A Methodology to Analyze Short Term Impacts of Electric Vehicles on Costs, Emissions and Energy Consumption: Case of Turkey

by

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ABSTRACT

In today's world, where sustainability of energy supply chains is questioned intensively, electric vehicles (EV) are emerging as a solution to reduce emissions and increase efficiency of the road transportation sector. Impacts of this emerging technology, such as emissions, primary energy consumption and cost to end users should be analyzed before introduction of the technology, in order to get the best benefit and avoid a case where they perform worse than conventional vehicles (CV). Studies in the literature are based on average energy mix or pre-defined generation scenarios and they aim to construct policy recommendations solely on the cost minimization objective. However, the performance of EVs depends on the sources that are used to generate the marginal electricity that charges the batteries and single objective models provide a limited analysis on the benefits of EVs. Moreover, impact analysis studies always used pre-defined scenarios for charging hours without any optimization effort to determine the best hours of charging and there are no studies that analyze Turkey, which is an important potential market for EVs.

In this study, gaps above are addressed by a methodology that analyzes performance of EVs under different charging and market penetration scenarios and compares the performance with CVs. The methodology uses a bi-objective optimization model representing the electricity market to determine the efficient set of options for marginal generators that charge EVs. The model is applied by using real data from the Turkish electricity market. Results show that, electric vehicles provide an opportunity to decrease costs, emissions and primary energy consumption significantly compared to CVs in Turkey. Single objective models are shown to prevent the sector from getting the best environmental benefit and may end up in a solution where EVs perform worse than CVs. Hence, decision makers should use bi-objective models to make better use of EVs and take specifications of the marginal electricity into account before shaping EV policies.

ÖZET

Günümüzde çevresel sorunların artışı ve enerji kaynaklarının hızla azalması enerji sektörünün verimliliğinin ve sürdürülebilirliğinin giderek artan bir şekilde sorgulanmasına sebep olmaktadır. Bu şartlar altında elektrikli arabalar, karayolu taşımacılığının verimliğini artırmak ve egzoz gazı emisyonlarını azaltabilmek adına önemli bir seçenek olarak ortaya çıkmaktadır. Bu yeni teknolojinin vadettiği faydaları getirebilmesi için pazara girişlerinden önce birincil enerji tüketimi, emisyonlar ve son kullanıcıya maliyetleri gibi etkileri inceleyen kapsamlı araştırmalar yapılması gerekmektedir. Literatürde karşılaşılan çalışmalar elektrikli arabaların performanslarını sabit senaryoları üzerinden bulundukları bölgenin ortalama elektrik santrali portföyüne bakarak tahmin etmeye çalışmakta ve tek amaç fonksiyonlu modellerden yararlanmaktadır. Oysa elektrikli araçların gerçek performansı şebekeye getirdikleri yeni yükün karşılandığı santrallerin özelliklerine bağlıdır ve tek amaçlı modeller çözüm kümesini kısıtlayarak çevresel açıdan çok faydalı çözümleri gizleyebilmektedir. Ayrıca araçların şarj edileceği saatler hep önceden kabul edilen sabit senaryolar olarak modellere girilmiş ve bu değişken üzerinde herhangi bir eniyileme çabasına rastlanmamıştır. Son olarak elektrikli arabaları için önemli bir potansiyel pazar olan Türkiye’deki geniş çaplı bir elektrikli araç kullanımının etkilerini inceleyen bir çalışma bulunmamaktadır.

Bu tez çalışmasında literatürde tespit edilen bu eksiklikleri gidermek amacıyla elektrikli arabaların performasını hesaplayan ve içten yanmalı araçlarla karşılaştıran bir metot önerilmektedir. Bu metotda kullanılan çift amaçlı optimizasyon modeli sayesinde marjinal yükü karşılayacak çözümler sadece en ucuz şarjı sağlayacak şekilde kısıtlanmamış, emisyonları da azaltması mümkün olan tüm etkin jeneratör kümeleri tespit edilebilmiştir. Türkiye Elektrik İletim Anonim Şirketinden alınan gerçek verilerle yapılan çalışmada elektrikli arabaların egzoz gazı emisyonu, birincil enerji tüketimi ve son tüketiciye maliyetleri konusunda içten yanmalı araçlara üstünlük sağladığı görülmüştür. Ancak tek amaçlı çözümlerin, kimi örneklerde elektrikli arabaların emisyon ve enerji tüketici avantajlarını yok edecek şekilde çözümler önerdiği ve marjinal jeneratörler ile yapılan analizlerin sonuçlarının ortalama değerler ile yapılan çalışmalardan farklı sonuçlar verdiği de gösterilmiştir. Bu sebeplerden teknolojinin mevcut durumu kötüleştirmemesi ve etkilerinin doğru olarak tahmin edilebilmesi için bu çalışmada önerilen metot ile yapılacak analizler önem teşkil etmektedir.

To those who dedicate their lives to the pursuit of better tomorrows for all…

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NOMENCLATURE

GHG	Greenhouse Gas
ICE	Internal Combustion Engine
ICEV	Internal Combustion Engine Vehicle
BEV	Battery Electric Vehicle
PHEV	Plug-In Hybrid Electric Vehicle
EV	Electric Vehicle
TEİAŞ	Turkish Electricity Transmission Company
NASA	National Aeronautics and Space Administration
OPEC	Organization of the Petroleum Exporting Countries
LPG	Liquefied petroleum gas
LNG	Liquefied natural gas
HEV	Hybrid Electric Vehicles
TCO	Total Cost of Ownership
WWF	World Wide Fund for Nature
IEA	International Energy Agency
PETDER	Association of Petrol Sector Members in Turkey
OECD	Organization for Economic Co-operation and Development
PMUM	Turkey Electricity Market Operation Centre / Piyasa Mali Uzlaştırma Merkezi
MYTM	National Load Dispatch Centre / Milli Yük Tevzi Merkezi
KPTF	Unconstrained Market Exchange Rate

NPTF	Final Market Exchange Rate
$APEC$	Annual Primary Energy Consumption
$AGHG$	Annual Greenhouse gas Emissions
AEC	Annual Cost of Energy
$DPEBC$	Daily Primary Energy Consumption of Marginal Generators
$DPEC$	Daily Primary Energy Consumption
$DGHGBC$	Daily Greenhouse Gas Emissions of Marginal Generators
$DGHG$	Daily Greenhouse Gas Emissions
DEC^1	Daily Energy Cost to the Energy Supply Chain
σ	Percentage of Costs of Energy Before Taxes
DEC^2	Daily Energy Costs to End Users
RP_t	Retail Price of Electricity at Time *t*
$fc_{vehicle}$	Fuel consumption of the Vehicle (litre/km)
e_{fuel}	Energy Content of the Fuel (kWh/litre)
d	Average Annual Kilometres Driven Under Urban Conditions (km)
θ	Energy Efficiency of Well-to-Tank Operations
cc_{fuel}	Amount of Greenhouse Gas Emitted by Combustion of a Litre of Fuel (g/litre)
γ	GHG Emission Coefficient of Well-to-Tank Operations
c_{fuel}	Cost of the Fuel
t	Index Representing Hours of a Day
s	Index Representing Charging Status of an Electric Vehicle Battery
n	Index Representing Electric Energy Demand Nodes
i	Index Representing Generators
b	Index Representing Day-Ahead Market Bids
h	Index Representing Transmission Lines

