ESTIMATING THE CARBON EMISSIONS CAUSED BY ELECTRIC VEHICLE USE IN TURKEY USING MARGINAL EMISSION FACTORS

by
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Submitted to the Graduate School of Engineering and Natural Sciences
in partial fulfillment of
the requirements for the degree of Industrial Engineering

Sabancı University
August 2020

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ABSTRACT

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Industrial Engineering M.Sc. Thesis, August 2020

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Keywords: Electric vehicles, Carbon emissions, Marginal Emission Factor (MEF), Marginal power plant, Simulation, Electric load profile

Electric vehicles (EVs) produce zero carbon emissions during their use. However, generation of the electricity to charge EVs does cause emissions. In this study, we calculate the carbon emissions caused by the introduction of 10,000 hypothetical EVs in Turkey. To this end, we first develop a simulation model that characterizes the hourly power demand of EVs based on distributions of EV model characteristics, trip times and lengths as well as charging decisions of EV users. We then characterize the supply side by determining the marginal power plants and estimating the Marginal Emission Factor (MEF) for the Turkish power system. We use real hourly generation data of the country by different fuel types, under four different seasons and three time-of-day periods, for years 2014 and 2019. We find the MEFs for Turkey in 2019 to range between 100-332 kgCO_2/MWh, which are much lower than the MEFs reported for other countries. Finally, we bring the supply and demand studies together to calculate the carbon emissions of the hypothetical EV fleet. We observe the EVs fleet to cause between one fifth and one third of the emissions of a similar internal combustion engine car fleet.

ÖZET

ELEKTRİKLİ ARAÇ KULLANIMININ SEBEP OLDUĞU KARBON SALINIMININ MARJİNAL SALINIM FAKTÖRLERİ KULLANIMIYLA TAHMİNİ

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Endüstri Mühendisliği Yüksek Lisans Tezi, Ağustos 2020

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Anahtar Kelimeler: Elektrikli araçlar, Karbon salınımı, Marjinal Salınım Faktörü, Marjinal elektrik santrali, Benzetim, Elektrik yük profili

Elektrikli araçlar (otomobiller) kullanım sırasında karbon salınımına sebep olmazlar. Ancak, bu araçların şarj edilmesi için gerekli elektriğin üretimi salınıma yol açar. Bu çalışmada, Türkiye'de 10,000 farazi elektrikli aracın kullanılması durumunda ortaya çıkacak ek karbon salınımını tahmin etmeyi amaçladık. Bu amaçla, araç modeli, yolculuk zamanı ve mesafeleri, ve araç kullanıcılarının şarj kararlarının dağılımlarına göre ortaya çıkacak saatlik elektrik yük dağılımlarını ortaya koyan bir benzetim modeli oluşturduk. Tedarik tarafında da, ülkenin elektrik sistemindeki marjinal elektrik santral tipini tahmin ettik ve marjinal karbon salınım faktörünü hesapladık. Bu amaçla, 2014 ve 2019 yılları için dört ayrı mevsim ve üç ayrı gün zamanı kırılımında farklı santral tiplerinin gerçek üretim verilerini kullandık. Türkiye elektrik sistemindeki marjinal emisyon faktörünün 2019 yılında başka ülkelerden daha düşük bir seviyede (100-332 $kgCO_2/MWh$) gerçekleştiğini tespit ettik. Son olarak, çalışmanın tedarik ve talep taraflarını bir araya getirerek farazi elektrikli araç filosunun yol açacağı karbon salınımlarını hesapladık. Elektrikli araç filosunun, içten yanmalı motorlu araç filosunun beşte biri ila üçte biri arasında karbon salınımına yol açtığını gözlemledik.

To my parents, for their support and patience.
To Tolstoy, for his confession showed me the truth.
To Alija, for showing me that greatness is not perfection.

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1. INTRODUCTION

With the increasing threat of climate change and global warming, there is a growing interest in greenhouse gas (GHG) emissions mitigation. Many nations within the EU and UN must abide by strict mitigation efforts enforced by the Kyoto Protocol and the Paris Agreement. Climate change poses a significant threat to Turkey since not only has it raised the average temperatures, but it has also caused drought. Therefore, it is of high priority to introduce climate change mitigation actions, such as decommissioning more fossil fuel based power plants and introducing renewables, or implementing a new carbon tax.

The transportation sector produces 24% of the overall global CO_2 emissions, with road vehicles being responsible for almost 75% of the sectors CO_2 emissions (IEA, 2019). For several years, the automotive industry has been keen on reducing fossil fuel dependency and on supporting environmental policies, thus increasingly shifting their focus on the development of electric vehicles (EVs) from conventional internal combustion engine vehicles (ICEVs). The global EV fleet has been continuously growing with EVs becoming more technologically advanced and adhering to more of the needs of the general public. The share of EV sales in several countries has become quite large; in 2019, around 56% of the vehicle sales in Norway were comprised of EVs and PHEVs, in Iceland around 18% and in China 5.6% (Statista, 2020), where a large portion of the global passenger vehicle fleet exists. Nevertheless, the expected increase in the number of EV sales around the world provides several challenges to the electricity system brought about by EVs charging. Moreover, it is often the case that EVs charge at peak load times (Lojowska, Kurowicka, Papaefthymiou & Van Der Sluis, 2011; Morrissey, Weldon & O'Mahony, 2016; Qian, Zhou, Allan & Yuan, 2011; Schauble, Kaschub, Ensslen, Jochem & Fichtner, 2017) which may be exigent for the electricity grid. A single EV can increase a household's electricity consumption by 50% (Brouwer, Kuramochi, van den Broek & Faaij, 2013). In this thesis, our goal is to understand how a shift to EVs in Turkey would affect the country's CO_2 emissions abatement.

Our particular research interest is the consequential effect of EV charging on abated

CO_2 emissions in Turkey. Throughout this study, we consider an EV to be a battery electric vehicle (BEV), i.e., it only relies on its electrical battery and does not use any other fuels, such as diesel or gasoline. EVs are considered to produce zero emissions during travel, however, one must also consider that EV charging puts an extra load on the electricity grid, prompting power plants to produce more electricity which often results in carbon dioxide emissions. In countries with low carbon intensity in their electricity generation system, EVs can be advantageous in CO_2 mitigation. However, in countries like the U.S. where there are regions which rely heavily on electricity generation from coal, EVs have been shown to be only slightly better than ICEVs. In countries such as China and India which have high carbon intensity in the electricity production, it was found that diesel cars can mitigate more or equal levels of GHG emissions when compared to EVs (Doucette & McCulloch, 2011). Therefore, it is crucial to determine the resulting emissions from EV charging to properly assess the abated GHG emissions.

In the first section of this chapter, we discuss the different approaches to finding the extra electricity load resulting from EV charging. Next, we discuss the different approaches to quantifying the abated CO_2 emissions resulting from EV charging. Finally, we provide the roadmap for the thesis.

1.1 Determining the Extra Power Load Resulting from EV Charging

Electrifying a passenger fleet would significantly reduce the carbon dioxide emissions coming from conventional combustion engines. However, the introduced EVs would also require charging, which would increase the load on the electricity grid. To quantify and analyze the consequent effect of EVs charging on the electricity load, mainly whether peak loads will shift or significantly increase, one must have access to existing data or somehow simulate the travel behavior of EVs. Depending on an EVs travel behavior, its electricity demand varies.

To properly assess and quantify the impact of EV charging on a region's electricity demand, it is essential to first grasp the travel patterns and charging behavior of EV owners. Unfortunately, in regions or countries where EVs have not been widely adopted, such as Turkey, EV data in terms of surveys or field trials is scarce. Despite having small scale trials or surveys in regions with very low numbers of EVs, these trials or surveys do not properly represent the general population. The scarcity of data prompts researchers to find alternative methods which simulate or estimate the EV travel and charging behavior. In regions with ample numbers of EVs, researchers conduct surveys, field trials, interviews or questionnaires to gather data from EV owners; on which they conduct statistical analysis to create charging profiles and reach conclusions on EV charging and travel behavior (Corchero, González-Villafranca & Sanmartí, 2015; Franke & Krems, 2013).

One of the shortcomings of most travel surveys is that they are often based on driving behavior of owners of conventional internal combustion engine vehicles who may not have the same driving habits as EV owners. In addition, travel surveys are often recorded by hand and are susceptible to human error. Hence, assumptions must be made to estimate the time EVs are charged and the duration of their charging time. Although there are a couple of studies that employ EV travel and charging surveys (Morrissey et al., 2016; Quiros-Tortos, Navarro-Espinosa, Ochoa & Butler, 2018), they often lack representative numbers of EVs and also neglect the use of accessories, such as lights and air conditioning; which also contribute to battery drain. Moreover, results from field trials and surveys are usually only valid for the region where the data was gathered.

Using limited real data, researchers develop statistical or stochastic models for the entire charging and use process of an EV to bypass the assumptions made in travel surveys. Such use processes include start times of charging events, travel patterns as well as the resulting loads on the electricity grid. The arrival and departure times of the EV, as well as the initial and final state of charge (SoC: The level of charge in the battery) i.e., the level of charge at which EV begins and ends a charge event, respectively can often be considered as random variables, and so stochastic modeling is often quite useful.

Stochastic models are best suited to capture the uncertainty in the travel and charging patterns of EV users. Stochastic electricity load models produce probability distributions of electric demand rather than one single estimate. The variability in these stochastic models originates mainly from both the vehicle usage pattern and the charging behavior. For example, Brady & O'Mahony (2016) employed a stochastic simulation while also using Bayesian inference to generate travel patterns. Brady then employed copula functions to examine the dependence structures between the random variables. In another stochastic model, Crozier, Morstyn & McCulloch (2019) identified unique EV usage profiles using K-means clustering, then formulated a model and parameterized it by using field trial data.

Due to the lack of travel pattern data for both conventional vehicles and electric vehicles in Turkey, a stochastic simulation is necessary to properly model the possible charging and travel behavior of the EVs introduced to the Turkish passenger fleet. In our model, we simulated travel patterns for EVs as well as their charging to generate the data required to calculate the extra hourly load on the electricity grid. Using travel pattern probability density functions and other data provided by certain studies, we conducted a stochastic simulation using the Arena simulation software (Simulation with Arena, 2009). Arena is a discrete event simulation software that is used to model complex systems with a large number of interactions. Our model simulates EV travel between home and work. The model also simulates the charging behavior of EVs at the workplace and at home. The output of the model is an hourly load profile for the EVs charging in the system. This load profile is then used as an estimate of the electricity demand of the EVs. In the next section, we discuss the different approaches to quantifying the CO_2 emissions resulting from the extra generation needed to meet the estimated demand.

1.2 Approaches to Quantifying Carbon Emissions

Researchers are often interested in the changes in electricity demand that will result from an intervention, such as switching from fossil fuel based heating to electric heating, applying pricing incentives to shift peak loads or in our case, to estimate the extra power demand resulting from EV charging. It is thus necessary to quantify how much CO_2 emissions will be abated when there is a mitigation action to evaluate its efficiency and effectiveness.

When decision makers and researchers wish to evaluate demand side mitigation actions, they often use average emissions factors (AEFs) or marginal emissions factors (MEFs). For a power grid, an AEF is defined as the CO_2 emissions per average unit of electricity delivered for the entire grid (Hawkes, 2014), while an MEF is defined as the unit change in CO_2 emissions related to a unit change in electricity demand. AEFs can often be misleading while assessing the benefit of an intervention and have been shown to result in high errors (Bettle, Pout & Hitchin, 2006; Hawkes, 2010; Siler-Evans, Azevedo & Morgan, 2012). Not all power plants in an electricity system respond proportionally to a change in demand, it is rather the opposite, only specific power plants respond to unit changes in demand. Such power plants are known as marginal power plants. Hence, depending on the fuel resource and efficiency of the marginal power plants, the emissions abated by reducing the electricity load vary. Previous research has shown that the effects of marginal interventions are significantly different from those calculated by system averages. In some cases using AEFs greatly underestimate avoided emissions as much as 50% (Bettle et al., 2006; Hawkes, 2010; Marnay, Fisher, Murtishaw, Phadke, Price & Sathaye, 2002; Siler-Evans et al., 2012).

Finding the marginal power plant in a power system in a given period of time is often difficult because of political, economic and technical constraints in the electricity grid. Additionally, the type and quality of fuel consumed by the marginal power plant affects the marginal emission factor, which may vary from one region to another. Estimates of carbon emissions may also not be available for a given region or country. These difficulties prompt researchers to find ways to circumvent the lack of data.

Researchers have devised multiple approaches to find the marginal emissions factors, including the merit order approach. The merit order is defined as the order at which power plants respond to incoming marginal demand, where a plant responds to demand before another if its marginal cost for producing a unit of electricity is lower. This approach implicitly assumes that the only factor that determines whether a plant is a marginal power plant or not is the marginal cost of production of electricity, which may not be the case in practice. An example of this would be a dam hydro plant, the price of generation may be low of this plant, however, its operators may not generate electricity during a dry season.

An alternative approach is to use empirical methods. For example, some researchers employ regression analysis to obtain MEFs from historical electricity generation data (Hawkes, 2014; Siler-Evans et al., 2012). One advantage of using the regression approach over the merit order approach is that one can temporally disaggregate the results by year, by season or by time-of-day. In our study, we adopted a similar approach and have applied linear regression to hourly electricity generation data to find the MEFs for Turkey. Our dataset is obtained from the transparency platform of by Enerji Piyasaları İşletme A.Ş. (EPİAŞ) available at https://seffaflik.epias.com.tr/transparency/index.xhtml. Finding the MEFs for Turkey is essential to evaluate the efficiency of CO_2 abatement of the intervention we analyze, electrifying a portion of the Turkish passenger vehicle fleet.

1.3 Thesis Goals

Our goals in this study are as follows:

- Simulating the travel patterns and charging behavior of EVs in Turkey by developing an appropriate simulation model.
- Generating the hourly electricity load profile resulting from EV charging.
- Determining the marginal power plants in the Turkish electricity system in different time periods.
- Estimating the MEFs for Turkey for each season and daily period.
- Comparing the marginal plants as well as MEFs between years 2014 and 2019
- Generating a carbon emissions profile using the calculated MEFs and the load profile.
- Comparing the carbon emissions produced from EV charging with carbon emissions that would be produced from a fleet of comparable internal combustion engine vehicles.

1.4 Contributions to Literature

In the demand side of our study, we contribute to the literature by generating a simulation framework for EV charging behavior and travel patterns in Turkey using the simulation software Arena. To our knowledge, this is the first such simulation model for Turkey. The charging and travel distributions produced, as well as the hourly charging profiles can be used by researchers and adapted for other research purposes related to EVs in Turkey.

In the supply side of our study, we calculated the Marginal Emission Factors (MEFs) for the Turkish power system separately for each season and daily period. We also estimated the marginal plant types in the merit order. These findings may be used by researchers for making calculations on the Turkish electricity grid and also in evaluating the carbon abatement resulting from various interventions.

1.5 Organization of Thesis

The following chapters are structured as follows: in the current chapter (Introduction), we present the problem definition, motivation and a general overview of our study. In the second chapter, we review recent and relevant literature on generating the load profiles due to EV charging. We then review existing work on quantifying emissions and literature on the methods to produce such metrics. Then, we discuss previous research that covers both load profile generation and emission measurement. In the third chapter, we present the simulation design that we used to produce the hourly load profiles. Then, we show the results of the simulation. In the fourth chapter, we present background information on the Turkish electricity grid, including generation shares and installed capacities for different fuel types, as well as the calculated MEFs for the Turkish electricity grid by season and time-of-day for two sample years. Finally, in the fifth chapter, we combine the demand side of the study, i.e., the load profiles, and the supply side of the study, i.e., the MEFs, and we analyze and discuss the results and present our conclusions.

