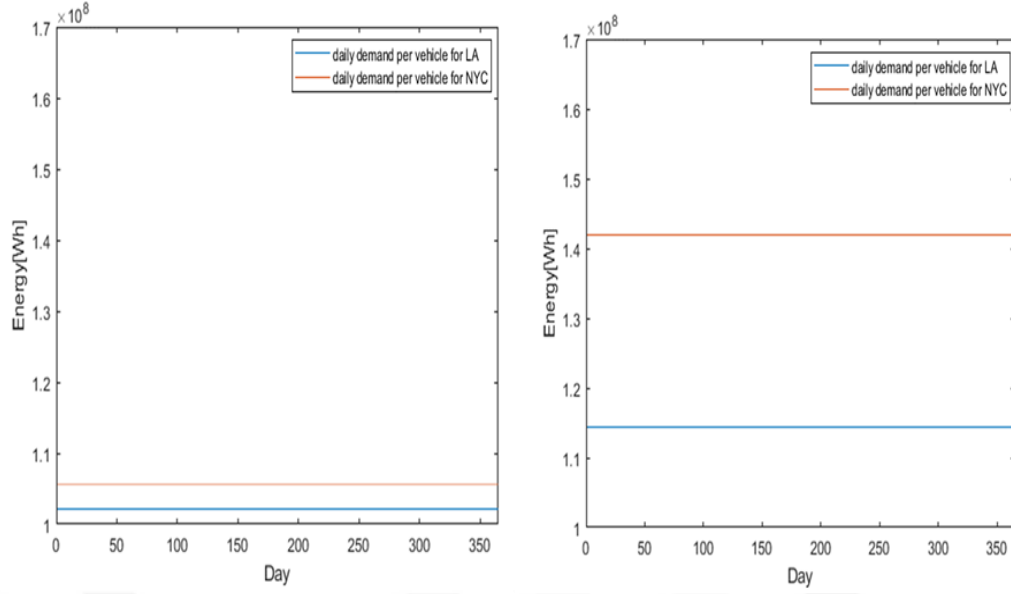


Figure 64. Energy demand for even vehicle numbers for CA and NY (a) drive cycle effect neglected & temperature effect neglected, (b) drive cycle effect is considered & temperature effect neglected.

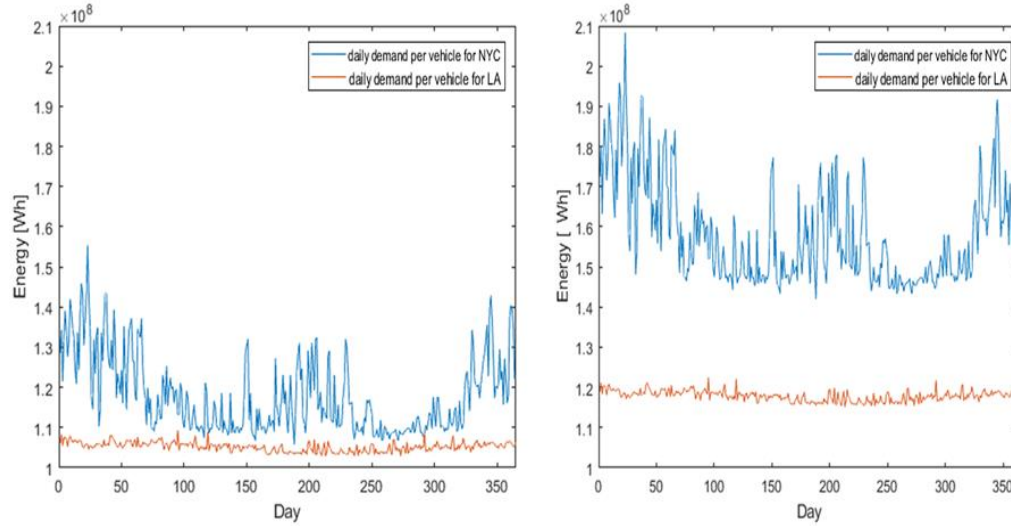


Figure 65. Energy demand for even vehicle numbers for CA and NY (a) drive cycle effect neglected & temperature effect considered, (b) drive cycle effect considered & temperature effect considered.

Table 25. Annual energy demand (neglected drive cycle effect).