T	Set of Hours of the Day
S	Set of Charge Status Indicators
N	Set of Demand Locations
H	Set of Transmission Lines
G	Set of Generators that Participate in Day Ahead Market
G'	Set of Conventional Load Generators
P_{itb}	Unit Cost of Generation (TL/kWh) of Bid *b*, by Generator *i*, at Time *t*
U_{itb}	Upper Bound of Generation (MW) of Bid *b*, by Generator *i*, at Time *t*
L_{itb}	Lower Bound of Electricity Generation (MW)
C_i	Unit carbon Emission of Electricity Generation (kg CO_2 / MW)
T_h	Thermal Transmission Capacity of Transmission line (MW)
d_{nt}	Conventional Electricity Demand of Region *n* at Time *t* (MW)
BEV_{nt}	Number of Battery Electric Vehicles Plugged in at Time *t* in Region *n*
δ_s	Amount of Power Transferred to Vehicle Battery in *s*th Hour of Charging
g_{int}	Conventional Load Supplied by Base Load Generator *i* at Time *t* (MW)
R_i^+	Ramp up limit for Generator i
R_i^-	Ramp down limit for Generator i
e_{hin}	Network matrix Representing Generator-line relations (0-1)
β_{in}	Loss coefficient
x_{intb}	Electric Load Supplied by Bid b of Generator i for Marginal in n at t (MW)
Y_{itb}	Binary Variable Indicating if the Bid b of Generator i is Accepted at Time t
μ_i	Efficiency of Generator i
PEV_{nt}	Percentage of Electric Vehicles that Start Charging at Time t
$NBEV_n$	Total Number of BEVs to be Charged in Region n
$NPHEV_n$	Total Number of PHEVs to be Charged in Region n
p_{nt}	Maximum Percentage of Vehicles in Region n that can be Plugged-in at Time t

Chapter 1

INTRODUCTION

In today's world, sustainability of industrial and economic activities is questioned more frequently than in the 20th century due to international agreements which aim to ensure sustainable development of mankind and increased environmental consciousness in the public. As defined by the United Nations, sustainable development is development that meets the needs of the present without compromising the ability of future generations to meet their own needs [1]. Two major threats on future generations to meet their needs are the extinction of natural resources and the damage caused to the environment. Despite the fact that there are numerous sectors contributing to these two, majority of research related to sustainability is conducted on energy supply chains.

Energy supply chains consist of raw materials, processes and technologies that are used to satisfy different types of energy needs of end users. No matter which sector the energy supply chains operate in, they pose a threat on sustainability by consuming energy sources, most of which are fossil based, and by emitting harmful gases into the atmosphere. In order to decrease consumption and emissions levels, intense research effort is carried out to find efficient and clean alternative technologies. These efforts are showing promising results in developed countries in all sectors except one. Between 1990 and 2006, greenhouse gas emissions in EU-27 have decreased by 13.4% in non transport sectors but in the same period greenhouse gas (GHG) emissions from the transportation sector have increased by 35.8%. The road transportation sector is the major contributor to overall emissions with its share of 71% and to the increase with its 61% share [2]. The cause of these worsening figures is not the act of road transportation itself but the technology that dominates the road transportation sector: the internal combustion engine (ICE).

The internal combustion engine is an engine which converts the chemical energy contained in a fuel into useful mechanical energy by combusting it. Today, most common fuels used in ICEs are liquid hydrocarbons such as gasoline and diesel fuels. The technology, which is being used by the road transportation sector since the invention of internal combustion engine vehicle (ICEV) by Karl Benz in 1885, has not faced a serious threat from an alternative technology to its complete dominance in the market. Therefore, the sector's addiction to liquid hydrocarbon fuels has deepened and it has become one of the most problematic sectors threatening sustainability. Two major disadvantages of the ICE technology, which are the root causes of the problems it creates, are inefficiency and carbon intensity of primary energy sources it is using.

Despite being a robust machine which is very suitable for mass production, ICE operates with very low efficiencies. Although it can reach higher theoretical efficiencies, gasoline powered ICEs have 18% efficiency on average whereas diesel engines can operate with an average of 22% [3]. This means that out of 100 units of primary energy stored in the crude oil, only 18 units of kinetic energy is obtained from the engine and 82 units are wasted in intermediate steps. Considering the scarcity of natural resources, this waste cannot be tolerated anymore where alternative and more efficient technologies are emerging. In addition to being inefficient, ICE dominantly use liquid hydrocarbons which emit 2,350 (gasoline) to 2,690 grams (diesel) of CO_2 when combusted [4]. Therefore, it is contributing to greenhouse effect which is considered to be the main root cause of the global warming. Hence, research to find and integrate alternative technologies to the ICE technology is important to help the creation of a more sustainable energy supply chain for the road transportation sector.

The alternatives developed to mitigate GHG emissions from the road transportation sector are classified under two titles: alternative propulsion technologies and alternative fuels. All alternative propulsion technologies discussed in the recent literature include some degree of electrification and are based on the idea of replacing or supporting the ICE by an electric motor supplied from an on board energy source. Alternative fuel technologies such as biodiesel, ethanol, LNG or LPG fuels that can be used by making slight modification on the internal combustion engine are not in the scope of this thesis. Among many different vehicle technologies battery electric vehicles (BEV) and plug-in hybrid electric vehicles (PHEV) are the most mature technologies that are ready for commercialization and they are expected to play a significant role in the road transportation sector's move towards a more sustainable path in coming decades [5]. In this study, electric vehicle (EV) term is used to cover both technologies and defined as a road vehicle that converts the chemical energy stored in an onboard battery, which can be charged from the electricity grid, to useful mechanical energy by using an electric motor to move the vehicle.

EV technology provides the opportunity to bring road transportation sector to a more sustainable path than ICEVs. The first main opportunity provided by the introduction of the electric vehicles is the mitigation of GHGs by using clean electricity generated by using renewable energy sources. Second, due to their higher tank-to-wheel efficiencies, they provide the opportunity to decrease energy consumption of the road transportation. The last benefit is the diversification of energy sources powering the sector by shifting the energy supplier from crude oil products to electricity, which can increase energy security and decrease energy costs of the sector. In order to harvest these promising potentials of the EVs automotive manufacturers are announcing production plans for EV models, governments are passing tax incentives to support EV buyers, utilities are planning new tariffs for EV charging and charging infrastructure is being built in major cities. However, these potential benefits can be actualized only when the electricity that charges the batteries of the EVs is generated from clean and efficient sources and can be supplied without harming supply of the conventional electricity demand.

At this point, another development in the energy sector that can have a positive impact on the success of electric vehicles, which is Smart Grid, can be coupled with EV technology to overcome these threats. With the advances in communication technologies such as Internet, data transfer is faster and easier than ever in 21st century. So far, these advances have shown impacts on our daily life but electricity sector has not made use of this technology yet. In conventional electricity networks, data flow is discontinuous and does not enable the suppliers and demand points to shape their decisions based on the instant changes in the specifications of electricity such as utilization, cost and carbon intensity. Smart grid is a general term that is used to express electricity grid operations where a real time two-way communication between the end user and suppliers, which enable computer control and optimization of the grid operations. This provides opportunity to make better use of clean energy sources to supply energy demand of transportation sector and enable suppliers to balance negative impacts of EV technology to the grid such as increased peaks.

Electricity mix changes significantly by magnitude, timing and location of charging, so do carbon intensity, overall efficiency and cost of electricity. Therefore, research to analyze the impacts of the EVs on the electricity grid and to determine the electricity generators utilized for charging the EVs must be conducted before the introduction of the EVs to get the best benefits from the technology and give insights to the policy makers which will have more room for optimization and more control over the network with the emergence of smart grid applications. This need for research creates a wide area of application for systems engineering and operations research methods.

The introduction of EVs will affect the electricity generation, distribution and transmission sectors by changing the demand profile of cities and results in an increase in total production and consumption in the system [5]. As discussed above, net environmental and economic impacts of EVs depend on how the electricity market is affected. Since it is intractable to conduct large scale experiments by charging EVs in different regions, mathematical modelling and optimization techniques come out as valuable tools to analyze impacts and determine possible outcomes of the introduction of the EVs. In recent years, many publications have analyzed the impacts of introduction of the EVs from a number of perspectives but gaps have been found during the literature review, which is given in detail in Chapter 2.