2. LITERATURE REVIEW

In this chapter, we cover the recent literature related to the demand and supply sides of our study. The first section covers literature on owners' EV charging and travel behavior as well as existing simulation models, which is important for understanding the demand side of the study and analyze the expected additional demand resulting from EV charging. The second section covers the different approaches to quantifying the consequent CO_2 emissions resulting from the electricity generation fulfilling the extra demand required by EV charging. The third section includes research that combines the demand side analysis and the supply side analysis.

2.1 Determining EV Charging Behavior and Travel Patterns

To properly assess the power consumption of EV charging, researchers study the charge profiles and travel patterns of EVs. These EV charge profiles, also known as load profiles, can either be empirical profiles, produced purely through empirical data, or synthetic profiles, generated from simulations which may or may not be based on empirical data. Empirical load profiles can be produced by analyzing existing data in terms of field trials (Franke & Krems, 2013), travel surveys (Moon, Park, Jeong & Lee, 2018), questionnaires and interviews. However, there is often a lack of charge event and travel data for EVs especially in regions where EVs have not been widely adopted. The scarcity of data prompts researchers to create synthetic EV fleet profiles using ample, limited or no historic data. Most synthetic load profiles are generated by stochastic simulations, since stochastic simulation models properly capture the uncertainty in EV travel patterns and charging behavior. Researchers have also compared results between empirical and synthetic load profiles (Schauble et al., 2017).

Different studies may adopt different temporal disaggregation for their empirical or synthetic load profiles, analyzing the power consumption of EV charging over a long period of time such as a season, several months or a year, while others analyze the power consumption over periods in a day, hour or half hourly. In our study's purposes, an hourly accuracy for the load profiles is sufficient since the highest temporal disaggregation possible in the electricity generation data used in the supply side of the study is also hourly.

2.1.1 Travel Surveys and Field Trials

One method to analyze EV owner travel patterns and charging behavior is to conduct surveys or field trials through GPS data or questionnaires. In questionnaires, data is collected by asking EV owners or prospective EV owners about their travel and charging behavior. Alternatively, GPS tracking devices installed in EVs may continuously collect travel and charging data. The data collected gets statistically analyzed to reach meaningful conclusions. Existing research in this field can be especially beneficial for our study since it provides insight into actual EV owner behavior, enabling us to create a more realistic simulation model. In addition, it allows us to validate our simulations results with real data.

A large group of researchers rely on data collected from GPS-tracked EVs. For example, Franke & Krems (2013) conducted a field trial for 79 EVs using GPS tracking over a course of six months in Germany and analyzed their charging patterns. Franke & Krems also compared EV charging behavior with phone charging behavior and observed that true vehicle ranges affect charging decisions. The authors found that EV drivers charge their vehicles three times per week on average rather than whenever possible, while their average daily distance traveled was 38 km. In addition, the authors observed that home charging accounted for 83.7% of charging events with 71% of drivers preferring to charge at home, while only 4.8% of drivers charged their EV in a public charging space. Similarly, while conducting an extensive analysis of charge event data collected in Ireland between the years 2012 and 2015 which included over 40,400 charge events, Morrissey et al. (2016) found that the majority of EV drivers prefer to charge their vehicles at home during peak load hours in the evening. In addition, given the choice between home or public charging, the authors observed that the majority of EV users charged their vehicles at home or at work rather than using public charging.

Corchero et al. (2015) gathered charging and travel data from 2011 to 2013 from 689 EVs in six European countries; covering more than 140,000 trips and 230,000 charging events. Corchero found the average state-of-charge (SoC) when EV owners recharged their vehicles to be 60%, which suggests that EV owners do not wait until their battery is empty to charge. Quirós-Tortós, Ochoa & Lees (2016) gathered results from over 200 EVs in the UK, which included 68,000 charging events. The data was used to create probability density functions such as the one for the initial SoC when charging starts and the final SoC at which charging ends. These probability density functions aide researchers in designing stochastic models that represent EV demand. Expanding on their original work, Quiros-Tortos et al. (2018) used probability density functions based on Gaussian mixture models (GMMs) to statistically represent charging metrics of EVs. The GMMs were formed by using real data gathered from 221 EVs over the course of two years in the largest EV trial in the UK and Europe. The EV analysis in the study showed that EVs may charge more than once per day and that most EV owners begin charging their EVs when its SoC is between 25% and 75%, with 70% of charging events ending with a fully charged battery.

Coban & Tezcan (2019) surveyed 50 plug-in Hybrid EV and full EV owners in Turkey. The EVs in the dataset were both public and private EVs. The authors then produced the home and work arrival time distributions, the daily trip distance distribution and evaluated the effects of the EVs' charging on power transformers. The average daily distance traveled of the EVs in this survey was found to be 32 km which is in line with the value we used in our model.

2.1.2 Synthetic EV Load Profiles

An alternative approach to using travel surveys and field trials is to develop synthetic EV load profiles through simulation models. A synthetic model must properly capture the stochastic nature of EV travel and charge event durations, such as departure time, travel distance, plug-in time and the frequency of recharging. Stochastic models are thus very well-suited when it comes to capturing variability and uncertainty in travel patterns and charging behavior of EV users. Researchers that develop stochastic models are often motivated by either modeling EV behavior to generate travel patterns and charging profiles to aide other researchers; develop load profiles to estimate when EVs will charge and quantify their hourly demand; to determine the effectiveness of load shifting actions; or to analyze the effect of EV charging on the electricity grid itself (Sadeghianpourhamami, Refa, Strobbe & Develder, 2018). The data available on EV charging and travel patterns in Turkey is extremely limited, making synthetic and empirical load profiles especially attractive for our study. Therefore, the first motivation cited above is relevant to our research. The second motivation is also relevant, since through it we are able to compare our own simulation results and generated load profile with results from other research works. The third motivation, although not directly related to our research, invites an interesting discussion by providing insight into future actions that can help ease the strain on the electricity grid. The last motivation is not directly related with our research, so we will not dwell deeply into it.

The initial travel models were developed before EV use became widespread, and were based on data from internal combustion engine vehicles' owners (Grahn, Alvehag & Soder, 2014; Lampropoulos, Vanalme & Kling, 2010; Mousavi Agah & Abbasi, 2012; Pashajavid & Golkar, 2014) especially in countries where EVs have not yet been introduced. Since EVs have recently penetrated global markets on a larger scale, recent studies and stochastic models conducted have relied on historic EV data. For example, Schauble et al. (2017) presented a model that made use of empirical data from three electric mobility studies to estimate the potential increase in electricity demand due to EV charging. Using the data set, which was collected over a period of more than two years, Schauble simulated different EV charging profiles. The authors found that uncontrolled EV charging could lead to peaks during the day, which will strain the power grid. Tehrani & Wang (2015) used the National Household Travel Survey database to develop a stochastic model based on queuing theory to predict EV charging and the consequent load on the electricity grid. The authors also used a copula approach to represent dependence structures between the random variables. They found that PEVs can increase the load power demand at certain hours.

Shaaban, Atwa & El-Saadany (2013) tested four probability density functions on travel data from the NHTS: Exponential, Lognormal, Gamma and Weibull. The authors categorized the travel data by travel purpose such as business, commuting and education. The authors then used the maximum likelihood method to estimate the parameters of probability density functions that best fit the real data. Data for purposes with low average distance traveled per trip were most likely fitted by a Lognormal distribution. The data for purposes with high average distance traveled per trip were more likely fitted by using a Weibull distribution, which concurs with Tehrani & Wang (2015)'s work. Qian et al. (2011) formulated a stochastic model for EV charging to analyze its effect on the electricity grid, with the charging start time and the initial SoC as random variables. A comparative analysis was carried out on four EV charging scenarios: uncontrolled domestic charging, uncontrolled off peak domestic charging, smart domestic charging and uncontrolled public charging throughout the day. Uncontrolled charging denotes charging that occurs at any time of day without an incentive for EV users to charge at certain periods through a lower cost, essentially meaning that the price of electricity is fixed throughout the day. Controlled charging denotes charging that is incentivized by lower costs during non-peak hours. In a smart charging scenario, EVs are able to feed electricity into the electricity grid for profit. In the uncontrolled charging scenario, an EV market penetration of 10% is found to result in an increase in daily peak demand by 17.9%, while a 20% market penetration is observed to result in an increase of 35.8% in peak load. The authors assumed that half of EVs charge at their workplace and the other half charge at home using only slow charging at both locations. These assumptions, however, are not necessarily realistic.

Several stochastic models are based on Monte Carlo simulations (Ashtari, Bibeau, Shahidinejad & Molinski, 2012; Chen, Chen, Huang & Jin, 2016; Harris & Webber, 2014; Lojowska et al., 2011; Lojowska, Member, Kurowicka, Papaefthymiou, Sluis & Member, 2012; Su, Lie & Zamora, 2019; Wang & Infield, 2018; Zhou, Li & Wu, 2018). The Monte Carlo approach uses random sampling to estimate a mathematical function. For example, Harris & Webber (2014) examined the effects of EV charging on the regional level by a Monte Carlo simulation. The results of the simulation were compared and validated with empirical charging data gathered from households in three U.S. states. The authors found that uncontrolled PEV charging in the three regions would increase peak load power demand by less 2% if medium improvements and growth to the grid occur. Using actual traffic data, Zhou et al. (2018) created probability distribution models and formulated a Monte Carlo simulation model to simulate EV travel patterns and charging behavior. The authors also developed a multiobjective charging strategy with multiple constraints to determine the optimal charging strategy that would reduce the grid peak load, lower charging costs and achieve success in EV travel plans. Lojowska et al. (2012) presented a Monte Carlo simulation that made use of three variables selected from data provided by the Dutch Ministry of Transportation: EV arrival times and departure times from charging locations, and trip distances. Due to the statistical independence property of the selected variables, the authors used a copula function to join the univariate distribution functions to form the multivariate distribution functions for both single and double journeys, which was in turn used to in the Monte Carlo simulation to model vehicle travel and charging patterns. The authors then generated the load profile for the EVs. Ashtari et al. (2012) examined vehicle usage and charge pattern data collected from 76 EVs using GPS recording devices in Canada. The authors developed one deterministic method and three stochastic methods to predict the EV charging profiles. Results show that the load due to EV charging peaks at evening hours when EV owners return home.

Some other stochastic models rely on Markov chains (Fischer, Harbrecht, Surmann & McKenna, 2019; Iversen, Møller, Morales & Madsen, 2017; Shepero & Munkhammar, 2018; Ul-Haq, Cecati & El-Saadany, 2018; Wang & Infield, 2018). EVs may be assumed to occupy one state at a given time from a set of finite states (such as parked and charging, traveling, and parked but not charging). Thus, it is possible to model EV charging and use as a discrete state and time Markov chain process based on historical data. For example, Ul-Haq et al. (2018) designed a Markov chain Monte Carlo model with three states: drive, park and charge. Ul-Haq observed different peak loads for uncontrolled charging on weekdays and weekends. After statistically analyzing German mobility data, Fischer et al. (2019) proposed a stochastic bottom up model to describe EV usage by using a non-homogeneous Markov chain, considering socioeconomic and sociodemographic factors. The model's results were compared with a mobility study's dataset for validation. The authors found that an additional EV in a household can increase the duration of evening peak times as well as the level of the annual peak of the system. In addition, the authors found that the daily evening peak would begin 45 minutes earlier than usual due to EV owners charging their vehicles once they arrive home. Wang & Infield (2018) combined both of the earlier ideas and created a time-inhomogenous Markov chain Monte Carlo (MCMC) simulation.

Hu, Dong & Lin (2019) developed a model based on cumulative prospect theory and using NHTS data from 2017 to study EV charging behavior and power demand profiles. Among the key findings was that EV drivers charge their vehicles on average when their SoC is 41%, with most charge events starting between 40-50% SoC. Most charging in the day time occurred at workplaces, while most charging at evening time occurred at homes.

Other researchers rely on big data and data mining techniques to estimate EV travel patterns, charging behavior and the load on the electricity grid. For example, Arias & Bae (2016) used big data methodologies along with historic traffic and weather data from South Korea to create a model that forecasts EV charging demand that takes weather and traffic conditions into consideration. Crozier et al. (2019) applied K-means clustering to identify three unique EV usage modes in the UK. To properly model the uncertainty in both EV travel and EV charging, the authors then formulated a stochastic model and parameterized it by trial data and then applied it to data obtained from the National Travel Survey. The formulated stochastic model successfully predicted 80% of charges from the EV trial data, while assuming charging occurred after the final trip in the day successfully predicted 42% of the data. In addition, the predicted peak demand resulting from aggregated EV charging in this model was 30% lower than the standard assumption, showing that studies using the latter assumption most likely overestimate demand peaks.

2.1.3 Applications to Synthetic EV Load Profiles

Researchers are often interested in employing policies that can change EV charging behavior, such as pricing techniques, to inducing a change in the habits of EV charging that can shift the load on the electricity grid from the peak periods to other low load periods.

EV charging can be classified into three types (Zhou et al., 2018): (a) uncontrolled charging (simple or dumb charging); (b) controlled charging (tariff-driven charging), i.e., charging where there are different pricing options for electricity depending on the time of day such that peak times are usually the most costly; and (c) intelligent charging, i.e., when an EVs extra battery energy can be utilized as a source of energy for the grid where the EV either returns electricity to the grid (vehicle-to-grid or V2G) or reduce their charging rate. Several researchers have studied different scenarios of controlled and uncontrolled charging and their impacts on the electricity grid. For example, Kara, Macdonald, Black, Bérges, Hug & Kiliccote (2015) collected data from more than 2000 non-residential electric vehicle supply equipment located in California over the course of one year. 580,000 charge events were analyzed and load flexibility and trends were found. The goal of the study was to better understand the benefits of smart charging for different stakeholders. Two case studies were also developed; a case where loads were shifted from high cost periods to low costs periods, and a second study where EV aggregations were used to decrease current contribution to peak load times in the grid.

Babrowski, Heinrichs, Jochem & Fichtner (2014) examined six European mobility studies and developed an algorithm that extracts EV load curves for weekdays and weekends by assuming different charging scenarios. The authors analyzed the effect of different parameters such as the charging location and charging power on the EV load curves in three different scenarios. Their results show that the ability to charge at work significantly affects the uncontrolled charging curve. In addition, the results show that controlled charging could ease the strain on the electricity grid due to peak loads. Canizes, Soares, Costa, Pinto, Lezama, Novais & Vale (2019) used a travel simulation tool to simulate EV owner behavior. Analyzing the effect of variable electricity prices on the EV owner behavior, Canizes found variable price charging to be beneficial to EV owners in all scenarios, compared to fixed price charging. The variable prices were determined based on distribution marginal price (DLMP) and continuously updated according to the EV owners' trips and travel behavior. The study's results show that variable prices for EV charging is beneficial to EV owners in all scenarios.

2.2 Quantifying CO_2 Emissions

Adding a significant number of EVs to the Turkish passenger vehicle fleet would lead to an increased demand of electric power from the grid due to EV charging. To respond to demand, active power plants would need to increase their output or other additional plants may need to kick in, causing additional carbon emissions. Thus, it is important to quantify the extra emissions coming from the additional generation in order to properly assess the effects of EV introduction.

Mitigation actions are often evaluated using two metrics, Average Emissions Factors (AEFs) and Marginal Emissions Factors (MEFs). For a power grid, an AEF is defined as the average CO_2 emissions per average unit of electricity delivered to the entire electricity grid. MEFs are defined as the unit change in CO_2 emissions caused by a unit change in electricity demand. When evaluating a mitigation action (such as the introduction of EVs in a transportation sector), results based on AEFs have been shown to lead to high errors and often underestimate the abated emissions (Bettle et al., 2006; Hawkes, 2010; Marnay et al., 2002). In certain regions where renewable energy sources are used extensively, the AEFs calculated to be lower than the MEFs; whereas, in regions where coal is extensively used, the AEF is higher than the MEF (Siler-Evans et al., 2012). Use of the AEF metric assumes that all plants in an electricity system respond equally to changes in demand implicitly, which is not the case. Only specific power plants, known as marginal power plants, respond to unit changes in demand. The second type of power plants in an electricity grid are known as base-load power plants (Zheng, Han, Li, Member & Zhu, 2015). These power plants are responsible for the base load in the electricity grid. It is important to note that the two types of power plants are not mutually exclusive, for example, a base-load power plant during day hours may become a marginal plant during night time hours. Similarly, a certain power plant may be responsible for a large portion of the base load and also respond actively to changes in demand, thus being marginal as well. Moreover, when analyzing an intervention's effectiveness using AEFs, it is assumed that the structure of the energy system will not change (Hawkes, 2014), which is rarely the case. New power plants are commissioned and old ones are decommissioned, thus there are often long term changes in the electricity system.