Drive Cycle Effect is Neglected (Figure 64a&65a)	LA			NYC		
	Energy Demand		Difference	Energy Demand		Difference
	$\times 10^{10}$ [Wh]		[%]	$\times 10^{10}$ [Wh]		[%]
Temp Eff.	Neglected	Considered		Neglected	Considered	
Energy[Wh]	3.73	3.84	2.9	3.86	4.31	10.4

LA and NYC have different energy demand due to their different ambient and driving conditions as discussed above. In addition, the energy generation from a renewable energy system for these states might differ because their locations, climate and ambient conditions are different. To have a functional comparison, the renewable energy potentials for PV systems in these two cities are also required to be compared. In that regard, the same size of PV system is designed for both cities, and their annual performance is compared. The PV system size is selected such that the annual energy production would be enough cover the total energy demand of NYC due to EV charging. As shown in Table 26, 1826.7 kWh energy can be generated annually for each kW of rated power in LA, while it is only 1524.4 kWh in NYC. It can be said that solar potential of LA is better than NYC. For the same size of PV plant 16.6% more energy can be generated in LA than in NYC due to higher solar potential in LA.

Table 26. PV design and performance parameters.

Region	Rated Power	Generated Energy	Energy Generated per Rated Power	Capacity Factor
	[kW]	[kWh]	[kWh/kW]	[%]
LA	37929	6.93×10^7	1826.7	20.83
NYC	37929	5.78×10^7	1524.4	17.40

4.1.7 Economic Analysis

Levelized Cost of Electricity (LCOE) and Net Present Value (NPV) are used for comparison of two cities in terms of financial feasibility. The lifetime of the typical PV is 30 years [88]. There are several incentives available for PV systems in both cities, and these incentives decrease LCOE. These incentives are not included in LCOE calculations in this study, because available incentives for both states are alike to each other. Table 27 represents LCOE for the designed PV systems as well as the grid prices. LCOE is 11.01 and 13.17 ¢/kWh for LA and NYC, respectively. The LCOE in NYC is higher than LA as expected because the capacity factor of NYC is less than LA. If the same capacity of the PV is designed for both cities, the energy generation will be higher in LA, although the initial and operating costs are almost the same. Higher energy generation directly decreases LCOE. Moreover, grid retail prices are 16.06 and 14.74 ¢/kWh for LA and NYC, respectively [89]. LCOE values for PV are less than grid retail price for both cities. In addition, being environment-friendly, if the EVs are charged by renewable energy, the cost will be less compared to grid.

Table 27. LCOE values for PV systems and grid tariffs in LA and NYC.

City	LCOE	Retail price from the grid [89]
	[cent/kWh]	[cent/kWh]
LA	11.01	16.06
NYC	13.17	14.74

Another metric which is used to assess the economic feasibility is Net Present Value (NPV). If NPV is positive, the project is considered as profitable or vice versa. Figure 66 represents the NPVs of PV system for CA and NY states. As can be seen from the figure, the NPVs start with negative values and at some point, they turn into a positive value. The point where NPV becomes positive is called breakeven point. The year

which breakeven occurs is called payback period. NPV is higher for LA compared to NYC, which is mainly because the capacity factor in LA is higher than the capacity factor in NYC. PV system in LA paybacks in 9 years while it paybacks in NY in 15 years. Thus, PV systems payback in shorter duration in LA compared to NYC.

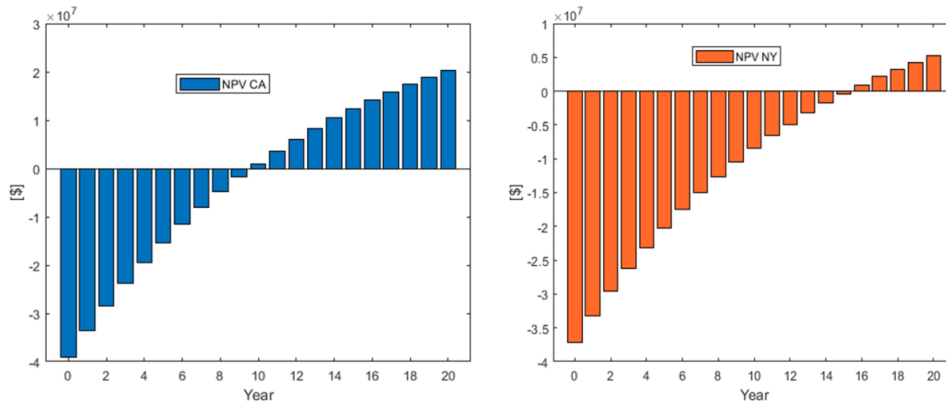


Figure 66. Net present value for PV system in (a) Los Angeles (CA), (b) New York City (NY).