Despite the fact that there are many studies dating back to 1990 which analyze the impacts of the EVs, almost every study has conducted a scenario analysis, in which impacts of electric vehicles are analyzed by general assumptions about the average energy mix, without proposing any mathematical models or optimization efforts. The emissions are calculated by using average emissions of the grid, which can lead to results far from the actual case in certain cases. The business as usual model in the electricity market aims to satisfy the total demand with minimum cost. If the electricity market will handle the EVs together with the conventional demand and continue with business as usual model, the EVs' net impacts will directly depend on the marginal electricity generators that are put into operation when the EVs are introduced. If the carbon intensity of these generators differs from the average mix, the studies using average mix for calculation would mislead the policy makers. Therefore, the emphasis of the proposed methodology is on determining the marginal generators. The limited number of studies which use mathematical modelling and optimization methods has used a single objective function which minimizes total costs of the system and proposes policies that minimize costs, without a few exceptions where more than one objective was taken into account. In general, cheaper generators in the electricity market such as coal generators generate more emissions than costly generators like hydro power and natural gas plants. Therefore, single objective models would lead to undesirable results regarding emissions in regions where cheap electricity is generated from carbon intensive energy sources. As stated above, cost and environmental performance of the electricity market are two conflicting objectives, which can be handled by the methods in bi-objective decision making. Use of bi-objective decision tools lead to generation of all efficient solutions for a region which can enable policy makers to choose among different options depending on their preferences of being more cost or emissions oriented. Another major gap in the studies using optimization methods was the use of scenarios for representing charging demand. Charging patterns are given as inputs to the model and results from different scenarios are compared without finding optimal charging hours from different regions and periods of the year. This approach limits the ability of the model to optimize performance of the EVs. Therefore, charging hours should be defined as decision variables to determine the most appropriate charging hours. The last gap addressed in this work is the lack of research about Turkey. There are no studies in the literature that analyze the impacts of a possible introduction of the EVs into the Turkish electricity market. The methodology in this thesis is an attempt to fill these gaps in the literature.

The proposed methodology can be summarized in four steps. For different market introduction scenarios, a number of conventional vehicles that will be replaced by the EVs are determined and annual emissions, energy consumption and energy costs are calculated. In order to determine the marginal electricity generators that will be used to charge the EVs, a bi-objective mixed integer programming model is developed to represent the bidding in the day-ahead electricity market. The model's objectives are minimization of total generation costs and CO_2 emissions resulting from the charging of EVs which are based on certain scenarios under technical constraints coming from the generators and transmission lines. In the second step this model is run only for the cost function, which represents the business as usual behaviour of the system. In third step, the model is run as a bi-objective model and the efficient frontier is determined to show all possible options to satisfy charging demand under predetermined scenarios. In the last step charging hours are defined as decision variables and optimal charging hours for minimizing costs and emissions are found. Results obtained from the models are compared to conventional vehicles to determine the magnitude of net environmental and economic impacts of the EVs. The results also give insights to policy makers to see which hours the EV owners should be encouraged to charge their vehicles to get the best benefits from the technology. This methodology is applied to the Turkish electricity market with real world data taken from Turkish Electricity Transmission Company (TEIAS) but it can be applied to any region with their own data set.

The chapters of the thesis are organized as follows: The second chapter gives a more detailed analysis of threats on sustainability of today's energy sector, investigates contribution of the transportation sector and provides information about the alternative technology of electric vehicles. The electric vehicle technology's relation with the electricity network and the literature review about prior research on analysing electric vehicles' environmental and economic impacts are also given in second chapter. Chapter 3 starts with explanation of the experimental design proposed to analyze and optimize impacts of the electric vehicles in detail, which is followed by a bi-objective mathematical model that represent day ahead electricity bidding systems. Solution method that is used to solve the models is described briefly at the end of Chapter 3. Chapter 4 is dedicated to application of the methodology to Turkish market. Assumptions and data are given at the beginning of the chapter and followed by extensive analysis of the results. Net environmental and economic impacts of the electric vehicles are presented in detail. The fifth chapter concludes the thesis by discussing applicability of the model, giving policy recommendations for the Turkish case study and suggesting future improvements and studies on the subject.

Chapter 2

BACKGROUND

2.1. Sustainability in the Transportation Sector

The climate change is one of the biggest challenges facing today's world. Despite the fact that the debate on the cause of the changes in the climate continues among scientists, a growing number of them now agree that human activities are playing an important role in this change [6]. According to National Aeronautics and Space Administration's (NASA) Goddard Institute of Space Studies' global average temperature measurements, 2010 has been recorded as the warmest year on record since the first year in record (1880), and the current average temperatures are 0.62^{o}C higher than the average global average temperatures between 1950 and 1980 [7]. The climate researchers agree that the average increase should be kept below 2^{o}C compared to the pre-industrial era to avoid catastrophic climate disasters [8]. Increasing temperatures are attributed to excessive concentrations of greenhouse gases (GHGs) in the atmosphere, which are largely caused by energy related activities that are dependent on combustion of fossil fuels, such transportation activities using ICE. GHGs are defined as gases that absorb radiation within the thermal infrared range and cause solar radiation to be trapped in the atmosphere, causing an increased warming effect. Most important GHGs are water vapour, CO_2, CH_4, N_2O, ozone and chlorofluorocarbons. Concentrations of these gases in the atmosphere are increasing consistently since pre-industrial era due to anthropogenic activities and now far exceed pre-industrial values determined from ice cores spanning many thousands of years

[9]. According to Mauna Loa Observatory -one of the most widely accepted measurement institutions in the world- global CO_2 concentrations have increased from 315 ppm to 394 ppm between 1959 and 2012 [10]. Continued GHG emissions at or above current rates would induce many changes in the global climate system during the 21st century that would very likely be larger than those observed during the 20th century, therefore scientists propose emissions to be decreased before the change in the climate gets irreversible [8]. Therefore, efforts to stop global warming and climate change concentrate on finding ways to mitigate GHG emissions caused by human activity.

CO_2 is the most important anthropogenic GHG since it attributes to 77% of global anthropogenic emission and annual CO_2 emissions grew by about 80% between 1970 and 2004 [3]. The largest growth in CO_2 emissions between 1970 and 2004 has come from the power generation and road transport sectors, whereas the industry, households and the service sector have been growing at a lower rate [6]. In the European Union, every sector has decreased GHG emissions between 1990 and 2006 whereas emissions from the transportation sector have increased by 27.3% [11]. Since 1970, GHG emissions from the transport sector have grown by over 120%; therefore it is important to understand the reasons of this growth and conduct necessary research to decrease GHG emissions from the sector. The emissions from road transportation vehicles will keep on increasing as more vehicles are put on the roads unless new ways to make clean use of fossil fuels in ICEs is found or new power train technologies that use cleaner fuels are commercialized. Only then GHG emissions from the sector can be decreased and climate protection targets can be reached.

Another problem related to the dominance of the road transportation is the poor energy efficiency of the technology which increases total primary energy used by the sector. According to International Energy Agency’s energy statistics, the transportation sector consumed 26.7% of the total global final energy in 2008 [12]. Share of transport is slightly higher in developed regions like Europe where transportation sector consumes 31.4% of total final energy and road transport accounts 81% of total final energy consumption of transportation sector [11]. In Turkey, the transportation sector has consumed 20.1% of total final energy, whereas 85% of transport energy was consumed by road transport [13]. Although ICE can reach higher theoretical efficiency, the average energy efficiency of a conventional engine is around 18% for gasoline powered engines and 22% for diesel powered engines [3]. Taking friction, heat and noise losses in other parts of the conventional cars into account, well-to-wheel efficiency of the conventional vehicles decrease to 12-15% [2]. This means that more than 85% of energy stored in crude oil is wasted as heat, noise and other by products during the energy supply chain of the road transportation sector. In today’s world, where experts say that proven reserves can supply oil for only around 50 years, such an inefficient technology must be replaced with more efficient alternatives.