Depending on the fuel type, the efficiency of the marginal plants and the technology used, the amount of produced emissions varies. Various methods have been devised by researchers to determine the marginal power plants to find the electricity grid's MEFs. This is often difficult to do with lack of data, which motivates researchers to develop methods that circumvent the need to find the marginal power plants. Next, we discuss the alternative methods for calculating an MEF.

Approaches developed by researchers to find MEFs can be classified into two groups (Ryan, Johnson & Keoleian, 2016): (1) power system optimization models and (2) approaches based on empirical data. Power system optimization models include economic dispatch models such as unit commitment models, and models which follow the merit order approach. Approaches based on empirical data include statistical relationship models that are based on historic data. The main advantage of the statistical approach is that it reduces model complexity, but it also relies greatly on empirical data. Power system optimization models and economic dispatch models estimate MEFs using sophisticated techniques, but their complexity and strict assumptions restrict broad use (Li, Smith, Yang & Wilson, 2017).

Economic dispatch models determine the order by which power plants respond to demand. One approach to finding that order is the merit order approach. The merit order is defined as the order at which power plants respond to incoming marginal demand, where a plant responds to demand before another if its marginal cost for producing a unit of electricity is lower. Several researchers have used the merit order approach to calculate emission factors (Bettle et al., 2006; Hitchin & Pout, 2002; Marnay et al., 2002). There are several methods by which the merit order can be found. A couple of studies rely on real historical data, for example, Hitchin & Pout (2002) used an unconstrained merit order approach to find the AEFs and MEFs, however, they did not consider plant availability, maintenance schedules or bottlenecks in the transmission system. Bettle et al. (2006) revised and improved on Hitchin's model by designing a model using historical half hourly data for England and Wales to determine the merit order. However, the merit order was found by ranking generating plants in order of their level of utilization, meaning that power plants that were generating close to a full capacity were assumed to be first in the merit order since they are On most of the time.

An alternative method to finding MEFs or AEFs is to use unit commitment models. This method is particularly useful in determining the emission factors in future scenarios. Unit commitment models are optimization models that determine which will be utilized first to meet forecasted electricity demand. The objective of the model is to minimize total operational cost while adhering to electricity demand and technological constraints. For example, one of the three methods that Marnay et al. (2002) developed was a unit commitment model. Howard, Waite & Modi (2017) developed a unit commitment model for the State of New York and New York City to determine the average emissions and MEF. Razeghi & Samuelsen (2016) examined the environmental and economic impacts of EVs, finding that using a unit commitment model would avoid an increased capacity investment in the system.

Many researchers prefer empirical methods that employ statistical relationship models, such as regression analysis, to the merit order approach. There are several advantages to regression analyses, for example, it circumvents the assumptions made about the generator merit order (McKenna, Barton & Thomson, 2017). In addition, with regression analysis one can temporally disaggregate the results and thus analyze the data by season, month or hour. For each temporal disaggregation, a specific MEF can be produced. Moreover, knowledge of the exact marginal power plants is not necessary when determining the MEF using regression analysis. A popular approach is to use linear regression (Hawkes, 2010,1; Li et al., 2017; McKenna et al., 2017; Siler-Evans et al., 2012). To calculate the MEF with regression analysis, the total hourly change in electricity generation and the total hourly change in emissions produced are calculated. Next, due to the fact that these two variables are highly correlated, linear regression can be utilized. The slope of the produced line of best fit in the linear regression is defined as the MEF. This method circumvents the need to know the marginal plants beforehand or any information on the structure of the electricity grid, the two mentioned variables are the only prerequisites for calculating the MEF. For example, Hawkes (2010) estimated marginal CO_2 rates for Great Britain by applying linear regression to half-hourly change in the grid emissions versus half hourly change in electricity generation using 2002-2009 data. Hawkes's approach allowed fine temporal disaggregation of results, showing that the electricity grid in Great Britain does not necessarily obey merit order principles. Hawkes reported that MEF was 690 $kgCO_2/MWh$, while the AEF was 510 $kgCO_2/MWh$.

Improving on their earlier work, Hawkes (2014) introduced the concepts of long and short term MEFs, taking into consideration structural changes in the mix of generators. Short term MEFs can be calculated in the same manner as Hawkes did in his earlier work, while long term MEFs take into consideration the decommissioning or commissioning of marginal power plants due to future increases or decreases in electricity demand. The long term MEFs were estimated in Great Britain based on historic data from 2009 - 2012, and were found to be around 260 - 530 $kgCO_2/MWh$ for the following decade in the British power system. Similar to Hawkes's calculations for Great Britain, Siler-Evans et al. (2012) used linear regression to determine the MEFs for the U.S. electricity grid and compared AEFs and MEFs. However, Siler-Evans's approach was limited since it considered fossil fuel generation as a proxy for total generation, which is not necessarily true, with the share of renewables increasing everyday in the U.S. electricity grid, renewables are found to be at the margin for some hours or levels of demand (Thind, Wilson, Azevedo & Marshall, 2017). Citing the earlier limitation of Siler-Evans's approach, Thind et al. (2017) built on Silver-Evans's work and extended it by using the total generation for their analyses and not just fossil fuels. Furthermore, Thind et al. (2017) explored how AEFs and MEFs vary by state in the U.S. and corporation. Thind found that average MEFs are often lower than AEFs, which indicates that policy makers who use AEFs may overestimate the emissions reductions due to an energy efficiency program.

Numerous researchers have employed MEFs to determine emissions abatement associated with interventions in the electricity sector, such as energy efficient buildings (Min, Azevedo & Hakkarainen, 2015), electricity storage (Hittinger & Azevedo, 2015) and vehicle charging (Brouwer et al., 2013; Gai, Wang, Pereira, Hatzopoulou & Posen, 2019; Razeghi & Samuelsen, 2016; Tamayao, Michalek, Hendrickson & Azevedo, 2015; Yuksel, Tamayao, Hendrickson, Azevedo & Michalek, 2016). For example, McKenna et al. (2017) followed in Hawkes's steps and used linear regression to calculate the MEFs for Ireland, then analyzed the impact on CO_2 emissions of electrical storage systems under different scenarios for storing electricity generated from wind power. In the next section, we discuss literature that evaluates the emissions produced from electricity generation fulfilling extra demand from EV charging.

2.3 Evaluating Abated CO_2 Emissions from Introducing EVs into the Passenger Vehicle Fleet

Research in this field has been carried out by several groups (Razeghi & Samuelsen, 2016): the first group of researchers focus on the generation side of the electricity grid, attributing the level of success of EVs in mitigating GHG emissions on the charging profiles, charging levels and the grid mix. The second group focuses on the interaction of EVs with the distribution system, the distribution transformers and the distribution substations, as well as the consequences of using vehicle-to-grid (V2G) approaches. Other studies focus on the impacts of EVs on electricity market prices. Our study is part of the first group, therefore, we shall not cover literature related to other groups.

Similar to our approach, several researchers have calculated the expected load due to EV charging under different scenarios, either through simulations or by extrapolating historic data, and have determined MEFs to evaluate the abated greenhouse gas emissions (Gai et al., 2019; Razeghi & Samuelsen, 2016; Tamayao et al., 2015; Yuksel et al., 2016). For example, Tamayao et al. (2015) characterized regional lifecycle marginal CO_2 emissions of EVs across several regions in the U.S. and found that different regions have significantly different MEFs. In addition, Tamayao observed that delayed charging in EVs after peak hours results (i.e., charging after midnight) in higher CO_2 emissions as a consequence of increased marginal generation from coal during night time hours. Yuksel et al. (2016) investigated how marginal emissions produced from conventional vehicles, charging of plug-in hybrid vehicles and battery electric vehicles vary as a result of different regional grid mixes, travel patterns and air temperature. Climate often has a significant effect on the charging patterns of EVs especially in colder regions, since heating contributes greatly to the battery drain of EVs.

3. DETERMINING THE ADDITIONAL POWER DEMAND FROM EVS

We have developed a stochastic simulation model in Arena that considers the variability in travel patterns, arrival times, departure times and the uncertainty as to whether to charge the EV or not. We consider an EV population of 10,000 vehicles. We determine the charge profiles for each of these vehicles in order to quantify the hourly extra generated electricity needed to meet the charging demand and observe the consequent abated CO_2 emissions.

We developed our simulation model using the Arena simulation software. Arena is a discrete event simulation and automation software which uses the SIMAN simulation language and processor. In Arena, simulation models are designed by creating modules, which are the basic building blocks of Arena. Modules in Arena are nodes through which entities pass, originate or exit the model. Modules are connected by connector lines that specify the direction of the flow of entities. Entities can be anything from vehicles, people, products. Each entity may have a set of attributes or variables. In our model, the only entity type is the EV. The process type modules are used to model processes within the simulation. These processes can represent machining, time spent in queues, servicing, or in our case, EV travel and EV charging events.

This chapter on the demand side of the study is organized as follows: In Section 3.1, we discuss the simulation model's design and logic. We also list the general model assumptions (labeled with G), travel-related assumptions (labeled with T) and charge-related assumptions (labeled with C). In Section 3.2, we display and analyze the simulation results. Finally, in Section 3.3, we discuss the important conclusions and observations on the simulation results.

3.1 Simulation Design

The uncertainty in EV electric demand may originate from a variety of sources, such as the uncertainty in the daily travel distance of an EV, the departure time, the arrival time to the destination, the time between arriving to the destination and beginning to charge, the ability to charge at work or not, the battery capacity, the EV's on road efficiency, the weather conditions, and several behavioral factors such as the EV owner's choice of when and where to charge. Therefore, we develop a stochastic simulation model to properly address several of these variables.

Six EV models are considered in our simulation model, Tesla Model 3, Nissan Leaf, Renault Zoe, Hyundai Kona, BMW i3 and Tesla X. These EV models were selected based on the highest number of sales of EVs in the worldwide market, excluding Chinese EV models. The percentage share of each EV in the model is also based on the sales history of these EV models. Each EV model we consider is characterized by its battery capacity (kWh) and on road efficiency (kWh/km). The efficiency may or may not include energy losses due to factors such as heating, air conditioning or lighting. EVs in our model as considered to be personal or private EVs, i.e., they are not used for business or public use, such as taxis or delivery vehicles (assumption G1). We assume the initial state of charge (SoC) of the vehicles to come from a uniform distribution between 80% to 100%. All days in the simulation are workdays (assumption G2), and are assumed to be identical in nature, i.e., the exact workday has no effect on the random variables in the model, which is concurrent with what was found by Quiros-Tortos et al. (2018).

The travel patterns and distances traveled by EV owners are necessary to model the energy dissipated while driving. EV owners only travel from their home to work and from their work back to home (assumption T1). Average distances are available on occasion for certain countries and regions, however, they are not sufficient to create a realistic model. Due to the lack of travel data in Turkey for both conventional vehicles and EVs, we use parameters from other studies such as travel distance distributions. We model the distance between work and home as a random variable coming from a Weibull distribution with $\alpha = 15$ and $\beta = 1.23$ (assumption T2). This average distance is similar to what Coban & Tezcan (2019) found for Turkey in their survey study with EV owners. The authors found the daily average distance traveled to be 32 km, while our average daily distance traveled is 30 km (twice the one-way trip average distance).

In literature, we observed Lognormal distributions for relatively low average distances and Weibull distributions for relatively longer average distances (Calearo, Thingvad, Suzuki & Marinelli, 2019; Shaaban et al., 2013; Tehrani & Wang, 2015; Ul-Haq et al., 2018). Our average daily traveled distance (which is twice the average trip length), α, is within the range of average daily travel distances found in several research articles (Coban & Tezcan, 2019; Corchero et al., 2015; Fischer et al., 2019; Franke & Krems, 2013; Hu et al., 2019; Zhou et al., 2018). Some researchers have preferred different distributions (Zhou et al., 2018) such as the Birnbaum-Sanders distribution. Similar to Fischer et al. (2019), we assumed that the distance traveled back from work to home is identical to the distance traveled earlier from work to home and it is sampled once from the distribution at the beginning of the simulation (assumption T3). The distance traveled between work and home is also considered to be an attribute of the EV (assumption T4). The SoC of the battery of an EV in the model decreases linearly with distance traveled (assumption T5).

We added a lower bound of 5 km for the trip length since it is infrequent for an EV owner to use his vehicle if the trip is less than 5 km in length. In addition, we added an upper bound of 60 km for the trip length, since few EV drivers would drive more than 45 each way in their daily commute. The resulting trip length distribution is shown in Figure 3.1.

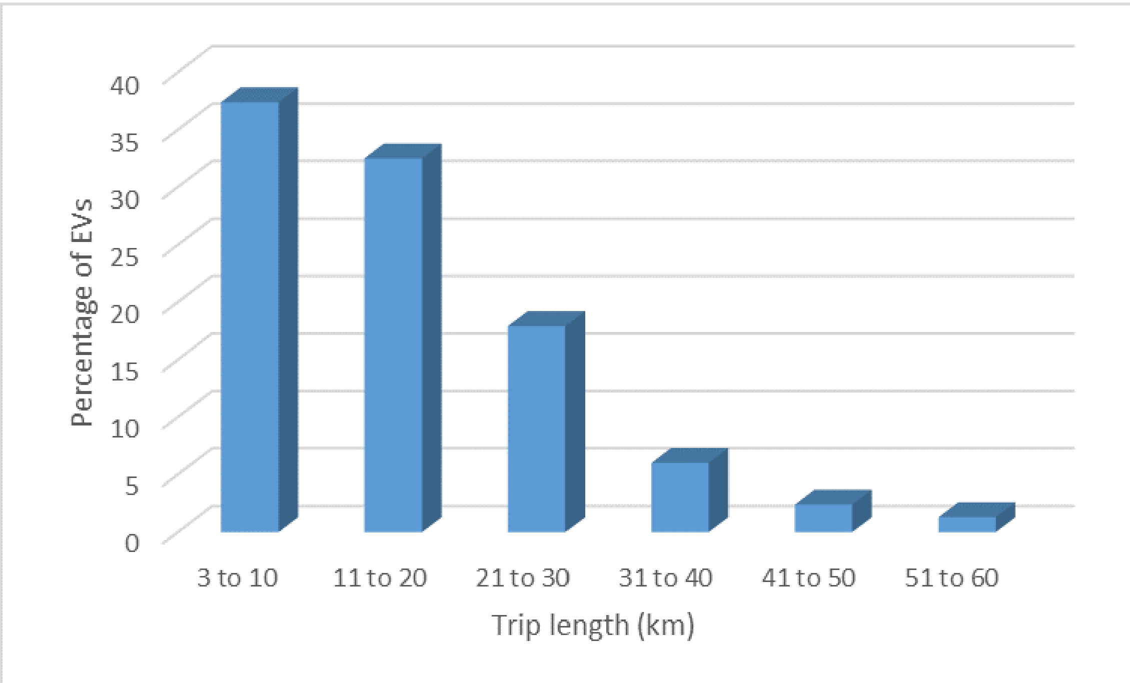

Figure 3.1 Trip Length Distribution

According to our chosen distribution, around 73% of EVs travel between 5 km and 20 km per one way trip, while just over 27% of EVs travel between 20 and 45 km. We only consider home-work travel and thus two daily trips. Zhou et al. (2018)

observed that 25% of EVs traveled once per day (one way trip), around 40% of EVs traveled twice per day, under 20% of EVs traveled thrice per day and under 15% traveled more than three times per day. Analyzing a German mobility study's results, Fischer et al. (2019) found that the average daily number of trips was 2.06. Therefore, our distribution s not conflicting with available the data in literature. In our model, an EV travels at 25 km/h if the trip distance is below 30 km, and 50 km/h if the trip distance is above 30 km (assumption T6).