4.1.8 Impacts of PV-EV Charging on Grid

The EVs are generally charged by electrical grids. Thus, high penetration of EVs will have a negative effect on the grid by imposing additional loads. In this section, the impacts of the PV-EV system on the grid will be investigated by assuming that all the vehicles in the selected cities (LA and NYC) are replaced by EVs. Furthermore, in the following scenarios, the energy demand that cannot be met by the PV system, is met by the grid, and how the PV system helps to mitigate the negative impacts of high penetration of EV is investigated. There are two different scenarios assumed. In Scenario 1, the EV is plugged-in after the last trip of the day. Also, plug-in times are shifted for couple hours. However, close investigation of NHTS data shows that there is enough time between each trip which EV can be charged. In Scenario 2, it is assumed that if there is more than 1-hour difference between each trip, vehicle is considered as being charged at this time interval.

4.1.8.1 Impact of PV-EV Charging on Grid: The-end-of-day Charging Scenario

The PV systems for LA and NYC is designed in such a way that the annual energy demand is equal to annual energy generation. However, if hourly and daily demands are investigated, it can be seen that daily or hourly demand cannot be entirely covered. For example, there will be some energy deficit at nights. This deficit is required to be compensated by either taking from the grid or storage system. On the other hand, the energy generated is higher than the demand in some hours, so there is surplus energy. The energy demand and generation should be balanced, so that deficit and surplus energy values would minimum and all the energy generated from sun is directly used to charge EVs. To estimate the hourly energy demand, the number of EVs which are being charged at the specific time of the day should be known. Thus, EVs are assumed to start to be charged after when their last trip ends in **Scenario 1**. Figure 67 shows the hourly energy generation from the PV system and hourly energy demand for LA and NYC. As clearly illustrated in the figure, substantial amount of energy is demanded after the sun is set. It means that the energy generated from the sun is not used directly to charge the electric vehicles. As above mentioned, a one-day demand profile is generated by using NHTS data and the generated demand profile is projected to other days of year including temperature effects. Although Figure 67 depicts energy demand only for 1st of January, the energy demand for the other days will follow same trend. To increase the amount of solar energy which is directly used to charge the vehicles, the energy demand should be shifted. Figure 68 represents the case which electric vehicles start to be charged 2 hours after the last trip on each day. Basically, the load is shifted 2 hours ahead. It can be seen that the total amount of demand within the region of energy generation decreases. In other words, the amount of energy which

is directly used to charge electric vehicle decreases. The hourly energy demands should somehow be shifted to left to increase the amount of directly used energy from the PV system. Figure 69 represents a hypothetical case which vehicles are plugged-in 2 hours before last trip. In the previous cases which are presented in Figure 67 and Figure 68, the energy demand starts at around 12:00-14:00, while it starts around 10:00 in the last case presented in Figure 69. In other words, demand is shifted though the hours which PV generates energy. Therefore, the amount of directly used energy is almost doubled compared to previous cases. The energy which is demanded from the grid is directly related to the plug-in times of the EVs. Optimization of EV plug-in times will increase the direct use of generated solar energy.

If the PV plant is on-grid most of the demand is covered from the grid. The net metering scheme is available in LA and NYC, so surplus energy that is given to the grid can be taken back when needed. On the other hand, if the systems are designed as off-grid, an energy storage system is needed so that surplus energy can be stored and used when needed. Implementing an energy storage system will increase the cost of energy.