Energy diversification is another problem related to sustainability of the road transportation sector. The source of energy where the energy demand of the sector is supplied leaves transportation sector in a unique place regarding diversification. Approximately 95% of primary energy consumed by the transport sector derives from crude oil whereas this share is higher in road transport [8]. This dependence brings two major problems: threatened energy security and high energy costs. Around 75% of the proven oil reserves are in the hands of Organization of the Petroleum Exporting Countries (OPEC) member states and an additional 8% of the reserves lie in Russian Federation [8]. The current geographical distribution of reserves and the rise of state owned oil companies pose an energy security threat to net oil importer countries such as US and EU-27 countries with the exception of Denmark, which is still a new exporter of oil. The current structure of the market does not enable countries to stock crude oil to use for long periods of time, hence oil dependent road vehicles are running on an imported source facing a threat of being un-operational in case of a conflict with oil producing countries. In 2008, Turkey imported 94% of total crude oil to satisfy demand, around 50% of which came from the transportation sector [13]. Creating alternatives to ICE technology and diversifying energy sources would eliminate dependency on oil and hence create a more secure energy market.

After a century of extraction and production efforts, age of cheap oil is discussed to come to an end. This can be readily seen from the market price of crude oil which recorded an all time high price of $147 per barrel in July 2008. After a year of rebalancing acts, the barrel price was drawn back to levels below $100 in 2009-2010 period but since then the price has climbed up levels between $100-$110 [9]. The reason lies in simple economic supply-demand theory. The population grows and crude oil demand increases, whereas the supply of crude oil is about to reach a maximum, which is named in the literature as Peak Oil. Whether Peak Oil is in the close future or not, energy professionals share an idea that Peak "Cheap" Oil has already been reached [14]. Today, the road transportation has no other choice than using oil products because ICE consumes gasoline or diesel fuels. As opposed to ICE, alternative technologies which provide an opportunity to break dependency on oil products and put the transportation sector on a more sustainable path that can be powered by many different energy sources should be found and integrated into the road transportation sector. EV technology is the most mature technology in the market as of today and this alternative technology will be analyzed in detail in the coming subsections as EV is the heart of this study.

2.2. Electric Vehicles

EV is a mean of transport, which converts the chemical energy stored in onboard batteries to mechanical energy by using an electric motor used in the drive train. The first developments in electrical vehicles date back to the mid 19th century. Following the technological progress shown in the scientific field of electricity and the invention of batteries, electric power became an alternative way to mobilize people and goods which were dependent on horse or steam power. Prior to the invention of ICEV by Carl Benz in 1885, some EV models were produced in small quantities. By 1900, the market for automobiles was shared between three technologies: steam, electric and gasoline. In 1900, there were 1684 steam driven, 1575 electric powered and 963 gasoline powered (internal combustion engine) vehicles on US roads [15]. The EV was able to beat the ICEV in those days although it had serious limitations about the range. Gasoline powered engines of the day were too noisy and dirty which made them undesirable in cities, whereas EV was operating silently and leaving no smoke behind. Another drawback of the gasoline powered car was that they needed a hand crank to start the car which was hard especially for women drivers, and this made EV more preferable because they could be started instantly [15].

Two developments in the first decades of the 20th century changed the fate of the automotive industry in favour of ICEV. Costs of EV and ICEV were comparable to each other until the introduction of assembly line technology to automotive manufacturing by Henry Ford in the 1900s. The assembly line helped ICEV to overcome a bottleneck whereas battery production rates were still a problem for EV. As production capacity increased, ICE technology took advantage of the economies of scale and lowered its market price to nearly a quarter of EV prices. Despite low costs, hand crank start remained a problem for ICE but electric technology has ironically helped it overcome this by introducing an electric starter to the market in 1912. This technology made it possible to start ICEVs instantly and accelerated sales. After 1912, the number of EVs produced decreased sharply and by the early 1920’s almost all manufacturers were out of business [15].

In the following years ICE technology has received great success in the market and intensive research effort was given to ICEV and the engine itself. Lack of demand has been a barrier for developments in battery technology and electric motors as well as EV. This dark age of EV continued until the 1960's when air pollution and traffic congestion started to concern people. Increased concern has lead to development of small scale EV projects like Ford Comuta, Enfield 8000 in Europe, but none of these cars has made a success in the market [15]. Despite being an unfavourable technology in the mass market, EV has two advantages over ICEV in two niche markets. EVs operate silently which make it preferable where sound is undesirable like golf courses, retirement pensions or holiday resorts [15]. Another advantage of EV is that it is emission free, which makes it a successful product for indoor transportation activities such as warehousing or airport operations.

Until 1970's, liquid hydrocarbons have supplied a great demand from ICEVs without raising any concern and receiving any question from the community. The first questions against the ICEVs have risen during the oil crises of 1973 and 1979. The crises increased the governments' concerns about energy security and actions decreasing crude oil consumption were taken. Following these two crises crude oil was substituted with other primary energy sources such as natural gas, coal or nuclear especially in the power generation sector. However, actions taken to decrease crude oil consumption in the transportation sector such as fuel consumption regulations, speed limits, biofuel research could not break dominance of oil in the sector because there were no feasible alternatives to ICE drive train technology [15]. Rebalancing acts dropped the price of oil in the 1980's and this has lead to an increase in personal car sales as the public has kept on enjoying cheap energy and passenger car sales have increased. Starting from the last decade of the 20th century, global road vehicle sales have started to increase more sharply than ever before, resulting in a growth in oil demand. Today half of the crude oil extracted goes to the transportation sector and this share has increased as oil is excluded from other sectors such as power generation [15]. As the experts discuss that Peak Oil is about to be reached, and the oil prices increase, the governments are more interested in alternative transportation technologies, then they were three decades ago.

Although economic issues are an important motivation for research about EV the most influential reason is the recent discussion about global climate change and the transportation sectors contribution to today's environmental problems. Increased transportation activity has resulted in a growth in GHG emissions and today's world, where a single CO_2 molecule saved from being released to the atmosphere can be vital. As will be discussed below, the problems concerning the transportation sector are not because of the act of transportation itself but by the dominating ICE technology. Therefore, governments are now interested in EV technology which has zero direct emissions and promises to decrease the life cycle emissions. This rising interest has motivated the allocation of funds for EV, which lacked for decades.

California was the first state to take action and announced a Zero Emission Vehicle regulation in the early 1990's to force major car manufacturers to sell ZEVs equivalent to 2% of their total number of sales by 1998 [15]. Although this regulation was modified in following years to decrease EV shares, this regulation has motivated major car manufacturers to start research and development projects in the EV field. GM's famous EV1 and Ford's Ecostar are among most notable models manufactured in these years but all of these cars were far from being a success in the market. Currently, alongside strict emission regulations and targets, rising environmental consciousness among customers has created a boost for EV. A "green market" in which all major automobile manufacturers want to have a share is now growing. In this section, technology of EVs will be introduced and compared with the ICEVs.

Depending on the degree of electrification and use of different power sources in the drive train, electric vehicles are classified under four categories. Each type of electric vehicle has its own advantages and disadvantages.

Hybrid electric vehicles (HEV) are the first step towards electrification of ICEV. HEVs are mainly driven by a conventional internal combustion engine which is supported by an electric propulsion system to improve fuel economy and overall environmental performance. HEV can be categorized under two concepts depending on the degree of electrification. Mild hybrid electric vehicles have an electric propulsion system that helps the vehicle during acceleration, stores energy by utilizing regenerative brakes and includes an engine start-stop system. Mild hybrid electric vehicles cannot be driven solely by the electric motor since the motor is small scaled and the capacity of the battery is limited. Research indicates that mild hybrid electric vehicles are 10-15% more fuel efficient compared to ICEVs [2]. One of the most recognized mild hybrid vehicles is the Honda Insight. Full hybrid vehicles are a further step in the electrification of ICEV since they allow pure electric driving. Similar to mild hybrid vehicles, the internal combustion engine remains as the main propulsion system but full hybrid vehicles include a larger battery pack and a larger electric motor that can drive the vehicle on its own at low speeds and a limited range. Recharging the battery can be accomplished by ICE or regenerative breakes. Research shows that full hybrid electric vehicles achieve fuel efficiency gains of 25-30% compared to conventional vehicles [2]. Toyota Prius, which exceeded sale of 1 million in 2008, is today's the most successful full hybrid vehicle on the market.