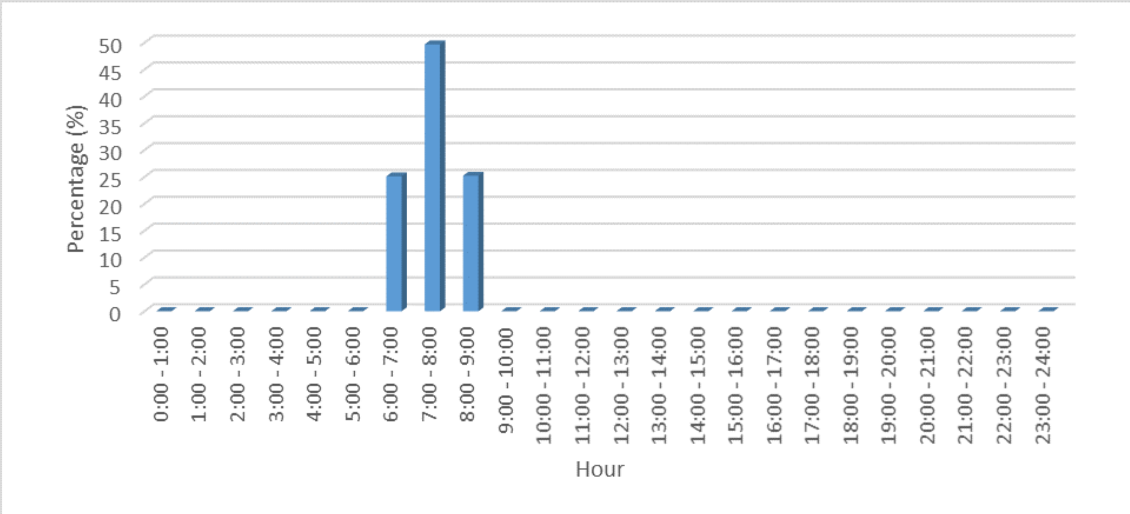

Figure 3.2 Home Departure Time Distribution

The departure time of an EV from home or work is a random variable. Departure from home begins at 6 a.m. where EVs are delayed using a time delay variable sampled from a uniform distribution between 0 and 2 hours (assumption T7) to simulate EV departure between 6 a.m. and 8 a.m. As shown in Figure 3.2, the EVs first depart from home sometime between 6 a.m. and 9 a.m. with the majority of them leaving between 7 a.m. and 8 a.m. This is expected since the departure time of an EV is based only on our assumption that it is a random variable coming from a uniform distribution that results in a departure time between 6 a.m. and 8 a.m. This distribution is very similar to what Lojowska et al. (2011) found in their analysis which is based on empirical data. Lojowska found that a very low portion of EVs departed from home after 9 a.m.

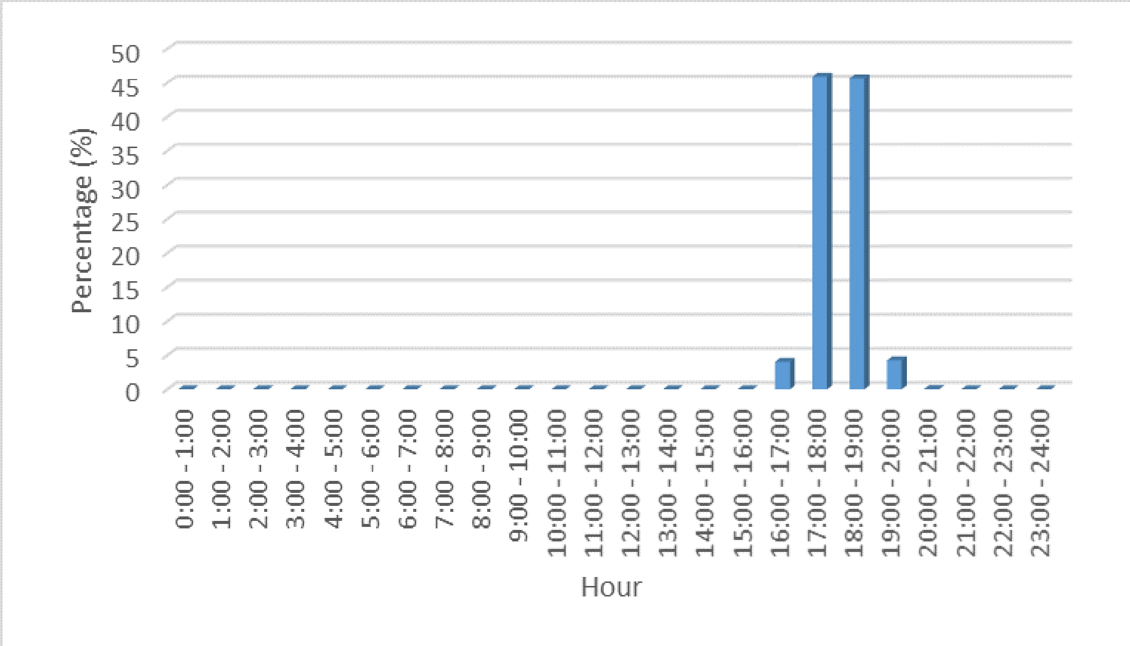

Figure 3.3 Work Departure Time Distribution

As shown in Figure 3.3, EV owners begin to leave their work at 4 p.m. or later and travel towards home, with their departure time being sampled from a normal distribution with a mean of 1.5 hours and a standard deviation of 0.5 hours (assumption T8). Analyzing real traffic data, Zhou et al. (2018) found that the normal distribution best fits the departure time of an EV from work during evening hours.

As mentioned in the literature review chapter, EV charging can be categorized into three types (Zhou et al., 2018): simple charging (dumb or uncontrolled charging), controlled charging (tariff-driven charging), and intelligent charging (charging that allows V2G). We assume that only uncontrolled charging will take place, since these EVs will be considered as early adopters. It is important to incorporate workplace charging in the simulation model, since several researchers have found that the ability to charge at work significantly influences the charging curve (Ashtari et al., 2012; Babrowski et al., 2014). However, we assume that no public charging occurs. This assumption is based on several pieces of literature that conclude that most EV charging happens at home (Franke & Krems, 2013; Morrissey et al., 2016). It is also assumed in our model that an EV may be charged at most twice per day, once at the workplace and once at home (assumption C1). This assumption is based on the fact that very few EVs charge for more than two times a day. Analyzing empirical data Quiros-Tortos et al. (2018) found that 70% of EVs charged only once per day, while daily second charging events consisted less than a third of all events. EVs that charged three or more times per day consisted less than 8% of all EVs. In addition, Zou, Wei, Sun, Hu & Shiao (2016) observed that EV taxis in Beijing charge on average 1.84 times a day, albeit covering an average distance of 117.98 km a day - a much higher distance than our average daily traveled distance. Indeed the decision to charge among EV owners not only depends on the level of SoC and the need to charge, but also upon behavioral reasons.

The EV owner charges their vehicle at home or at work if their SoC is below a certain level that we may refer to as the "charging threshold". We assume the charging threshold to come from a triangular distribution (25%, 50%, 75%)(assumption C2). This assumption is in parallel to what is observed in studies based on empirical data and travel surveys such as in Franke & Krems (2013); Hu et al. (2019); Leou, Su & Lu (2014). This assumption is based on the observation that 65% of EV owners charge their EVs if their SoC is between 25% and 75% Quiros-Tortos et al. (2018). Some studies assume EVs to charge if their SoC drops below 50% (Lojowska et al., 2011), however, this assumption is not accurate given the results of (Quiros-Tortos et al., 2018). Some other researchers assume charging upon arrival for every parking event, however, this assumption contradicts empirical data (Fischer et al., 2019).

We assume that only 40% of EVs have the infrastructure to charge at work. Those that can do so using a level two 22 kW charger (assumption C2). Charging at home is always available and occurs using a standard 3.7 kW charger (assumption C4). The battery SoC increases linearly with time during charging (assumption C5). The time at which EVs begin to charge at work depends on the work arrival time and a time delay, which we sample from a Weibull distribution with a mean of 1 hour and a shape parameter 1 (assumption C6). This random variable models the concept that a large portion of EVs begin charging soon after they arrive to work, but also some may begin to charge later. In fact, simulation results of Chen et al. (2016) indicate that 60% of EVs wait between 0 to 5 minutes before charging at public charging stations. On the other hand, around 5% of EV owners waited for more than an hour to charge their vehicle, which may indicate that waiting times at work would be negligible, especially in a scenario where the number of EVs is only a small portion of the passenger vehicle fleet. Thus, the decision to wait before charging at work is considered to be due to EV owner behavioral preferences, not on whether the charging spots are taken by another EV owner or not. Similarly, Quiros-Tortos et al. (2018) found that it is highly likely that EVs begin charging once they arrive home on weekdays or weekends.

Our simulation model is based on several assumptions to properly model the complex EV charging behavior and travel patterns, without loss of generality. Some of these were already mentioned. Here, we summarize all under three categories: general model assumptions; travel-related assumptions; and charge-related assumptions.

General Model Assumptions:

G1 All EVs are considered to be personal/private EVs, i.e., not EVs for business use such as delivery vehicles or taxis.

G2 Only a typical workday is modeled repeatedly. All workdays are assumed to be identical.

G3 The energy efficiency values of EVs are taken to be between to 15 and 16 kWh/100 km depending on the EVs model. Note that this may or may not include energy losses due to accessories such as lighting, AC and heating.

Travel-related Assumptions:

T1 Trips only occur between work and home.

T2 Trip distances are sampled from a Weibull distribution with α = 15 km and β = 1.23.

T3 Distance between work and home is identical for both daily travel events and is sampled once from the distribution at the beginning of the simulation.

T4 Distance between work and home is an attribute of the EV and does not change throughout the simulation.

T5 The SoC is assumed to decrease linearly with distance traveled.

T6 Travel speed is 25 km/h if the travel distance is below 30 km, and 50 km/h if the travel distance is at or above 30 km.

T7 Departure time from home begins at 6 a.m. and a time delay is introduced which is sampled from a Uniform distribution with a minimum of 0 and maximum of 2 hours. This time delay simulates EV departure from home between 6 a.m. and 8 a.m.

T8 Departure time from work begins at 4 p.m. and is distributed with a normal distribution that has mean 1.5 and stdev 0.5 hours, which is similar to departure time distribution found by Zhou et al. (2018).

Charge-related Assumptions:

C1 Charging can only occur at most once at home and once at work per day, which is similar to results found byFranke & Krems (2013); Morrissey et al. (2016)

C2 The decision to charge depends only on the level of SoC of the EV: if it is below a certain threshold, the EV owner charges their vehicle. The threshold is sampled from a triangular distribution (25%, 50%, 75%). This result is concurrent with distributions found by Franke & Krems (2013); Quiros-Tortos et al. (2018).

C3 Only level two charging is available at work (22 kW).

C4 Only slow charging is available at home (3.7 kW).

C5 SoC increases linearly with charging duration.

C6 40% of EV owners are able to charge at work. Most EV owners begin charging once they arrive at work. However, some of them may decide to charge later. This is modeled by introducing a delay between the arrival time and the plug in time where the delay is a random variable sampled from a Weibull distribution with $\alpha = 1$ hour and $\beta = 1.23$.

3.2 Simulation Results

We run the simulation for a duration of 30 workdays and for 10,000 EVs and observed over 60,000 charge events. We first present the time distributions observed, such as when EVs begin charging at work or at home, and when they arrive at home or at work. We then present the hourly power demand distribution i.e., the load profile of the EVs.

Since home departure time only depends on the home departure time random variable, as expected, EVs departed between 6 a.m. and 8 a.m., with the majority of them departing between 7 a.m. and 8 a.m. as shown in Figure 3.2. The work arrival time to work depends on the the departure time from home, the speed of the EV and trip distance. We observed most EVs to arrive to work between 7 a.m. and 9 a.m. as shown in Figure 3.4. This is similar to what Lojowska et al. (2011) observed.

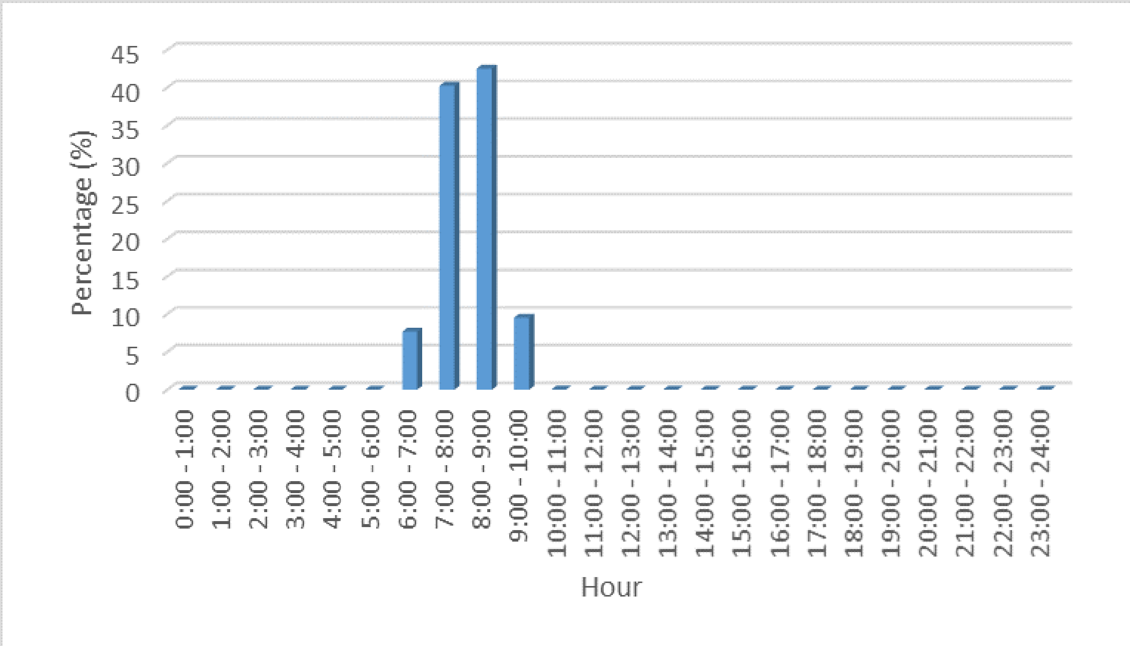

Figure 3.4 Work Arrival Time Distribution

Most EVs begin charge at work between 8 a.m. and 11 a.m. as shown in Figure 3.5. This is expected since the time at which EVs begin to charge is highly dependent on their arrival time to work, which was observed to mostly occur between 7 a.m. and 9 a.m. The majority of charge events that occurred at work ended with a full battery. Similarly, Quiros-Tortos et al. (2018) found that 70% of EVs fully charge their battery by the end of a charging event.