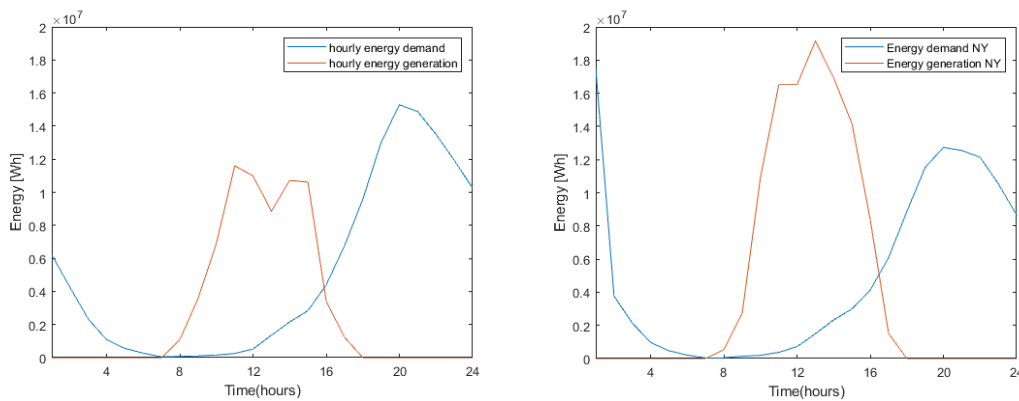


Figure 67. Hourly energy demand and generation for 1st of January for (a) LA, (b) NYC (Vehicle is started to charge after the last trip ends).

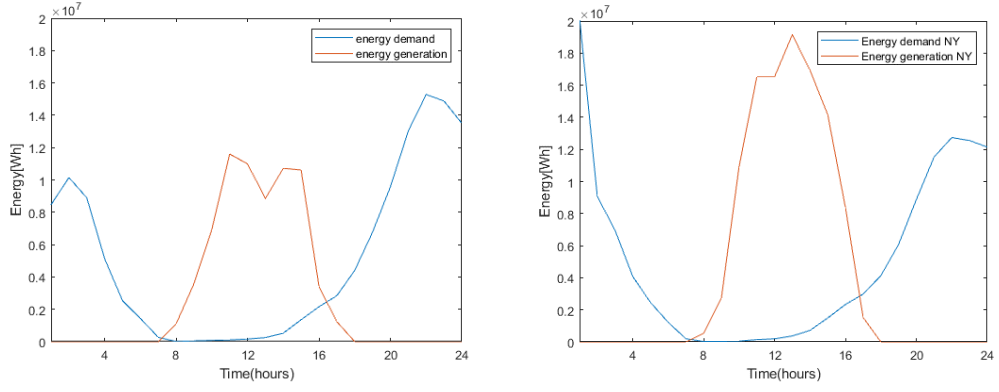


Figure 68. Hourly energy demand and generation for 1st of January for (a) LA, (b) NYC (Vehicle is started to charge 2 hours after the last trip ends)

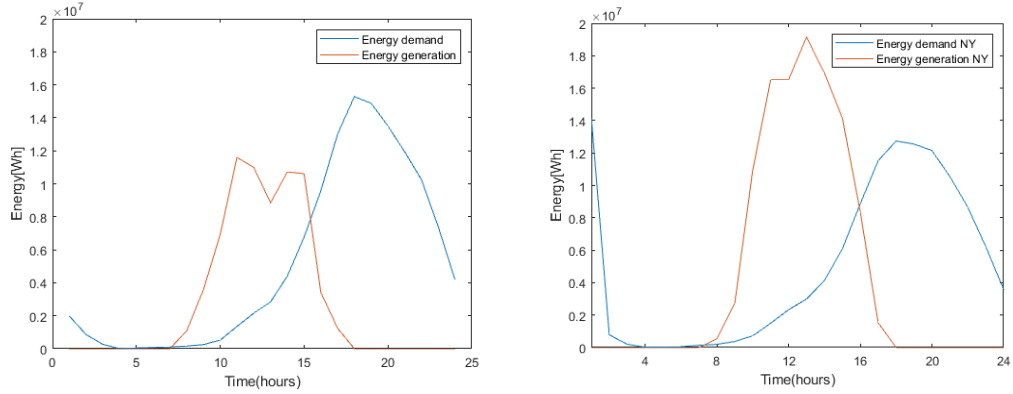


Figure 69. Hourly energy demand and generation for 1st of January for (a) LA, (b) NYC (Plug-in times assumed to shift 2 hours earlier).

To assess the performance of the designed PV system, some important parameters are investigated. One of these parameters is the deficit energy because it is either compensated from the grid or energy storage system. If the deficit energy is compensated by the grid, it is going to be put extra stress on the grid especially if it is already in a peak load hour. Figure 70 represents the hourly energy balance of the days of when the maximum deficit and surplus occurs. It also includes the real hourly CO₂ emissions of the grid for that specific day in year of 2018 [90][91]. As can be seen from Figure 70, there is surplus energy when the grid has also minimum CO₂ emission.