Full hybrid vehicles are also categorized into three depending on the arrangement of vehicle components. In parallel hybrid vehicles, the electric motor and the ICE can drive the vehicle individually or a combination of two can provide propulsion. Propulsion systems are independent of each other and it is not possible to charge the battery by using the ICE. The battery can only be charged by regenerative breaking. In a series hybrid electric vehicle it is not possible to drive the vehicle on ICE. ICE is used as a range extender for the vehicle since it is responsible for recharging the battery when needed. Series hybrid vehicles include a more powerful electric motor and a larger battery pack. In split hybrid (or series-parallel hybrid) systems ICE can both drive the vehicle and charge the battery pack. It is possible to drive the vehicle on pure-electric mode. This system combines parallel and split systems and possesses advantages of both. Simplified structures of these three hybrid vehicle concepts are given in Figures 2.1. to 2.3.

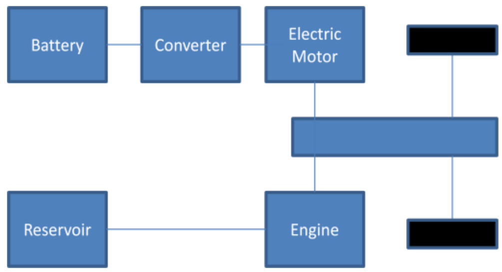

Figure 2.1 Basic Design of a Parallel Hybrid Drive train

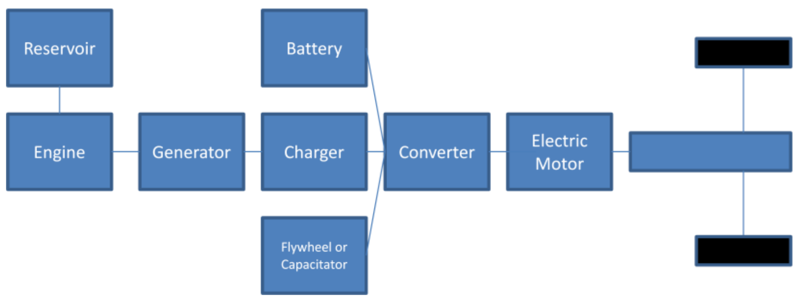

Figure 2.2 Basic Design of a Series Hybrid Drive train

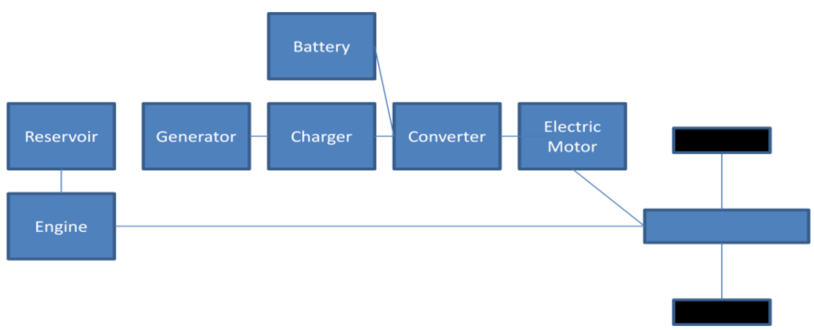

Figure 2.3 Basic Design of a Split Hybrid Drive train

Plug-In Hybrid Vehicles (PHEV) are hybrid vehicles that allow drivers to recharge the battery from an electric grid by plugging in the charging socket. PHEV also has the capability to recharge from regenerative breaking and ICE. PHEV is distinguished from HEV by its ability to travel only on energy stored from the grid, which enables zero-emission driving for a limited range. The main advantage of PHEV is that it can operate solely on electric energy for daily commuting and still provide the possibility to travel long distances by switching to ICE. PHEV install larger battery packs than most hybrid vehicles to extend all-electric range and increase environmental performance. PHEV can also use parallel, series or split systems to operate. GM’s Chevrolet Volt is an example of a PHEV which operates on series system.

Battery electric vehicles (BEV) are the last step in electrification of road vehicles. Possessing only an electric motor, BEV is entirely propelled by electricity stored in a battery pack which is charged from the power grid and has no connection to any gasoline product. BEVs have zero direct emissions since they do not use an ICE to power the car or charge the battery. Tank-to-wheel efficiency is higher than HEV and PHEV due to decreased weight and efficiency gains of the electric motor compared to ICE. Current BEV models are relatively small city cars with limited driving range and performance since current battery technology poses limitations on the maximum amount of energy that can be stored on board. GM’s EV1 car which was commercially available in California in 1996 is an example of BEV. Major manufacturers like Renault and Nissan have started production of BEV models, and most of the major manufacturers have announced plans to start production of BEVs before 2015.

2.3. Comparison with Today's Technology

Compared to today's dominant technology of ICEVs, the EV technology has some significant advantages as well as disadvantages. This subsection compares two competing technologies under major performance criteria titles.

2.3.1. Efficiency

As stated under ICEV title, the most important drawback of the conventional propulsion technologies is the inefficiency. Although ICE can reach higher theoretical efficiency, the average energy efficiency of a conventional engine is around 18% for gasoline powered engines and 22% for diesel powered engines [5]. Adding friction, heat and noise losses in other parts of the conventional car decrease tank-to-wheel efficiency of conventional vehicles around 12-15% [2]. The main reason behind this inefficiency is the relatively high number of moving parts in the mechanical drive train which causes energy to be lost as heat as a result of friction. The electric motor has a fewer number of moving parts and can reach an efficiency of 90% [5]. Since the electric drive train does not only consist of an electric motor, total tank-to-wheel efficiency range between 65-80% [5]. If a lithium battery pack is used detailed efficiencies are as follows: 88-90% for the charger, 85-95% for charging, 96-98% for electronic management and 90-95% for the electric motor [3]. These efficiencies result in an approximate tank-to-wheel efficiency of 72% for EV that carry lithium based battery pack [3]. Comparing ICEV and EV in tank-to-wheel efficiency show that EV are around 4-5 times more efficient than conventional ICEV. This means that the EV consumes 4-5 times less final energy than ICEV.

Despite the significance of tank-to-wheel efficiency in fuel economy, overall energy performance of EVs must be analyzed by their well-to-wheel efficiency. Conventional ICEVs use liquid hydrocarbons such as diesel and gasoline which are produced by distilling crude oil. The average gasoline and diesel distillation process is 83% [5]. This means that only 17% of energy stored in crude oil is lost in the refinery and 83% is stored in gasoline and diesel fuels that are pumped into the tanks of conventional cars. However, producing electricity for use in EV is not as efficient as the distillation process. Today, conventional efficiencies of coal power plants range around 36-44% and efficiencies of gas powered power plants average 43% [16]. This means that around 60% of energy stored in primary energy sources is lost in the electricity generation process. Despite being half as efficient as the crude oil distillation process, high tank-to-wheel energy efficiency of EV offsets low well-to-tank efficiency. Assuming a 15% efficiency for conventional cars and 72% efficiency for lithium based BEV, well-to-wheel efficiency is around 12-13% for conventional cars are around 25-30% for EV. Hence, EVs are twice as efficient as conventional vehicles in well-to-wheel efficiency and consume half the primary energy consumed by ICEVs. Figure 2.4 summarizes the efficiencies of EV and ICEV.