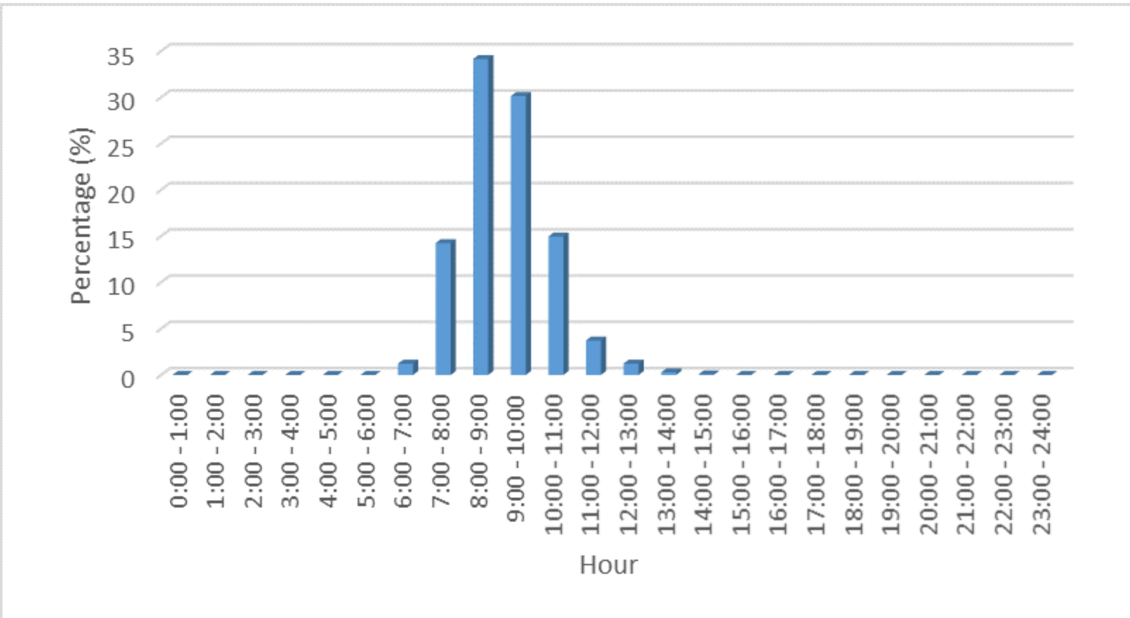

Figure 3.5 Work Charge Plug-in Time Distribution

As dictated by the relevant distribution, the majority of EVs depart from work between 5 p.m. and 7 p.m. as shown in Figure 3.3. This distribution is similar to what Zhou et al. (2018) found. As shown in Figure 3.6, EVs arrived home mostly between 5 p.m. and 8 p.m. The home arrival time is dependent on several factors; the work departure time, the trip length and the speed of travel.

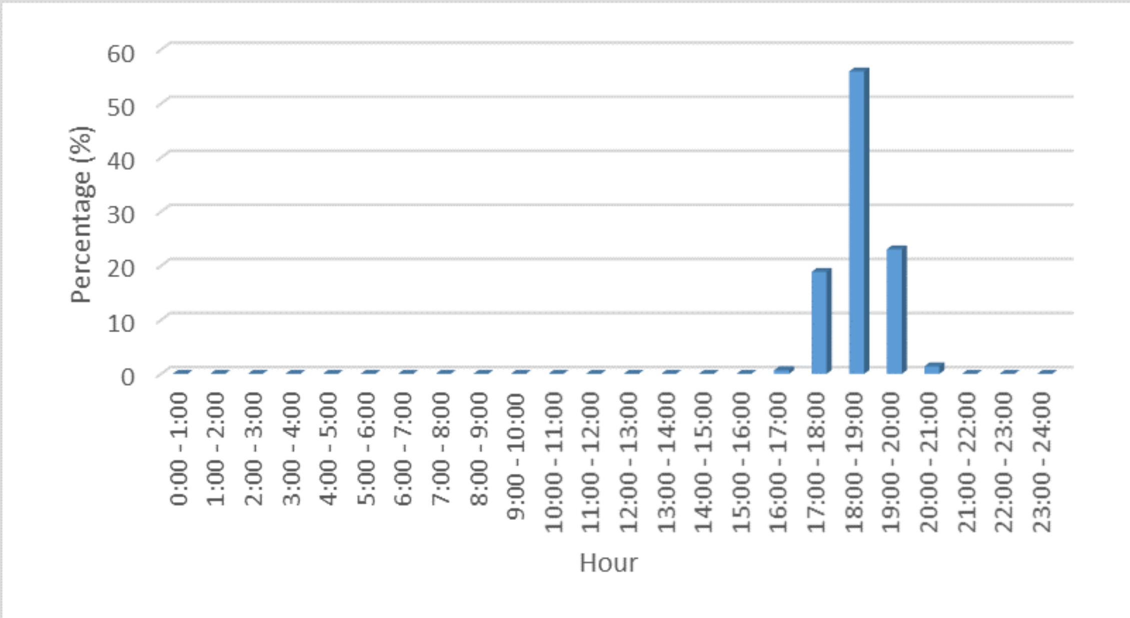

Figure 3.6 Home Arrival Time Distribution

The time at which EVs begin to charge at home depends on when an EV arrives home, and on the time delay mentioned earlier. A limited number of EVs begin charging after midnight. This is concurrent with results based on empirical data: Schauble et al. (2017) found that only 1.8% of charging events begin between midnight and 6 a.m. Moreover, the authors found that around 97% of EVs which charge at home end their charging event with a full battery.

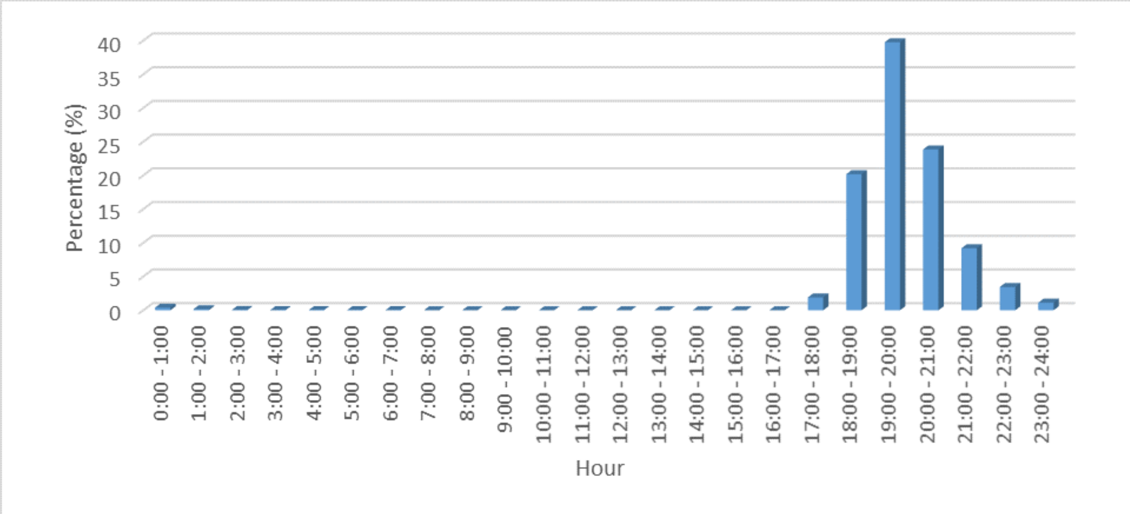

Figure 3.7 Home Charging Plug-in Time Distribution

Next, we present the resulting hourly power demand in Figure 3.10. We observe two peaks, corresponding to work charging (between 9 a.m. and 10 a.m.), and home charging (between 9 p.m. and 11 p.m.). The two peaks observed are concurrent with findings from several pieces of literature based on empirical data. For example, Quiros-Tortos et al. (2018) observed that the first charging event either occurs at 8 a.m. before work hours or after 6 p.m. On the other hand, if a second charging event does occur, it usually occurs after 6 p.m. Our hourly charging results are also in line with several simulation models' results. For example, Shepero & Munkhammar (2018) observe two peaks, at morning hours due to workplace charging, and during evening hours due to home charging. An evening peak was expected and has been observed in several other simulation results (Lojowska et al., 2011).

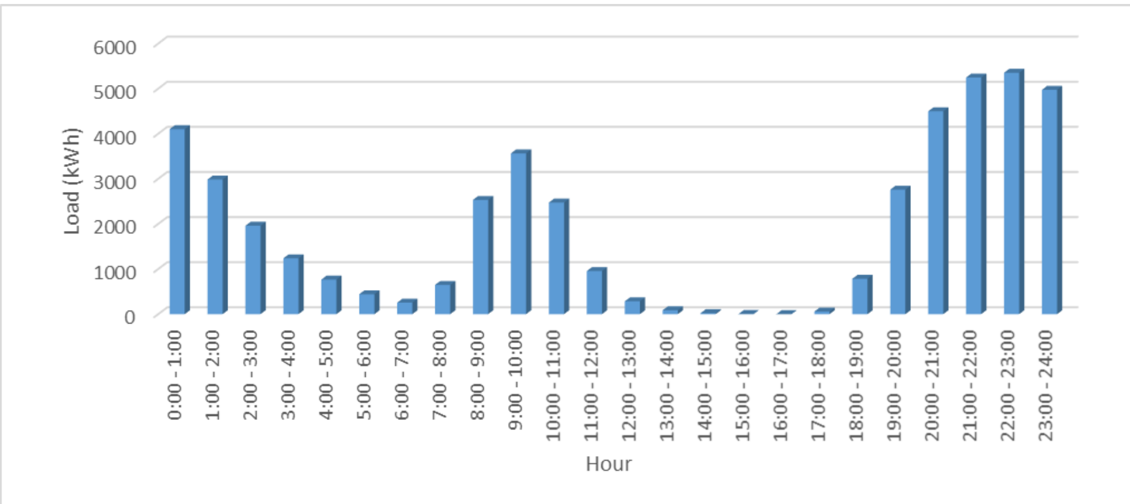

Figure 3.8 Hourly EV Power Demand in kWh

We observed that around 77% of charge events occurred at home, and around 23%

at the workplace. On average, an EV had zero charges on 79% of the days, charged at home on 15% of the days and has charged at work on 5% of the days.

We had run the simulation with lower number of EVs before for many iterations. We observe the results stabilize after 1000 EVs; hence we find it sufficient to consider only 10,000 EVs in this study. If the load profile of a larger number of EVs were to be generated, the current load profile would simply be multiplied by a factor which is equivalent to desired number of EVs divided by 10,000. This is a result of EVs in the simulation being independent from one another, i.e., charging one EV does not affect the availability of charging for another vehicle since there are no limited number of charging locations or queues for charging spots.

In order to check the effects of the availability of workplace charging, we conduct a sensitivity analysis. We test multiple scenarios for the availability of workplace charging by rerunning the model twice, once with a workplace charging availability of 20% and once with 60%. The significant change observed when 60% of EVs were able to charge at work was that the height of the peak corresponding to workplace charging became higher than that of home charging for the 20% and 40% workplace charging availability scenarios. In addition, the peak height of home charging was reduced as a result of more people charging at work. For the 20% workplace charging availability scenario, the height of the peak corresponding to workplace charging is even lower than that of the 40% availability scenario, and the peak height corresponding to home charging is higher. Moreover, the maximum peak height among the three scenarios is observed in the 20% scenario during the home charging period.

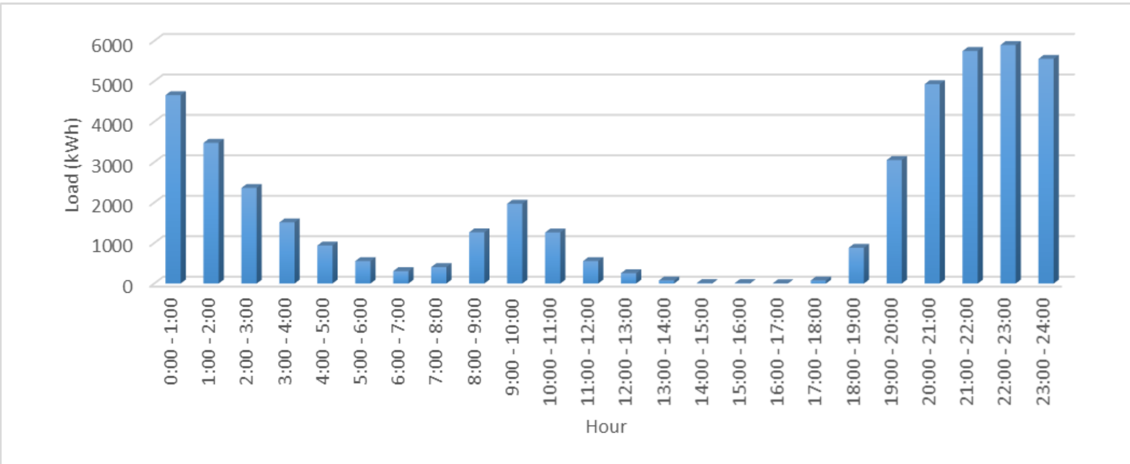

Figure 3.9 Hourly EV Power Demand in kWh with 20% Workplace Charging Availability

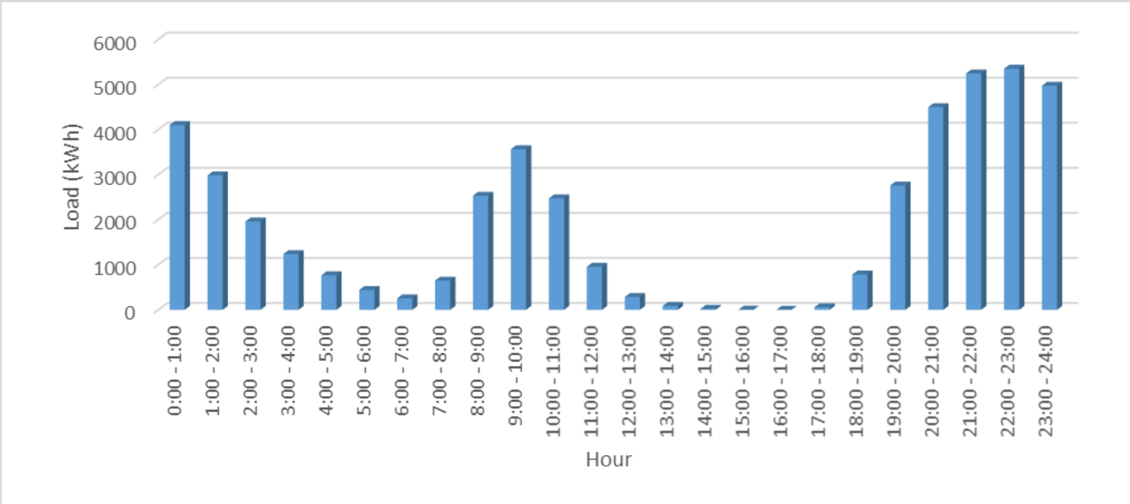

Figure 3.10 Hourly EV Power Demand in kWh with 40% Workplace Charging Availability

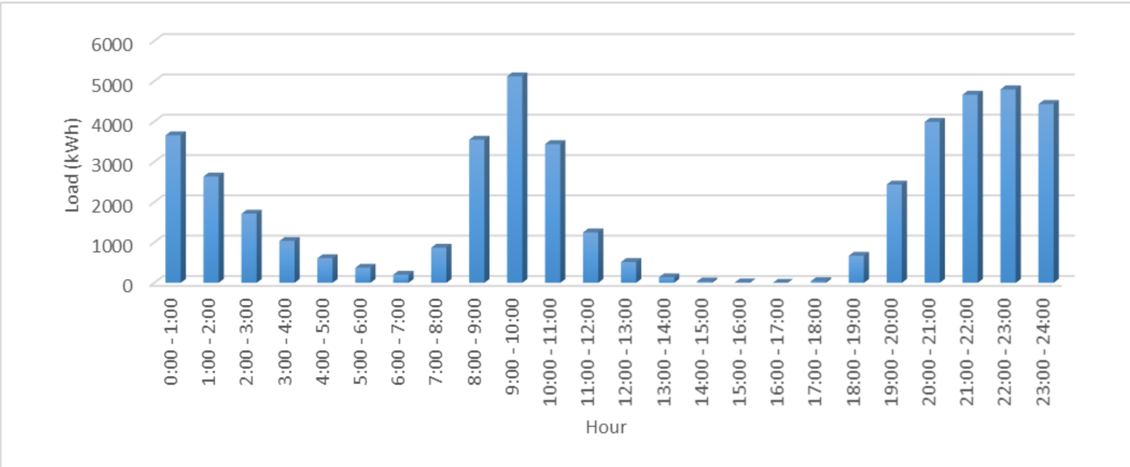

Figure 3.11 Hourly EV Power Demand in kWh with 60% Workplace Charging Availability

Figures 3.11 and 3.9 show the hourly EV charging distribution for 60% and 20% EV charging availability scenarios respectively. In the 60% charging availability scenario, 68% of charge events occurred at home and 32% of charge events occurred at work. As mentioned earlier, in the 40% charging availability scenario, 77% of charge events occurred at home and 23% of charge events occurred at work. In the 20% charging availability scenario, 88% of charge events occurred at home and 12% of charge events occurred at work. Thus we conclude that the availability of workplace charging would significantly affect the hourly load profile of the EVs.