On the other hand, at the hours when emission of the grid is maximum, the energy deficit occurs which will be compensated by the grid. In addition, Figure 70(b) represents the hourly energy balance of the day when the maximum surplus occurs. Figure 70(a) also follows the same trends as Figure 70(b), in other words, energy deficit occurs at the hours when CO₂ emissions emitted by the grid are maximum.

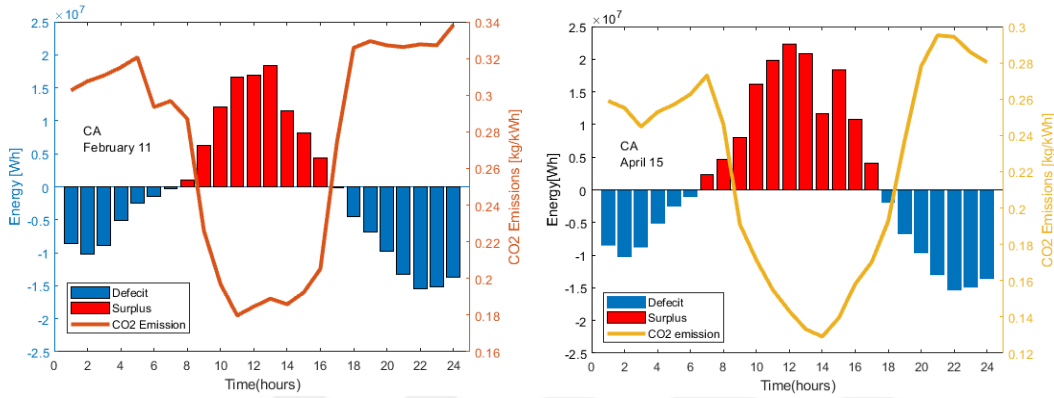


Figure 70. Deficit and surplus energy and grid CO₂ emission for the selected days which (a) deficit is the maximum, (b) surplus is the maximum [90].

Figure 71 represents the deficit and surplus energy with respect to grid load for the days which deficit and surplus energy values are the maximum. When deficit energy occurs, the grid is already overloaded as presented in Figure 71. Charging EVs at these hours would even increase the stress on the grid. Thus, whether the renewable system is implemented or not, the stress on the grid due to EV charging is required to be minimized at peak hours.

The cities of LA and NYC apply Time of Use (TOU) grid pricing which means that the retail price of the electricity changes within the day. During the hours when demand is higher, people are charged more for electricity. represents the TOU electricity prices for LA as well as the deficit and surplus energy on April 15th when the surplus energy is the maximum. It is clear that at the hours where deficit energy

occurs, the price of the electricity is higher. In other words, the deficit energy is compensated from the grid at a higher price rate. At the same time, the stress on the grid and CO₂ emissions of the grid are higher. Therefore, either an energy storage system or load shifting should be implemented to decrease the CO₂ emissions due to charging and the stress on the grid. Moreover, since the grid tariff is higher at the hours when deficit energy occurs, it may balance the increase of the cost of electricity due to implementation of storage systems.