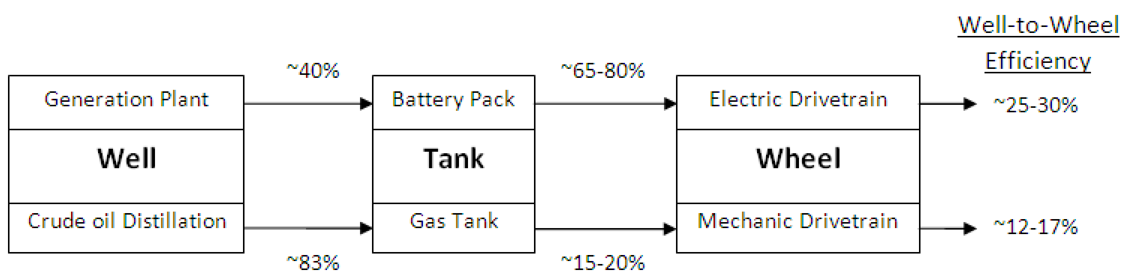

Figure 2.4: Approximate Efficiencies of EV and ICEV (Data from [3],[5],[16])

These efficiency differences may bring significant reductions in primary energy consumption of road transport. Assuming an annual distance of 14,400 kilometres travelled

(Daily average of 40 kilometres), conventional gasoline vehicles with a fuel economy of 7.0 lt/100 km consumes a primary energy of 11,800 kWh, assuming that gasoline contains 36.2 MJ/lt. Travelling the same distance by a BEV which consumes 0.14 kWh/km would consume 5,040 kWh. Substitution of one conventional vehicle with a BEV brings a yearly saving of 6,800 kWh primary energy. These savings might directly turn to savings in the amount of petroleum products imported and a decrease in dependency of foreign oil in many countries such as Turkey.

2.3.2. Emissions

Battery electric vehicles are characterized by zero tailpipe emissions and plug-in hybrid vehicles offer zero emission driving with their all electric range, whereas internal combustion engine vehicles produce a considerable amount of direct GHG. As stated in the introduction, the transportation sector is responsible for 19.2% of all GHG emissions and 22.7% of all CO_2 emissions in EU-27 countries [11]. The electric vehicle has the potential to reduce these figures if managed well. The first advantage of electric vehicles is a reduction in local emissions. The electric driving mode of PHEVs and all BEVs produce zero direct emissions of harmful air pollutants such as NO_X and volatile organic compounds therefore increase air quality in urban areas [2].

Despite producing zero direct emissions, electric vehicles account for GHG emissions on a well-to-wheel basis. GHG emissions come from the electricity generation process in power plants; therefore, the environmental performance of electric vehicles is strongly dependent on the energy mix of the electricity generation in the region. Every primary energy source has a different carbon intensity; hence, CO_2 released into the atmosphere by using that energy source varies. Coal power plants release approximately 1000 g CO_2 for every kWh of energy generated. Gas plants emit 380 g CO_2 / kWh and oil power plants emit 410 g CO_2/ kWh [5]. Currently, the EU average is around 400 g CO_2/kWh and 2030 estimations are 130 g / kWh. In the US, where coal is still an important source of energy in electricity generation, the average carbon intensity is 620 g /kWh [8].

Turkey, where half of the electricity comes from gas and 30% of electricity comes from coal the average is around 650 g / kWh [13]. Assuming a BEV that consumes 0.14 kWh / km, carbon footprint of a car can be estimated by using average carbon intensities. In the EU such a car would emit 56 g / km, in Turkey 90 g / km and in the US emissions would be around 86 g / km. These figures are promising on a road to reducing GHG emissions when compared to current ICE targets that limit emissions to 130 g /km but there are some regions where transition to EV could even worsen the environmental performance of a car fleet. In India, where more than 90% of electricity comes from coal plants, average carbon intensity of generation is 973 g / kWh. Charging an EV from electricity grid in India would result in an emission rate of 136 g /km which is worse than 2015 targets of EU [5]. Assuming an annual distance of 14,400 kilometres travelled (Daily average of 40 kilometres) by a conventional gasoline vehicle which emits 150 g / km, the annual carbon footprint is equal to 2,16 tonnes of CO_2. Travelling the same distance by a BEV which consumes 0.14 kWh/km and charging from average EU grid annual emissions would make 0,8 tonnes of CO_2. As seen in the calculations, EV can emit half the CO_2 if charged from an environmentally friendly electricity grid. EVs also help decrease the amount of undesired particles in urban conditions by moving the emissions away from the city. In a study by Thompson T. et al, it is shown that nitrogen oxide (NOx), volatile organic compound (VOC) and CO emissions from mobile emissions during daytime hours, shows a great decrease in urban areas [27]. However it must be noted that these are only estimations based on the average mix which can vary significantly from the marginal set of generators that will be used to charge EVs.

2.3.3. Range

The most important and widely discussed disadvantage of EVs to conventional vehicles is the driving range. Driving range is directly dependent on the energy storage system of vehicles, which is a battery pack in an EV and a gas tank in a conventional ICEV. ICEVs use the chemical energy stored in gasoline or diesel fuel to produce mechanical energy to move the car and benefit from high energy density of these fuels. Gasoline and diesel are great energy carriers since they can store around 13 kWh/kg of fuel whereas today's advanced Li-Ion batteries can store up to 0,25 kWh / kg [2]. For the same weight liquid hydrocarbons can store 65 times more energy than batteries and thus provide a great range for conventional ICEV. Average size cars have a gas tank capacity of 50-60 litres which provides a driving range up to 700 kilometres without refuelling. Since weight and volume constraints limit the maximum weight of the battery pack in BEV, the range is limited compared to conventional vehicles, whereas PHEVs can reach comparable ranges due to on-board range extender engines. BEVs that are introduced for market entry have ranges up to 200 kilometres which would be sufficient to cover daily driving needs assuming that the average daily driving distance in EU countries are 30 kilometres / day [17]. Charging time is another drawback of BEV. In addition to being energy dense, liquid hydrocarbons can be filled in relatively short times compared to BEVs. Visiting a gas station takes up to 5 minutes whereas recharging a BEV from grid can take up to 8 hours. There are variety of projects that are trying to solve this problem such as fast charging stations with high voltage that can bring charging times under 30 minutes or battery swapping stations where BEVs exchange depleted batteries with charged ones [18][19]. EVs are dependent on battery technology to reach a comparable range with ICEVs. The energy density of batteries need to be increased to overcome limited driving range problem and the charging time of battery packs need to be reduced to attract customers that are sceptical to electrification of road vehicles [20].

2.3.4. Energy Diversification

As stated in the introduction, liquid hydrocarbon fuels derived from crude oil provide 95 % of the primary energy consumed in the transport sector worldwide [8].There is no other sector that is dependent on one source of primary energy and this dependence threatens the energy security of oil importing nations. As opposed to crude oil, most nations are able to generate electricity by using a variety of natural resources. A transition to electric vehicles would allow governments to supply the energy demand of the transportation sector by using national sources. Today, electricity can be generated by using a variety of primary energy sources such as coal, natural gas, oil, hydropower, nuclear power, wind, sun, geothermal energy or other renewable sources. Diversifying the source of energy would increase energy security and enable a more environmentally friendly transportation sector by using renewable energy sources such as wind and sun. The use of a wider range of primary energy sources is assessed in the literature as an essential prerequisite to achieving decarbonisation of the transport sector fuels. In order to reach the promised benefits of electrification of transport and diversification of transport energy demand the electric network should be modified to adopt new loads and frequent charging of EVs. Besides the existing charging opportunities at private homes a dense charging infrastructure is needed to permit charging during daytime.