4. DETERMINATION OF THE MARGINAL PLANTS AND SYSTEM MEF

EVs are considered to produce zero CO_2 emissions in travel. However, one must also account for the generation of electricity required for their charging. Introducing EVs may increase the electricity load, especially at the peak load times in the evening when EV owners return from work and start charging at home. The increased load prompts power plants to generate more electricity and thus produce more emissions. Therefore, it is important to quantify the additional emissions produced from EV charging to estimate the abated CO_2. As mentioned in the literature review section, we chose the Marginal Emissions Factor (MEF) to measure emissions as this measure is more suitable for the task than the alternative metric, Average Emissions Factor (AEF). An MEF quantifies how much emissions are produced when an extra unit of electricity is generated. On the other hand, the AEF measures the average amount of emissions produced when a unit of electricity is generated. The power plants generating electricity at full capacity are not necessarily the ones responding to additional demand and so the generation mix at the margin is often not the same as the general generation mix. Thus, using AEFs to evaluate a mitigation action often results in high errors. Among alternative methods to calculate MEFs, we used a regression approach.

In the first section of this chapter, we discuss the capacity and generation shares of different fuel types in the Turkish electricity grid. We also introduce how we temporally disaggregate our dataset. In the second section, we present our methodology to determine the marginal power plant in the system for a given time period, and we compare and contrast changes in marginal power plants between 2014 and 2019. In the third section, we discuss the method by which we calculate the system MEF. Finally, we present the calculated MEFs, the key results of our analysis as well as our calculated AEFs for comparison.

4.1 Capacity and Generation Shares of Fuels in the Turkish Electricity System

Here, we first discuss the fuel types that power the Turkish electricity system and the datasets used in this study. Then, we discuss the trends in available installed capacities of each fuel type. Finally, we discuss the trends in the share of each fuel type in total power generation.

The capacity and generation mix in the Turkish electricity system has considerably changed in the last decade. In an effort to reach higher energy independence and to curb import costs, the Turkish government has taken several steps to diversify the country's energy portfolio and reduce reliance on imported energy resources such as natural gas. Several subsidies were given for renewable energy resources such as wind and solar, which is reflected in the increased capacity and generation from renewables. To increase reliance on local energy resources, investment has steadily increased in coal-based power plants.

The datasets used in this study are obtained from the transparency platform of Enerji Piyasaları İşletme A.Ş. (EPİAŞ) available at https://seffaflik.epias.com.tr/transparency/index.xhtml. The transparency platform has many useful datasets on the Turkish electricity grid, including the available installed capacity. The platform also reports the total hourly generation and the specific hourly generation of each fuel type, which we used in our calculations. The fuel types include natural gas, wind, lignite, black coal, imported coal, fuel oil, geothermal, dammed-hydro, biomass and run-of-river (r-o-r) hydro. Two separate types of hard coal are reported: "imported coal" and "black coal". The latter refers to the local hard coal produced in the Zonguldak region of Turkey. We combine these two categories under the "hard coal" label as they are both hard coals with similar calorific values.

We first disaggregate the data obtained from the transparency platform by year and then by season, according to each season's equinox. Table 4.1 presents the date ranges for each season of 2019. Note that the winter season extends to year 2020. The data is then further disaggregated according to three time-of-day periods: day hours (6:00 – 17:59), peak hours (18:00 – 22:59) and night hours (23:00 – 5:59). This disaggregation of times of the day follows from the three periods defined by the Turkish ministry of energy. Thus, for each year there are 12 datasets consisting of three time-of-day periods for each of the four seasons.

Table 4.1 Date Intervals for Seasons of 2019

Season	Dates
Spring	21/03/2019 – 20/06/2019
Summer	21/06/2019 – 22/09/2019
Fall	23/09/2019 – 21/12/2019
Winter	22/12/2019 – 19/03/2020

We study and compare the results between years 2014 and 2019 (hence 24 datasets) to understand the effects of recent developments in the Turkish power mix on emissions. As we see in Table 4.2, the total installed capacity has increased by 42% from 2014 in 2019. Consistent with the government's efforts to reduce reliance on imported fuels, the capacity of both natural gas and fuel oil has decreased (by 9% and 77% respectively). Again, consistent with the government's policy of increasing reliance on local resources, lignite and local hard coal capacities have increased by 58% and 42% respectively. The share of imported hard coal also increased significantly; in fact it almost doubled. Thanks to generous subsidies and decreasing costs, capacity increases in renewable fuels has been dramatic. Wind, geothermal and biomass installed capacities have increased by 415%, 1249%, and 67600% respectively. Hydro capacity has also increased; 21% for dammed-hydro and 312% for run-of-river hydro. Close to nonexistent in 2014, solar capacity has also increased greatly. However, most of its installed capacity is in unlicensed power plants. In fact, solar generation accounted for 95.5% of unlicensed generation in Turkey in 2019.

Table 4.2 Installed Capacities (MW) of Each Fuel Type in Years 2014 and 2019

Fuel	Total	Natural Gas	Wind	Lignite	Black Coal	Import Coal	Fuel Oil	Geo -thermal	Hydro (Dam)	R-o-r	Solar	Others
2014	42500	17100	1290	3810	547	3490	1010	79	13071	1700	0	300
2019	64300	14500	6500	5160	309	6970	239	1080	16252	6510	6000	828
Change	21800	-2600	5210	1350	-238	3480	-771	1000	3200	4810	6000	528

Next we discuss the shares of fuels in power generation. Power generation shares do not necessarily follow the capacity shares as the utilization rates (capacity factors) of plants using different fuel types differ from each other. Tables 4.3 and 4.4 present the generation share of each fuel type in 2014 and 2019 respectively. The shares are given separately for each of the four seasons and the three time-of-day periods

Table 4.3 Shares of Electricity Generation by Fuel Source in 2014

Fuel	Spring			Summer			Fall			Winter		
	Day	Peak	Night	Day	Peak	Night	Day	Peak	Night	Day	Peak	Night
Hydro (Dam)	12%	14%	6%	16%	14%	10%	10%	11%	3%	14%	15%	8%
Natural Gas	47%	46%	49%	48%	49%	50%	49%	48%	50%	42%	41%	40%
Hydro (r-o-r)	7%	6%	6%	3%	2%	2%	5%	4%	4%	8%	7%	7%
Hard Coal	14%	14%	16%	15%	15%	17%	16%	16%	20%	15%	16%	19%
Lignite	14%	14%	17%	13%	13%	15%	14%	13%	16%	13%	12%	15%
Wind	3%	3%	3%	3%	4%	4%	4%	4%	4%	4%	5%	6%
Others	3%	3%	3%	2%	3%	2%	2%	4%	3%	4%	4%	5%

Table 4.4 Shares of Electricity Generation by Fuel Source in 2019

Fuel	Spring			Summer			Fall			Winter		
	Day	Peak	Night	Day	Peak	Night	Day	Peak	Night	Day	Peak	Night
Hydro (Dam)	30%	32%	29%	24%	25%	17%	19%	21%	11%	21%	23%	15%
Natural Gas	14%	14%	10%	20%	20%	20%	24%	24%	21%	22%	22%	19%
Hydro (r-o-r)	14%	14%	16%	5%	5%	5%	3%	4%	4%	7%	7%	8%
Hard Coal	15%	15%	15%	23%	22%	26%	27%	25%	31%	23%	22%	27%
Lignite	15%	14%	17%	16%	15%	18%	17%	16%	20%	12%	12%	14%
Wind	6%	7%	7%	8%	10%	10%	5%	6%	6%	9%	9%	11%
Others	6%	4%	6%	4%	3%	4%	5%	4%	7%	6%	4%	6%

We find natural gas to be responsible for the largest proportion of electricity generation in 2014, followed by lignite, hard coal and dammed-hydro. 2014 was a particularly dry year for Turkey, causing a sharp decline in hydro power production in that year. In 2019, dammed-hydro share has significantly increased to become the main electricity generator, surpassing natural gas, hard coal and lignite. On the other hand, the share of natural gas has harshly decreased, which is in line with the efforts taken by the Turkish government to reduce reliance on imported natural gas. Reliance on hard coal in 2019 has visibly increased in summer, fall and winter seasons. Lignite's share is relatively the same for 2014 and 2019. Run-of-river (r-o-r) hydro's share has almost doubled between 2014 and 2019, however, there is no large seasonal variation within the year with the exception of spring seasons, when r-o-r hydro generation increases due to the increased volume of rivers caused by the melting of snow. Wind power generation has increased considerably, which is expected given the large increase in wind power capacity.

In 2019, we observe an increase in dammed-hydro generation share during peak hours in all seasons. Due to climatic reasons, dams in Turkey have quite limited water inventory. In order to make the most of this limited resource, dam operators often generate power at peak hours when the power price is highest. Moreover, the State Electricity Generation Company (EÜAŞ), which operates many of the largest dammed-hydro plants in Turkey, is also known to operate its plants primarily in peak hours to suppress electricity prices in the market. These motivations cause a comparatively high percentage of dammed-hydro generation in peak hours. This also explains why the generation share of dammed-hydro is quite low in night hours in all seasons in both 2014 and 2019.

We observe an increase in the lignite and hard coal generation shares during night hours for all seasons in both 2014 and 2019. This is expected since base load coal power plants are known to be active at close to full capacity, and have a little role in responding to additional demand.

4.2 Determining the Marginal Power Plant Types

As mentioned earlier, our dataset is comprised of hourly power generation data for Turkey for each fuel. We first disaggregate the data into years, then into seasons. The data is then further disaggregated according to three daily periods. Thus, we created 24 data sets consisting of three different time-of-day periods for four different seasons for each of 2014 and 2019.

Marginal Emissions Factor of a power system is determined by the marginal plants in the system. Thus, one often needs to first determine which plant types are on the margin for a given time period. Researchers such as Hawkes (2010), Siler-Evans et al. (2012), Thind et al. (2017) and Gai et al. (2019) used linear regression to calculate the MEF. This method circumvents the need to know the marginal plants prior to calculating the MEFs. In addition to calculating the MEF, Siler-Evans et al. (2012) and Gai et al. (2019) ran regression models between the total hourly change in electricity generation in a power system and the hourly change in electricity generation of a specific fuel type. The slope of the line of best fit of these two variables indicates approximately how much of the change in demand is met by that fuel type. A larger slope indicates that the fuel type is more likely to be on the margin. Despite not needing to find the marginal plant types to calculate the MEF, we also follow this approach because it invites an interesting discussion and provides insight on the electricity grid and generation mix on the margin.

For each season and time-of-day combination, for a specific fuel type f, we first calculate the hourly change in total electricity generation (represented by ΔT) and the hourly change in electricity generation (represented by ΔG). For an hour t and for fuel type f:

$$\Delta T_t = \Delta T_t - \Delta T_{t-1}$$

$$\Delta G_{t,f} = \Delta G_{t,f} - \Delta G_{t-1,f}$$

We then use linear regression to determine a line of best fit between these two variables. The resulting slope of the line of best fit, defined in this study as β_f, gives us a measure of how power plants using this fuel type respond to changes in total power. As a selected example, Figure 4.1 shows $\Delta G_{HydroDam}$ and $\Delta G_{NaturalGas}$ plotted against ΔT for all three time-of-day periods for the winter season of 2019. Figure 4.2 shows the corresponding plots for lignite and wind. The slopes in Figure 4.1 indicate that these fuels have a high β_f and actively respond to changes in demand. On the other hand, the very low slopes of the lines of best fit in Figure 4.2 indicate that these fuels generate electricity at a constant level and do not actively respond to changes in demand. The remaining graphs for year 2019 is presented in the appendix.

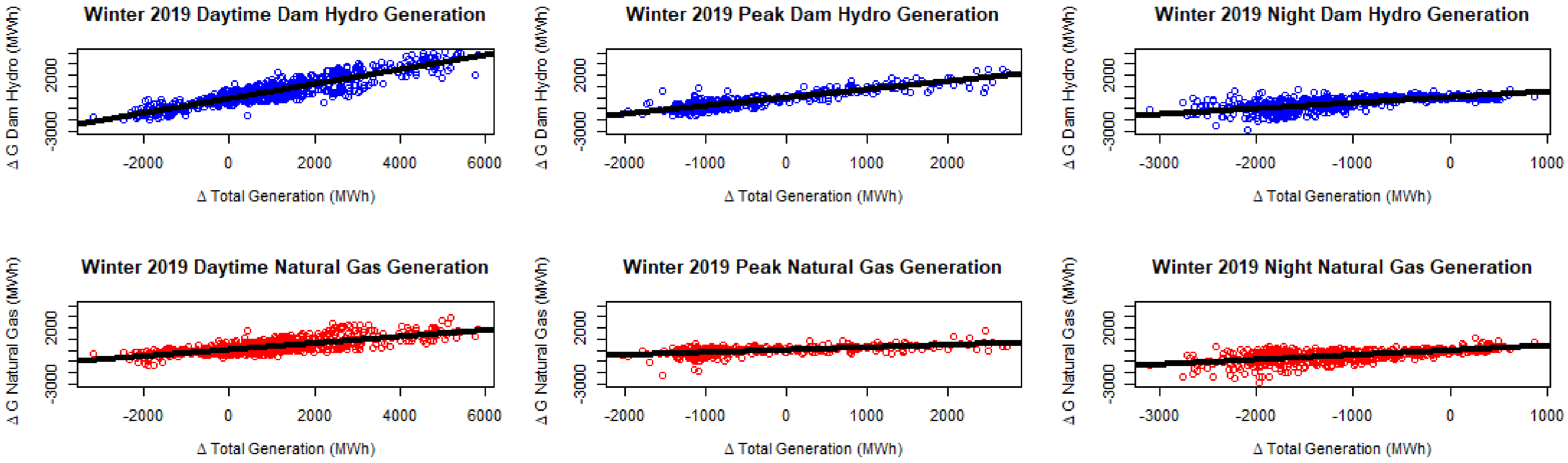

Figure 4.1 Winter 2019 $\Delta G_{HydroDam}$ and $\Delta G_{NaturalGas}$

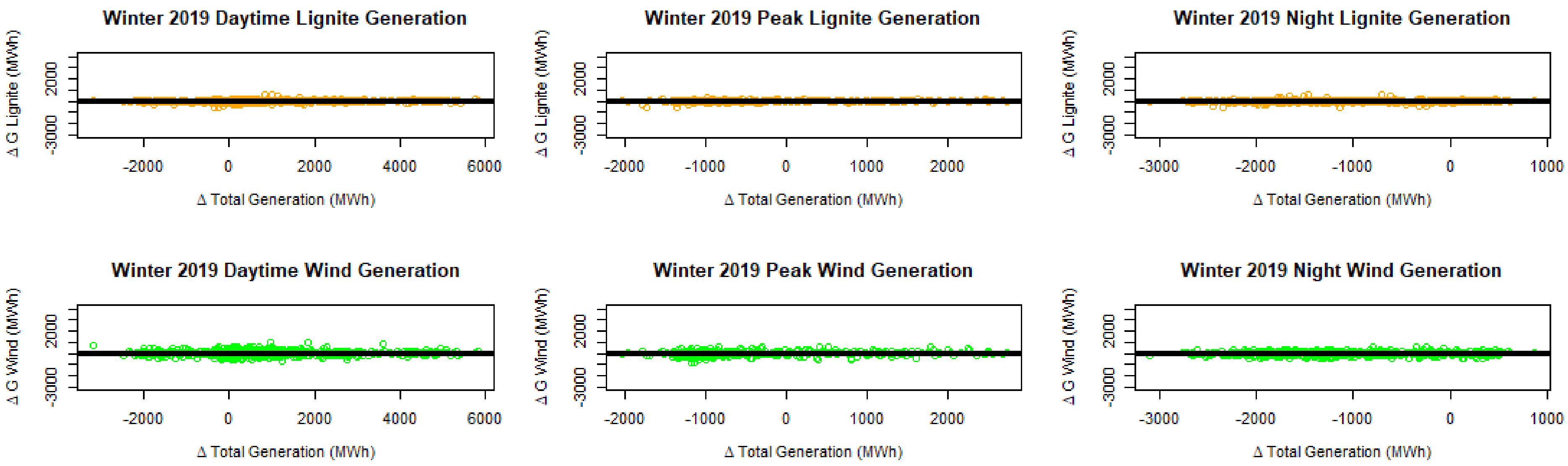

Figure 4.2 Winter 2019 $\Delta G_{Lignite}$ and ΔG_{Wind}

Table 4.5 shows our calculated β_f in 2014 and 2019 for each time-of-day, using winter values as an example. For both years 2014 and 2019, we observe dammed-hydro and natural gas to be the two main plant types on the margin. The proportion of extra electricity demand that these two plant types respond to differs between 2014 and 2019, and also between seasons and between time-of-day periods. However, these two plant types still remain on the margin. We find dammed-hydro in winter 2019 to have a higher $\beta_{HydroDam}$ regardless of time-of-day and thus is more active on the margin than in winter 2014. This is generally the case regardless of time-of-day or season when comparing 2014 and 2019. Natural gas on the other hand, is less often on the margin, its $\beta_{NaturalGas}$ is consistently smaller in 2019 compared to 2014. $\beta_{HardCoal}$ has generally decreased and is still not on the margin despite having an increasingly large installed generation capacity since 2014. Similarly, lignite is still not on the margin, since lignite plants are likely to be used as baseload power plants that operate all the time. Asphaltite is quite similar to lignite, but with a much smaller production share, and its $\beta_{Asphaltite}$ was observed to be very small in both 2014 and 2019. Fuel oil power plants can technically respond to changes in demand, however, they were not found to be on the margin either, having a very low $\beta_{FuelOil}$. Wind, solar, geothermal and r-o-r plants are still not on the margin. This is an expected result, since their generation cannot be increased to meet additional electricity demand, being dependent on uncontrollable environmental factors. The remaining tables that present the seasonal comparisons for β_f between 2014 and 2019 can be found in the appendix.