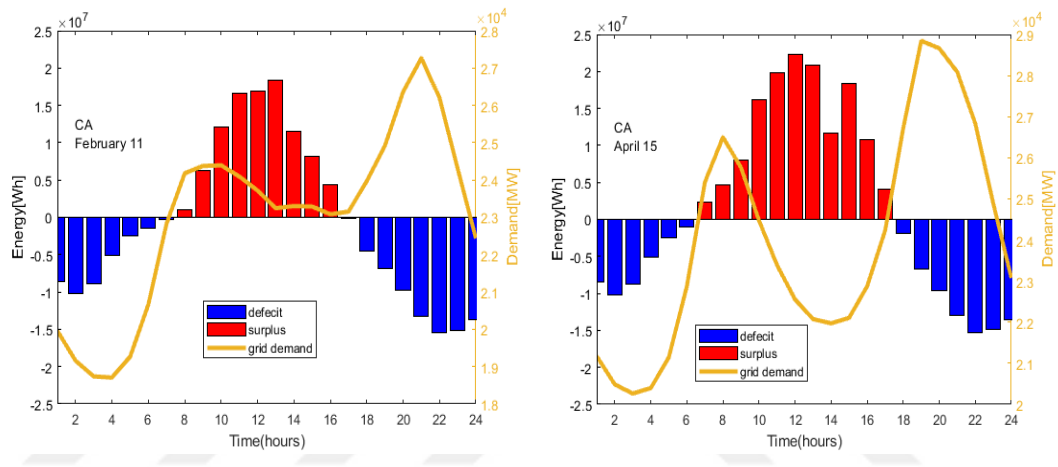


Figure 71. Deficit & surplus energies and grid total load emission for the day which (a) deficit is the maximum, (b) surplus is the maximum [90].

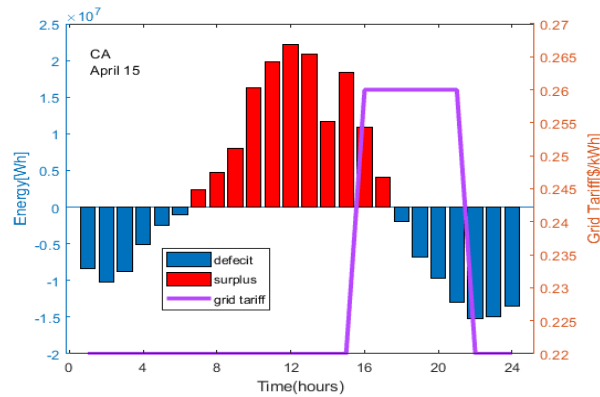


Figure 72. Deficit & surplus energies and grid total load emission for the day in which surplus energy is the maximum [90].

4.1.8.2 Impact of PV-EV Charging on Grid: Charge-when-ever-possible

Scenario

In Scenario 1, EVs are assumed to be charged after their last trip so most of the energy is demanded at late hours of the day. At the late hours, there is no solar energy and EVs are charged by the energy from the grid. In Scenario 2, the EVs are assumed to be charged if they are in park position more than one hour. Figure 73 shows the hourly energy demand for 1st and 2nd scenarios as well as energy generation for the 1st of January for NYC and LA.

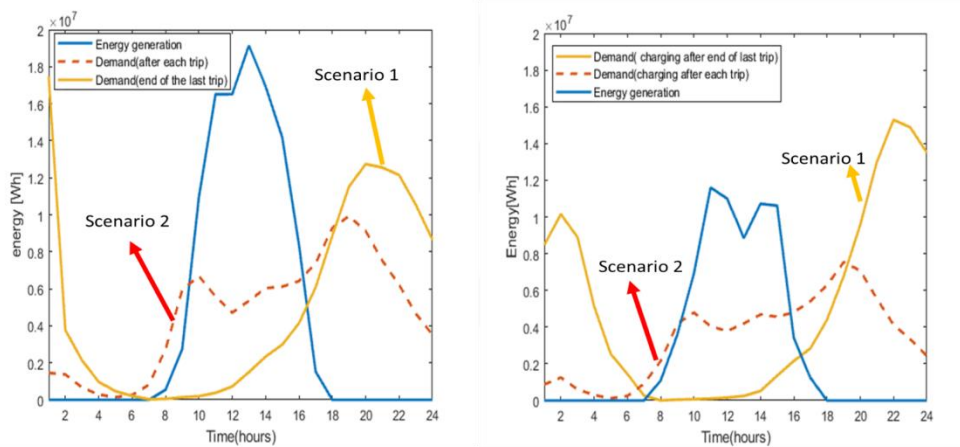


Figure 73. Comparison of 1st and 2nd charging scenarios for 1st of January for (a) NY, (b) CA.

From close inspection of Figure 73, it is clear that the energy demand in Scenario 2 is more evenly distributed within the day compared to Scenario 1. The direct use of solar energy also increases for Scenario 2, because of the demand at the time when solar energy is available increases. Thus, the total energy is taken from the grid, i.e., the deficit energy, decreases as presented in Table 28. Moreover, more generated energy is directly used for EV charging in Scenario 2. In Scenario 1, 40.8 GWh annual energy is taken from the grid, i.e., EV penetration creates 40.8 GWh extra load on the grid, while this number halves for Scenario 2. Both scenarios might be achieved by

implementing several incentives to encourage owners of EV to charge their vehicle at designated times. The PV systems for these cities are designed so that the annual energy demand is equal to the total annual energy generation. Thus, summation of deficit and surplus is zero.