2.3.5. Cost of Ownership

One of the main barriers to successful market introduction of electric vehicles is the total cost of ownership (TCO) for this technology. TCO is a financial estimate that helps consumers determine direct and indirect costs of using a product. For transportation products, TCO defines the cost of owning a vehicle from the time of purchase by the owner, through its operation and maintenance to the time it leaves the possession of the owner. The first component of TCO is sale price. The cost of batteries plays a critical role in determining commercial viability of EV, because at current production costs for high-energy lithium-ion batteries (about 2000 $/kWh) they correspond to a price difference of more than $15,000 depending on the all-electric range [2]. Low production volumes of high-energy battery systems avoid the use of economies of scales in battery production thus pose a barrier in decreasing the gap between ICEV and EV sale prices. However, a drop in battery prices is expected if production volumes reach desired levels. Between 1991 and 2005, the price of lithium ion batteries per unit of stored energy decreased by a factor of ten following increased production volumes with demand from the portable electronics market [2]. A similar increase in EV battery pack production is expected to bring costs down and make EV a feasible alternative for customers. Experts agree that EV can challenge ICEV prices only when battery costs are decreased significantly and relevant targets are set such as the United States Advanced Battery Consortium's $ 250/ kWh [21]. In the literature there are estimations that vary significantly due to the high level of uncertainty on EV technology. The Boston Consulting Group has conducted a detailed analysis to estimate future costs of battery and has predicted that the battery pack cost can be decreased by 60-65 percent ($600-700 / kWh) in period between 2009 and 2020 [21]. Another study by United Kingdom Department of Business, Enterprise and Regulatory Reform and Department for Transport concludes that it is unlikely that the price of lithium-ion batteries will fall significantly and that it will fall below \$300 levels in the near term [2]. These estimations point out that a considerable price premium compared to conventional vehicles is likely to remain on the sale price part.

The second part of TOC is operating costs. Rising oil prices have increased the sale price of gasoline and diesel; hence, operating costs of conventional vehicles have increased compared to past years. The retail price of gasoline in the US has increased from \$1.2 per gallon in 1990 to \$2.79 in 2010 seeing an all time high of \$4.05 per gallon in July 2008. Assuming a gasoline powered car in Turkey (gasoline retail price in 09/2010 is \$2.4 /lt) that consumes 7.5 lt / 100 km, an annual mileage of 14400 kilometres costs \$2650. The same annual mileage with an EV that consumes 0.14 kWh/km would cost around \$280, assuming that retail price of electricity is 0.14 \$ / kWh. The price gap between electric and gasoline running costs are closer in countries where the retail price of gasoline is cheaper, but even in Turkey the difference in operating costs can compensate the price premium of \$15.000 in 6.5 years assuming that the battery is never changed. Surveys such as Boston Consulting Group's, which suggest that customers want to break even on the higher purchase price of electric vehicles in three years, show that EVs need to decrease costs to break ICEVs' dominance in the market [21]. In summary, despite the moderate optimistic estimation of battery cost development and the low operating costs of EV, it is assumed that battery costs pose the greatest long-term risk to commercialisation of electrically-driven vehicles.

2.4. Literature Review

Starting with the emergence of the electric vehicles at the last decade of 20th century, number of studies that analyzed impacts of EVs has increased dramatically. Since the first large scaled policy mandate (Zero Emission Vehicle (ZEV) Mandate) was introduced in state of California most of the early studies were limited to United States but nowadays, with the rising interest in EVs in world markets due to increase environmental consciousness and pressure coming from international agreements, studies' geographical scope has spread to cover all important markets like EU, India and China. In addition to this, announcements about plans to introduce EVs from the major manufacturers made more data available about the EV technology which was a black box for most of the researchers at the early stages of emergence; hence more people were able to conduct analysis on this open subject. The literature consists of many different types of work from articles to doctorate dissertations, from conference proceedings to large scale reports prepared by consultancy companies or government agencies. This part aims to give a short review of the literature by making use of all these different types of work from various markets of the world.

Most widely analyzed impact of emerging transportation technologies is GHG emissions, as this is the starting point of the rising interest in electric vehicles. "Green Power for Electric Cars Development of policy recommendations to harvest the potential of electric vehicles" report prepared by CE Delft in 2010 compares the GHG emissions of EVs in different markets by assuming different CO_2 intensities of electricity networks in 2030. This is an important work to demonstrate that performance of the EVs show significant variance from region to region as the applications of the same methodology in Germany, France and UK has provided different results [5]. Plugged-In: The End of Oil Age published by World Wide Fund for Nature (WWF) also compares the performance of EVs with conventional vehicles but bases the calculations on average assumptions which do not incorporate the marginal impacts of EVs to the electricity network [8]. European Topic Centre's critical literature review published in 2009, gives an overview of different studies conducted so far in different regions which have different GHG emission rates [2]. In this overview emissions are shown to vary from 40 g CO_2/km in countries where clean energy sources like hydro power have a big share (like Austria) to 220 g CO_2/km in regions where energy mix is coal intense like some states of US and Greece [2]. This proves the necessity of impact analysis studies that can be applied to different regions because EVs impacts show significant variance based on the region's energy mix.

A good example of a study that takes regional specifications into consideration for the impact analysis is given by Perujo and Ciuffo on the Province of Milan case [22]. In this study impacts of EVs on GHG were analyzed for a time span covering 2030, and lots of valuable local data like penetration estimation were used to understand the region specific impacts. No effort was carried to optimize charging hours, and the energy was based on three different assumptions of the Italian average mix in the future. But the article proves that EV charging might impact load profile dramatically if not managed carefully and point to the necessity of optimization of charging hours. A similar analysis conducted for Ireland covering a time span between 2010 and 2030, also shows that PHEV have a potential to decrease GHG emissions compared to conventional vehicles but benefits are strongly dependent on the energy mix assumptions [23].

Another regional study that highlights the importance of local studies by showing how much results can differ from each other is written by Huo H. et al in 2010 [24]. Authors of this paper focus on emission impacts of EV in China. Since China is a country that gets majority of its electricity from coal (upto 98% in North China) environmental performance of EVs are very close or even worse than conventional vehicles. However in locations where hydro power is abundant EVs perform better than ICEVs. This shows that it is impossible to define a country wide regulation in regions where the specifications of the electricity grid shows variance. This study is also an important base to the idea of applying bi-objective decision making tools to problems about EVs because all cost effective solutions lead to coal intensive generation. This study also uses use average mix to calculate emissions of EV, which might be misleading the results. Sensitivity work added to the study shows that EVs would become less pollutant than ICEV only when coal share drops below 87% and less pollutant than HEV when coal mix drops below 60%. This shows that for China EVs have a long way to become environmentally preferable [24]. A similar study in Alabama has shown that EVs can decrease emissions only by 1% due to extensive use of coal resources [34]. Studies conducted in Europe also show a similar trend. A study by Kristien et al. shows that for Belgium, depending on different policies about electricity sector PHEV performance will change significantly and this new technology might perform worse than relatively mature technology of hybrid vehicles if no support to renewable energy sources is given in the near future [25].

In one of the most cited papers about the literature of EV's impacts, Samaras and Meisterling have analyzed emission impacts of alternative technologies on a life-cycle basis [26]. In life cycle calculations they have considered vehicle production, battery production, gasoline consumption, electricity consumption. This approach is an important aspect of the emission impacts that are also taken into account in this thesis depending on the references in the literature. Despite suggesting a strong method to compare new technologies, in electricity consumption case, no dispatch model was used. Authors have assumed 2 extreme cases (carbon intense - 950 g/kWh and low carbon case - 200 g /kWh) and one average mix (670 g/kWh) case to calculate emissions of PHEVs. Results prove that without having an idea about the energy mix it is impossible to reach a conclusion about the performance of EVs.

Another popular work in the literature is that of Craig and Sullivan's impact analysis by using a different approach to determination of energy mix emission and which has a wide geographical scope in the U.S. electricity network [35]. Authors assume that it is economical to use spare electricity at night times to charge PHEVs since operating costs are low. Assumptions are that all vehicles will be charged between 22:00-06:00 and there will always be a vehicle available to charge when utilities want to charge and CO_2

emissions are analyzed under these assumptions. Authors introduce the idea of marginal plants but state that a simple merit-order approach would be insufficient to analyze impacts of PHEV charging. Instead of using merit order approach they define an elasticity coefficient which relates the fractional increase in CO_2 emissions to a given fractional increase in load. If all power plants had equal emission rates, then the elasticity coefficient would be unity and CO_2 emissions would be strictly proportional to load. However, if plants brought online as demand increases have higher CO_2 emission rates than base load, the coefficient will be positive, reflecting the fact that CO_2 emissions increase more than proportionally to load. Similarly, if added plants have lower than base load CO_2 emissions, the coefficient will be negative. The magnitude of the coefficient changes with load, reflecting importance of marginal generators instead of using only average or other fixed assumptions. For many regions, the coefficient is close to or greater than 1 meaning that CO2 increases with the load increase. This is a valuable piece of work that puts emphasis on the differentiation of the marginal generators with a relatively simple approach.