Table 4.5 β_f for Winter 2014 and Winter 2019

Fuel	Day		Peak		Night	
	2014	2019	2014	2019	2014	2019
Hydro (Dam)	0.50	0.65	0.68	0.73	0.43	0.50
Natural Gas	0.39	0.30	0.24	0.21	0.47	0.41
Hydro (r-o-r)	0.10	0.04	0.05	0.03	0.05	0.04
Hard Coal	0.02	0.03	0.01	0.01	0.03	0.03
Lignite	0.00	0.01	0.01	0.01	0.02	0.01
Wind	0.00	0.00	0.01	0.03	0.01	0.01

Table 4.6 shows the comparisons between the different seasons in year 2019. Dammed hydro is most active on the margin in summer with slightly lower $\beta_{HydroDam}$ in fall. However, in winter and spring $\beta_{HydroDam}$ is visibly low. On the other hand, natural gas has the highest $\beta_{NaturalGas}$ in the winter and spring

seasons. $\beta_{NaturalGas}$ is highest during night time periods, which indicates higher reliance on natural gas to respond to extra demand at night. $\beta_{HydroDam}$ is significantly higher during peak time hours, which supports the hypothesis that dammed-hydro is used rigorously primarily to respond to changes in extra peak time demand. This, in turn can be explained by dam operators taking advantage of the relatively high power prices at these hours. Night time MEFs are observed to be much higher than peak or day time MEFs. This is also expected as most dammed-hydro plants choose not to operate at night hours due to low power prices.

Table 4.6 β_f for Each Season and Time-of-Day of 2019

Fuel	Spring			Summer			Fall			Winter		
	Daytime	Peak	Night	Daytime	Peak	Night	Daytime	Peak	Night	Daytime	Peak	Night
Hydro (Dam)	0.59	0.65	0.44	0.72	0.82	0.57	0.70	0.82	0.47	0.65	0.73	0.50
Natural Gas	0.29	0.22	0.32	0.25	0.13	0.30	0.27	0.08	0.45	0.30	0.21	0.41
Hydro (r-o-r)	0.02	0.03	0.05	0.02	0.03	0.06	0.02	0.05	0.05	0.04	0.03	0.04
Hard Coal	0.11	0.06	0.11	0.04	0.02	0.00	0.02	0.01	0.03	0.03	0.01	0.03
Lignite	0.01	0.01	0.02	0.00	0.01	0.03	0.01	0.01	0.02	0.01	0.01	0.01
Wind	-0.04	0.03	0.01	0.05	0.02	0.08	0.00	0.06	0.02	0.00	0.04	0.01

Based on the β_f's we calculated, we conclude that lignite, hard coal, asphaltite, wind, solar, hydro (r-o-r), geothermal, fuel oil and biomass are not on the margin in 2019. Throughout our analysis, the ΔG's of these fuel types have consistently had a low correlation coefficient with ΔT.

4.3 Calculating the System MEF

Here, we explain how we calculate the system MEF for a given season and time-of-day combination. Since we do not have access to the emissions data for each fuel, we obtained the hourly change in emissions for each fuel by multiplying the fuel's carbon dioxide intensity factor (IF) (measured in kgCO_2/MWh) by its $\Delta G_{t,f}$. Table 4.7 contains the list of Turkish electricity grid IFs we used, obtained from Ozcan (2016), Atilgan & Azapagic (2016) and Yilan, Kadirgan & Çiftçioğlu (2020).

Table 4.7 Emission Intensity Factors of Fuels Used

Fuel	Intensity factor ($kgCO_2$/MWh)
Natural gas	482
Hard Coal	1192
Lignite	1062
Hydro (Dam)	50

Then, we calculate the change in total emissions for a given hour (represented by ΔE_t) by summing each fuel type's $\Delta E_{t,f}$ for that hour. For every hour t and fuel type f:

$\Delta E_{t,f} = \Delta G_{t,f}$ x IF_f

$\Delta E_{t,f} = \Delta E_{t,f} - \Delta E_{t-1,f}$

$\Delta E_t = \sum_f \Delta E_{t,f}$

In our ΔE_t calculation, we chose to ignore the change in emissions of asphaltite, fuel oil and biomass, since their ΔG's and consequently their ΔE's were consistently low, having almost no effect on the MEF's value. Lignite, having a $\beta_{Lignite}$ with a much larger value than that of the latter mentioned fuels, only very slightly affected the system MEF when removed from the emissions calculation. Wind, solar, hydro r-o-r and geothermal were assumed to produce no emissions.

Once ΔE, the total hourly change in emissions produced (in kilograms of carbon dioxide) and ΔT, the total change in hourly electricity generation (in MWh) are calculated, we use linear regression to obtain a line of best fit between these two variables. The slope of the line of best fit is defined as the system MEF$_x$ for that x time combination (such as winter 2014 Peak). As mentioned in the literature review, Hawkes (2010) first used this approach to calculate the MEF. Similarly, Siler-Evans et al. (2012) used the same approach to calculate the MEFs for the US. Thind et al. (2017) criticized Siler-Evans MEF calculation since it only focused on fossil fuels and did not consider renewables to be on the margin. Similar to Thind et al. (2017), we consider both fossil fuels and renewable energy sources.

The calculated MEFs for season and time-of-day combination x for the years 2014 and 2019 are displayed in Table 4.8. In all but one time combination, MEFs noticeably decreased from 2014 to 2019. This is due to the fact that dammed-hydro appears more on the margin in 2019 than natural gas (as can be seen in the β_f values given in Table 4.6) which lowers the MEF. Interestingly, peak hours' MEFs are much lower than that of daytime hours or night hours. This is because dammed-hydro generates more electricity in response to demand during peak hours. MEFs are generally higher during night hours. This is likely due to natural gas and dammed-hydro plants shutting down in response to the decreased levels of demand, while hard coal and lignite power plants remain operational.

The R^2 values of the generated regression models range between 0.2 and 0.8. All R^2 values for 2014 and 2019 are reported in Table A.2 of the appendix. Using the Weka software, we conducted 10-fold cross validated regression method for several datasets; but this approach did not yield higher R^2 values compared to the ones of normal regression models.

Table 4.8 Calculated MEFs ($kgCO_2/MWh$) for Each Season and Time-Of-Day in Years 2019 and 2014

Year	Spring			Summer			Fall			Winter		
	Day	Peak	Night	Day	Peak	Night	Day	Peak	Night	Day	Peak	Night
2019	316	217	332	199	128	200	195	100	292	216	167	263
2014	241	230	241	248	191	320	238	207	328	236	177	298

We have also calculated the MEFs for each season in years 2014 and 2019 without the time-of-day temporal disaggregation (Table 4.9). As a selected example, Figure 4.3 shows the line of best fit between ΔE and ΔT for the spring season of 2019. The slope of the line of best fit is the MEF for the spring season of 2019. These regression models generally achieve higher R^2 values than our original models that have time-of-day disaggregation; however, one also loses valuable information due to pooling.

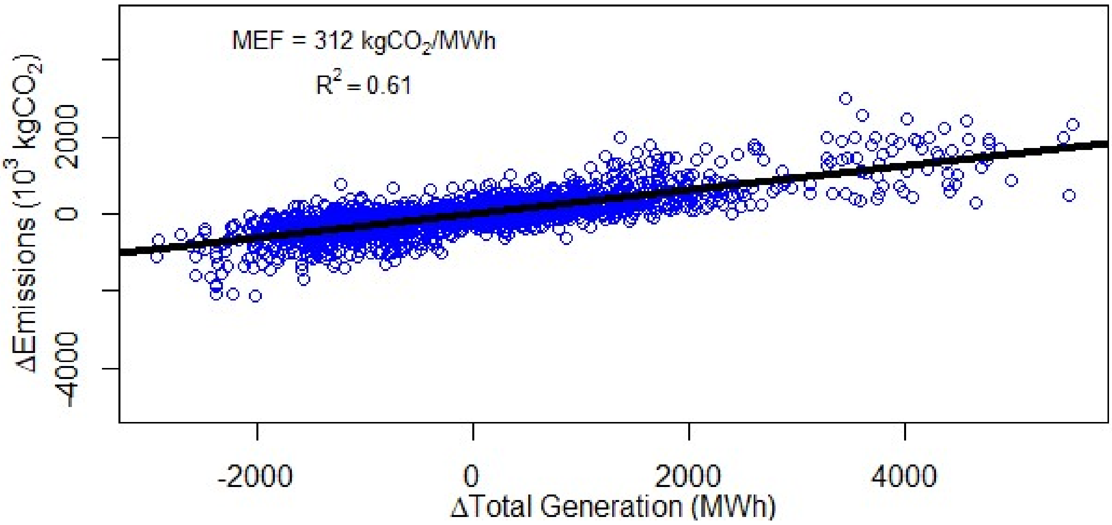

Figure 4.3 MEF for the Spring Season of 2019

Table 4.9 MEFs ($kgCO_2/MWh$) for Each Season in Years 2019 and 2014

Year	Spring	Summer	Fall	Winter
2019	312	191	208	254
2014	273	247	251	250

We calculated the average emissions factors (AEFs) for each season and time-of-day in 2019 to compare them with our calculated MEFs. Since the hourly emissions data in Turkey is not available, we multiplied the CO_2 intensity factor (in $kgCO_2/MWh$) by the hourly generation data (in MWh) to obtain the hourly emissions in a similar fashion to the earlier calculations for the hourly change in emissions. The IF of asphaltite was assumed to be that of lignite since they have similar calorific values. Table 4.10 presents the calculated AEFs for each season and time-of-day in 2019 and 2014. The AEFs in 2019 are consistently lower than the AEFs in 2014 with the exception of fall 2019.

Table 4.10 AEFs ($kgCO_2/MWh$) for Each Season and Time-Of-Day in 2019 and 2014

Year	Spring			Summer			Fall			Winter		
	Day	Peak	Night	Day	Peak	Night	Day	Peak	Night	Day	Peak	Night
2019	433	419	440	559	537	607	635	604	698	529	516	583
2014	559	554	622	562	570	619	591	583	658	550	548	614

As shown in the Table, AEFs consistently overestimate the emissions produced per unit of electricity generated, and would thus incorrectly evaluate the mitigation action and provide a lower abatement efficiency. If we had used AEFs, we would multiply the AEF by the hourly load profile of the EVs simulated in chapter 3. Since our AEFs are consistently higher than our calculated MEFs, the resulting emissions from EV charging would be significantly higher, and thus underestimate the emission abatement efficiency of the EVs.

5. CALCULATING THE ADDITIONAL EMISSIONS DUE TO EV USE AND COMPARISON WITH INTERNAL COMBUSTION ENGINE VEHICLES

5.1 Calculating the Additional Emissions due to EV use

After simulating the hourly load profiles for EVs in the third Chapter and calculating the marginal emissions factors (MEFs) for each season and time-of-day in the fourth Chapter, we are now able to combine both halves of the study and generate the hourly emissions profile. In our simulation model, there are no differences between days of the week nor between days in different seasons, therefore, the same load profile can be used for all four seasons. Using the calculated MEFs, we multiply each season's MEFs ($kgCO_2$/MWh) by the load profile (MWh). Each time-of-day MEF is multiplied by the load in the corresponding hours. For example, to generate the emissions profile for summer of 2019, we multiply the summer day hours MEF for 2019 by the load of each hour between 6 a.m and 5 p.m. Similarly, we multiply the summer peak hours MEF by the load for each our between 6 p.m. and 10 p.m., and we repeat the same for night hours to obtain the hourly emissions profile. Thus, for every hour t:

$\text{Emissions}_t = \text{Load}_t \text{ x } \text{MEF}_t$

Figure 5.1 presents the emissions profile for spring 2019. Spring 2019 had the highest peaks in its emissions profile since it had the highest MEFs among all the other seasons of 2019. Interestingly, our findings suggest that it is more environmentally friendly for EVs to charge during peak time hours, since MEFs are consistently low during these times as a result of dammed-hydro being more active on the margin. The general shape of the load and the location of its peaks do not change between seasons, however, the magnitude and height of each peak does change since MEFs change between times of day and seasons.

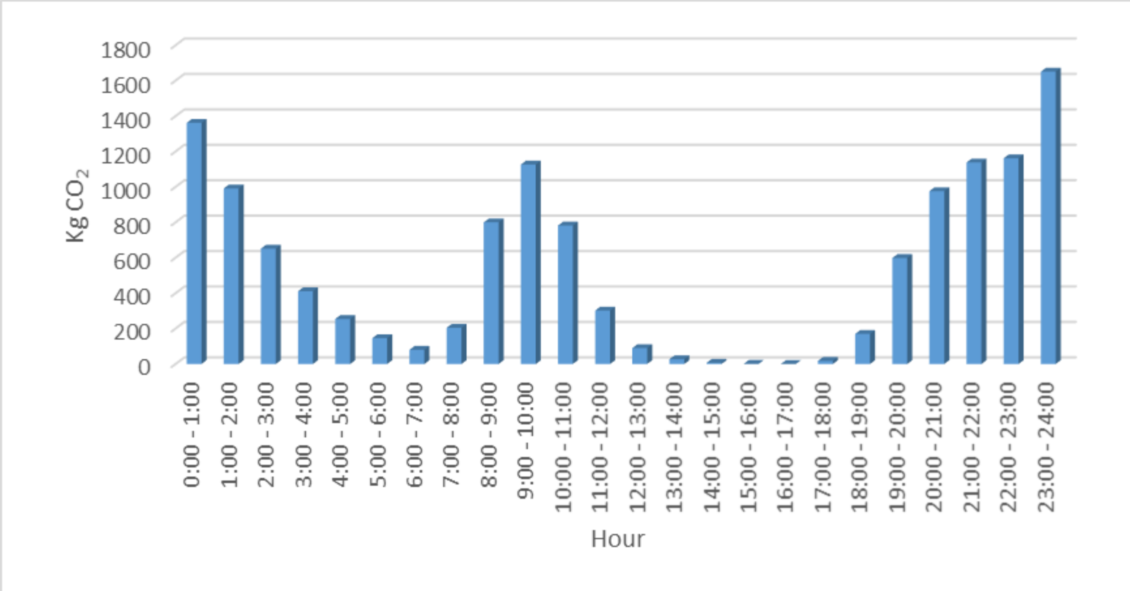

Figure 5.1 Emissions Profile for Spring 2019

The emissions profile for summer 2019 is presented in Figure 5.2. All the peaks in the emissions profile of summer are consistently lower than that of the other seasons. This is a consequence of the MEFs of summer 2019 being generally lower than the MEFs of the other seasons.