Table 28. Annual deficit and surplus energy for LA and NYC.

	Annual deficit		Annual surplus	
	x10³ [MWh]			
	LA	NYC	LA	NYC
Scenario 1	40.8	35.3	40.8	35.3
Scenario 2	22.2	21.7	22.2	21.7

CHAPTER 5. CONCLUSIONS

In this thesis, the feasibility of PV-powered electric vehicle charging stations is studied. A general model is developed to estimate the annual energy generation from the PV plant and energy demand for electric vehicles. The model is divided into two sections which are demand and generation side. For the energy demand section, the effects of the drive cycle and ambient temperature on the energy consumption of the EV are incorporated. It has been found that ignoring these effects leads to underestimation of energy demand up to 35%, which in turn would decrease the benefits expected from the designed PV system in the energy generation. On the generation side, impacts of the location on the PV system is studied by comparing two different locations LA and NYC. Also, the effect of optimization of PV module optimization is studied. For example, in LA 16.5% more energy can be generated for the same size of PV systems compared to NYC due to the fact that solar potential varies by location. Also, the optimization of the orientation of the PV module increases the annual energy generation. In Istanbul case study the optimum PV module orientation increases the annual energy generation about 7%. The developed model is applied for Istanbul (Turkey), Los Angeles (CA, USA) and New York City (NY, USA) as case studies.

In the Istanbul case study, a PV-covered parking lot designed for a parking lot with 10-car capacity. This parking lot covers about 150 m² which could utilize a 22.5 kW PV system. This PV system generates 36.7 MWh annually, while annual the energy demand of 10 car is about 36 MWh. Therefore, this PV system would decrease the extra demand on the grid, if EVs are charged by this system. If the drive cycle and ambient temperature effects were neglected while estimating demand, energy demand

would have been 20 MWh. Thus, the underestimation of demand would have occurred.

The CA and NY are two of the crowded states of the United States. They represent the different ambient conditions as well as driving conditions. To see how the feasibility of the PV-EV system varies by the ambient and driving conditions, Los Angeles (CA) and New York City (NY) are compared. LA represents the mild ambient condition, while NYC represents ambient conditions with fluctuations. It is found that LA is more feasible for PV-EV compared to NYC. For example, for the PV rated power of 1000 kW, the demand of 537 vehicles can be covered in LA, while demand of only 414 vehicles can be covered in NYC. This difference has two main reasons. The first reason is that solar potential in LA is greater than the one in NYC. Secondly, the energy demand per mile is lower in LA than in NYC, although the average traveled distance in both cities is almost the same. However, NYC driving conditions include more stop-and-goes than LA which lead to increase in energy demand. Also, the ambient temperature drops below 0°C and exceed 30°C in NYC, so the energy demand per mile increases. These variations in ambient temperature increase energy demand up to 25% compared to the energy consumption of an EV at 20°C. On the other hand, due to its mild climate, the energy demand in LA is almost constant and lower throughout the year.

Moreover, the economic feasibility of PV-EV for selected states is compared. The unit cost of energy generated by the modeled PV system is 110 USD/MWh in LA, while it is 131 USD/MWh in NYC. On the other hand, grid retail prices are 160.6 and 147.4 USD/MWh in LA and NYC, respectively. Thus, the benefits of PV charging are more pronounced in LA, although it is economically feasible in both cities. Therefore, the payback period is shorter in LA than in NYC. Electric vehicles should be charged by

renewable energy sources to be environmentally friendly. In this study, it is concluded that charging of EV using PV systems is feasible for LA, NY and Istanbul. Also, the effect of ambient conditions and ambient temperature effect should not be ignored in any similar feasibility study.

The huge penetration of electric vehicles will put extra demand on the grid. Although PVEV system decreases the stress on the grid, more sophisticated smart charging algorithms to increase the rate of use of direct PV energy are needed to increase the efficiency of PV-EV systems. As future work, optimum smart charging algorithms might be investigated. Moreover, storage system might be implemented as a future work because grid tariff is generally higher at the hours when deficit energy occurs. It may balance the increase in the cost of electricity due to implementation of storage systems.

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