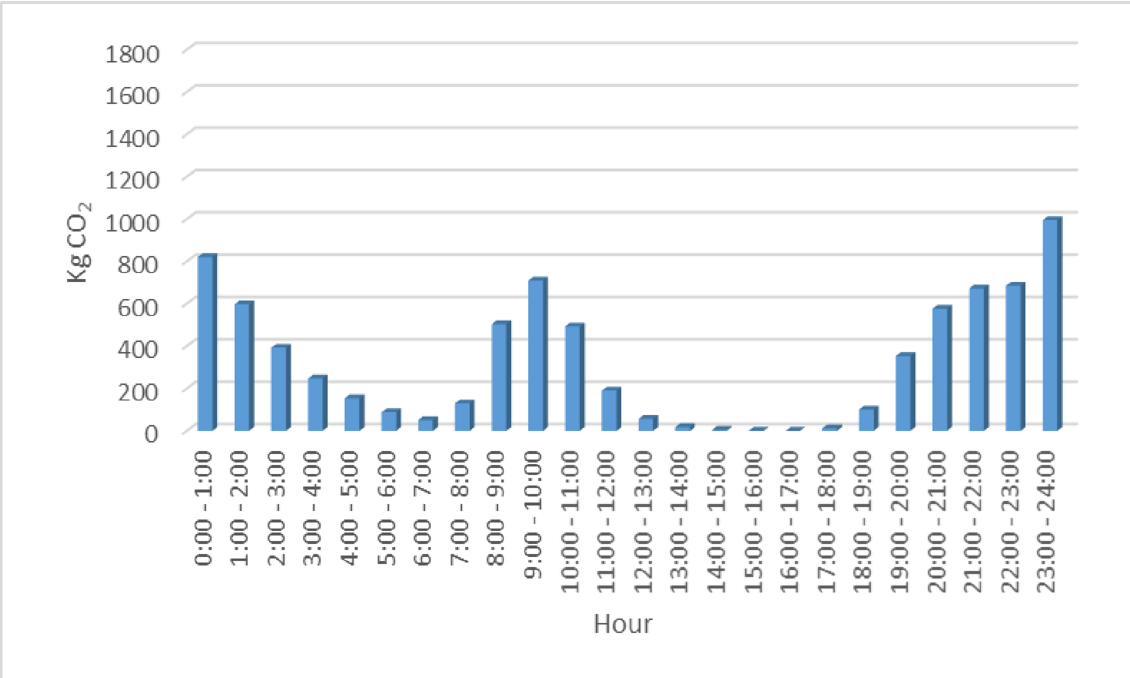

Figure 5.2 Emissions Profile for Summer 2019

In Figure 5.3, the peaks in the emission profile of fall 2019 are slightly higher than summer as a result of fall's MEFs being higher than that of summers.

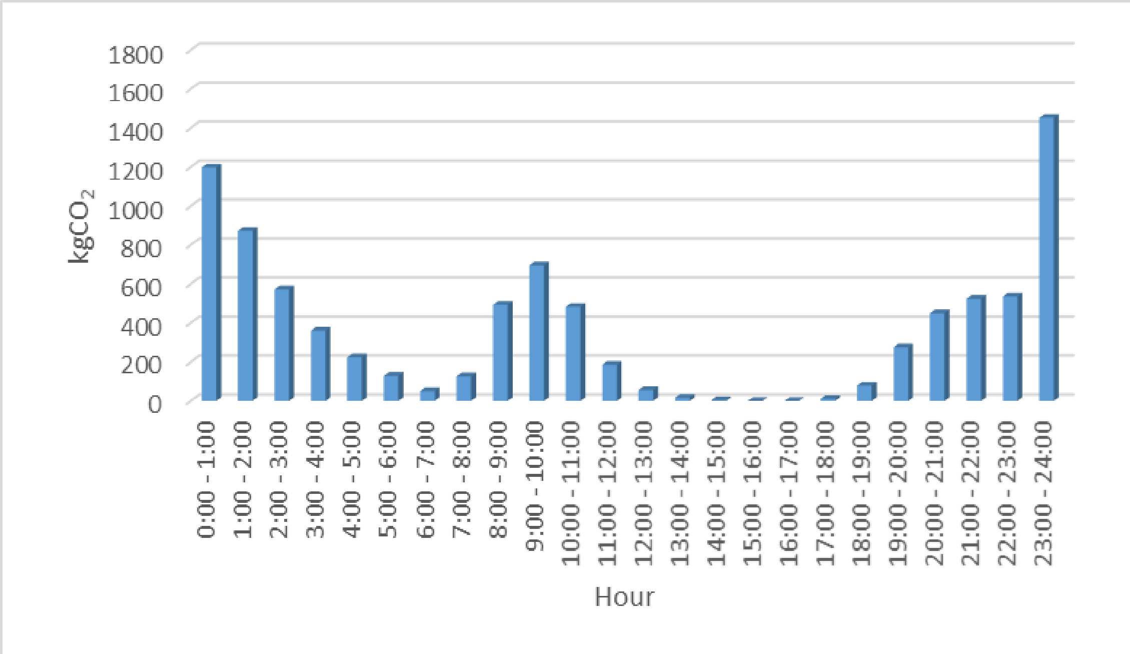

Figure 5.3 Emissions Profile for Fall 2019

The peaks in winter 2019's emission profile is slightly lower than that of fall but not too dissimilar as visible in Figure 5.4. The MEFs of winter 2019 are only slightly lower than those of the fall season for 2019.

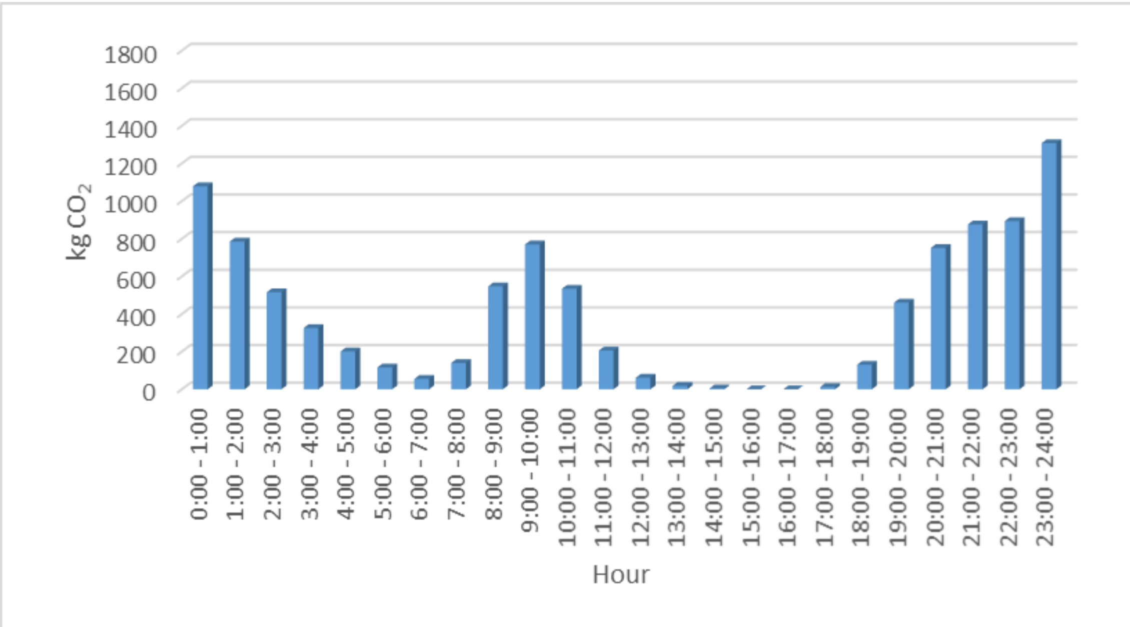

Figure 5.4 Emissions Profile for Winter 2019

Our results show that EVs, when introduced in Turkey, have a stronger carbon emissions abatement potential compared to other countries. The MEFs we estimate for Turkey are significantly lower than those found by other researchers for other countries. Hawkes (2010) calculated an MEF of 600 kgCO_2/MWh for Great Britain and Hawkes (2014) estimated that the long range MEF for Great Britain in 2050 would be between 260 and 530 kgCO_2/MWh. McKenna et al. (2017) calculated an MEF of 547 kgCO_2/MWh for Ireland. Thind et al. (2017) found an MEF equal to 597 kgCO_2/MWh for the Midcontinent Independent System Operator region in the United States. Siler-Evans et al. (2012) found an MEF of 834 kgCO_2/MWh Midwest Reliability Organization region of the United States. On the other hand, our calculated MEFs for Turkey ranged between 100 and 332 kgCO_2/MWh.

5.2 Comparison with an Internal Combustion Engine Vehicle Fleet

The 10,000 EVs in our simulation traveled a total of around 9,422,000 km in 30 days. To compare the emissions produced by this EV fleet with that produced by diesel fueled vehicles, we multiply the distance traveled by the EVs by the amount of emissions produced per km traveled by a diesel fueled vehicle. On average, a diesel fueled vehicle produces 0.1215 kgCO_2/km, which is quite close to that which is produced by gasoline fueled vehicles, 0.1234 kgCO_2/km (EEA, 2018). Hence, the emissions produced by diesel fueled vehicles when traveling 9,422,000 km would be around 1,144,773 kgCO_2 and gasoline fueled vehicles around 1,162,674 kgCO_2. The amount of emissions produced due to EV charging varies depending on the season the considered 30 days occur in, since the MEFs differ between seasons and time-of-day periods. Table 5.1 shows the monthly emissions resulting from EV charging for each season of 2019. It is observed that the highest amount of monthly emissions produced (observed in spring) is a third of the emissions produced by diesel and gasoline fueled vehicles. The lowest amount of monthly emissions produced (observed in summer) was a fifth of what was produced by diesel and petrol fueled vehicles in the same time period.

The primary factor that leads to our result is the dammed-hydro being on the margin. We should note, however, that if the EV power demand is realized at high values, the available dammed-hydro capacity on the margin would not be sufficient. In this case, the subsequent plants on the merit order will be used, in which case the system MEF will increase. With the completion of ongoing constructions, dammed-hydro generation capacity of Turkey will be increasing in the coming years; however this increase will be limited. Thus, in the future, it is highly likely that other fuel sources will step up to fulfill the increasing demand for energy, and consequently raise the MEFs for the Turkish electricity system. The direction of MEF change will be determined by whether Turkey increases generation from fossil fuels or renewables. In the long run, it may not remain environmentally beneficial for EVs to charge during peak hours. Our findings will be useful in devising incentive schemes to motivate EV users to charge during pre-determined times in which system MEF relatively small.

Table 5.1 Monthly Emissions Resulting from EV Charging for Each Season in 2019 (in kgCO_2)

Year	Spring	Summer	Fall	Winter
Emissions (kgCO_2)	388,623	235,409	263,899	293,902

The installed capacity for dammed hydro was 16.2 GW in 2019. The average generation of dammed hydro in 2019 was 7.9, 9.1 and 5.5 GW for the day, peak and night time-of-day periods, respectively. Thus, dammed hydro has between 7.1 and 10.7 GW of spare capacity. The highest generation electricity demand of EVs as a result of charging was 3.6, 5.3 and 5.0 GW for day, peak and night time-of-day periods, respectively. Upon inspection of our earlier calculated beta values, with the current installed capacity and the aide of other marginal plant types, dammed hydro can take on the extra power demand resulting from the charging of a relatively small number of EVs, such as 20,000. However, it is important to note that the generational capacity of dams falls as the water level is reduced. In addition, the dam operators may choose not to generate electricity due to socio-political reasons, since water is a valuable resource. Hence, the long term MEF might change with the increasing number of EVs. In the future, it would be useful for the analysis to obtain expert opinion on the maximum installed capacity that dammed hydro can reach in Turkey.

In this study, we have conducted a limited sensitivity analysis over the effects of the availability of workplace charging on the power load profiles of EVs. We observed that the availability of workplace charging greatly affects the power load peak heights for workplace charging and home charging. In addition, it also affects the maximum peak height in the power load profile. Further sensitivity analysis should be conducted over additional parameters once the simulation model is expanded further. This will enable a better understanding of the effects of different parameters and future scenarios.

Research in this topic can be improved further if emissions are calculated or reported separately for each individual power plant. This would circumvent the need to multiply the carbon intensity factor by the hourly generation data in order to obtain the hourly emissions. Using the reported emissions directly would be more accurate since using a single carbon intensity factor assumes that all power plants using a certain fuel type produce the same amount of carbon dioxide when generating a unit of electricity. However, this may not be the case, since the efficiency of power plants decline with their age. In addition, technological differences also contribute to the carbon intensity factor of each power plant. In a similar fashion, if more data on existing EVs in Turkey becomes available, such as the average trip distance, starting and ending battery State of Charge (SoC) and average traveling speeds, our EV simulation model can be improved.

Given the availability of the earlier mentioned data, a more realistic demand simulation may be further developed. This can be achieved by adding trips to other destinations, including limited charging spots (finite resources) and more realistic EV modeling in general. In addition, a more realistic supply model may also be further developed, hourly MEFs may be calculated as well as long term MEFs. Moreover, researchers may be interested in analyzing the effects of different electricity prices on the EV owners charging habits. Moreover, long term MEFs may be calculated for Turkey in a similar fashion to what Hawkes (2014) did.

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APPENDIX A

Table A.1 β_f for each season and Time-of-Day of 2014

Fuel	Spring			Summer			Fall			Winter		
	Day	Peak	Night	Day	Peak	Night	Day	Peak	Night	Day	Peak	Night
Hydro (Dam)	0.51	0.60	0.60	0.54	0.64	0.45	0.49	0.66	0.40	0.50	0.68	0.43
Natural Gas	0.34	0.25	0.27	0.38	0.31	0.40	0.40	0.24	0.47	0.39	0.24	0.47
Hydro (r-o-r)	0.12	0.08	0.05	0.07	0.05	0.03	0.10	0.06	0.05	0.10	0.05	0.05
Hard Coal	0.04	0.06	0.06	0.03	0.01	0.06	0.02	0.03	0.05	0.02	0.02	0.03
Lignite	0.01	0.01	0.01	0.00	0.01	0.03	0.00	0.03	0.01	0.00	0.01	0.02
Wind	-0.01	0.00	0.02	-0.02	-0.01	0.03	-0.01	-0.01	0.00	0.00	0.01	0.01

Table A.2 Regression Models' R^2 for Seasonal and Time-of-Day Disaggregated Datasets

Year	Spring			Summer			Fall			Winter		
	Day	Peak	Night	Day	Peak	Night	Day	Peak	Night	Day	Peak	Night
2019	0.60	0.43	0.30	0.50	0.37	0.18	0.47	0.21	0.43	0.56	0.42	0.35
2014	0.61	0.45	0.32	0.73	0.49	0.36	0.66	0.41	0.53	0.69	0.35	0.50

Table A.3 Regression Models' R^2 for Seasonal Disaggregated Datasets

Year	Spring	Summer	Fall	Winter
2019	0.61	0.53	0.55	0.55
2014	0.61	0.71	0.67	0.73