Not just energy mix, but different scenarios for charging also changes the performance of EVs significantly. In a study by Peterson S. et al in 2011, an experimental design for analyzing impacts of electric vehicles in proposed to compare impacts of different mix and charge scenarios [27]. This study is also important as it uses marginal generators but the model used to determine this is hidden in the study. After finding the generators it is easy to calculate emissions resulting from electricity generation and compare these to emissions from conventional vehicles. First, for a certain market scenario number of conventional vehicles in Pennsylvania and New York regions are determined and resulting emissions are calculated. Then for three charging scenarios power dispatch is done. There are four scenarios assumed for power dispatch. First model dispatches the extra load to current grid whereas the second scenarios assumed that all coal generators are equipped with carbon capturing and storage technology. In scenario 3 all power needed to charge the vehicles are supplied by natural gas plants and in scenario 4 wind turbines support natural gas plants. CO_2 benefits of EV in PJM region is not very significant because the region uses coal in night hours and the performance shows significant variance based on the scenario. In New York benefits are more significant since most generation is done by natural gas plants. The scenario based experimental design of this study is a base to the methodology proposed in this thesis. Another study that is a good reference for scenario analysis approach is the work of van Vliet O. et al [29]. In that study, the focus is on a similar set of performance measures and total energy use, total cost of ownership and net CO_2 emissions of a possible introduction of EVs in passenger car market is calculated. Electric supply used for charging electric vehicles is found by sorting generators in the region in merit order of cost and dispatching cost efficient generators until all demand is satisfied. This is a good approach as it puts emphasis to marginal generators however this study also lacks the bi-objective approach and is only cost oriented.

Thiel C. et al also showed that the performance of the alternative vehicle technologies is strongly dependent on the new energy policies that will shape the energy mix of Europe in 2020 and 2030 [30]. Silva C. et al gave a very good overview of the PHEV technology as of today and discussed how the performance can change depending on the charge scenarios [31]. Results of that study also puts emphasis on how the impacts change depending on the energy mix of the region and charging scenarios. Other studies which analyze the impacts of different alternative technologies also based their approaches on scenario analysis to model behaviour of new technologies under different settings and showed that performances of EVs might perform worse than conventional vehicles and hybrid vehicles under specific energy mix and consumption cases [32], [33]. Due to lack of large scale introduction of EVs, the number of studies that used real data was very limited. However, in a study by Williams et al, impacts of PHEVs were analyzed by collecting real world data from 12 California houses that drive NiMH Toyota Prius PHEVs [36]. 1676 driving and 437 charging events in 1 year period were analyzed. To find emissions from electricity generation three scenarios are were used without any effort to determine real time specifications of the electricity. Despite having a limited sample, this study is important as it gives chance to compare scenario approaches with real data studies.

The references given so far support the idea of this thesis that every introduction of EV fleet gives a different result; therefore, a generic methodology that utilizes the tools of operations research is essential in the pursuit of understanding the impacts of EVs. They also show that EVs might perform worse than conventional vehicles when energy mixes are carbon intensive. However, these studies have not proposed a structured operations research approach by creating a mathematical model. In the next paragraphs these attempts in the literature are given in summary.

Jansen et al analyzed impacts of PHEVs on western US grid by using a resources dispatch and emission model [37]. Based on a certain market scenarios extra PHEV load for two different charging scenarios are added on conventional electricity load. The charging scenarios considered in the study are best guess scenario which charges the vehicles when drivers comeback home and valley filling scenario which shifts charging hours to off-peak hours. For these two load profiles the authors run a resources dispatch model that is based on historical loads. Algorithm given in the study works on the merit order dispatch and accepts orders depending on their costs until all demand is satisfied. Outputs of the model are compared with real world data and they seem to be a good representation of the system. When marginal generators are known, CO_2, SO_2 and NO_x emissions of PHEV are known so performance of the EVs is given. Most important contribution of the study to the literature is to show how average mix emission rates differ from marginal generation rates by proposing a marginal dispatch model. However, this study does not make any comparison with conventional vehicles and does not take any environmental objective into account in the model. Therefore it becomes impossible to suggest new options in a case where EVs charged from marginal mix is more polluting than conventional vehicles. Another study conducted by Kristoffersen et al. also proposes an optimization model based on electricity market operations to find the most suitable hours for charging based on only cost minimization [38]. In the previous papers analyzed it was clear that this approach might end up in cases where the system is forced to charge in cheap but very polluting hours, especially with the high share of coal generators.

An important work on EV impact analysis is the work of Sioshansi et al where authors analyzed the impacts of PHEVs in Ohio power system [39]. Authors analyzed impacts of 5% PHEV integration on Ohio power system with two charge scenarios: controlled and uncontrolled. In controlled scenario system operator has near-total control over charging decisions, whereas in uncontrolled scenario PHEV users charge their vehicles whenever they want. For uncontrolled scenario a classic no-drive hours curve is used. To determine generators of electricity, a unit commitment model is used. To enable a linear model a step function was used to reflect variable costs. Model is not based on bids, it is based on operation costs therefore it has more technical depth than electricity market models. An important result from the paper is that in controlled charge scenario, where operator charges the vehicles in cheapest hours, more coal generators are in operation thus emission results are worse. In uncontrolled scenario, marginal electricity is generated in natural gas plants which are more expensive to operate but cleaner. This result is proof of the necessity of bi-objective models in EV impact analysis. Having higher emissions for both SO_2 and NO_X emissions compared to ICEVs highlights the need of a full assessment before any decision about EVs are taken.

One of the most recent and influential works on the EV impact analysis is the work of McCarthy and Yang [40]. This paper estimates CO_2 emissions from three different alternative technologies (BEV, PHEV and Fuel Cell vehicles) by running an economic dispatch algorithm to determine where marginal electricity that charge these alternative pathways is supplied. Results are compared with HEV and ICEV in California case. Also sensitivity analysis are done to determine best hours of charging. For analyzing each technology it is assumed that 1% of vehicle miles travelled in California comes from one of these technologies alone. Based on consumption data, this creates an extra demand on electricity network. To determine where this demand will be supplied from, authors run a dispatch model called EDGE-CA. Algorithm assigns nuclear, hydro and import power supplies to base load based on historical data so base load gets fixed similar to historical data. Than dispatchable plants (most of thermal generators and hydro sources) are listed in increasing order of cost of electricity and cheaper plants are put on operation until new demand is satisfied. By using this method, a set of marginal generators are found and emissions are calculated. Two charging scenarios are used; off-peak (vehicle idle hours) and load balance (3 in the morning). As a result it is found that marginal electricity mix (570-670 g CO_2/kWh) is more carbon intense than both gasoline (350 g CO_2/kWh) and average mix (250 g CO_2/kWh). However due to being more energy efficient EVs still perform better than ICEVs. Emission results for different times of the year are given so it is possible to see how the performance changes in time and shape charging incentives based on this data. Despite being a strong study in the field this lacks optimization of charge hours, has a very high view about technical constraints and does not incorporate any environmental objectives.

In summary, despite the fact that an extensive number of studies about EV impacts exist in the literature almost every study has conducted a scenario analysis, in which impacts of electric vehicles are analyzed by general assumptions about the average energy mix, without using structured or clearly defined mathematical models or optimization efforts that incorporates market or network operation constraints into account. The emissions are calculated by using average emissions or by predetermined fixed scenarios in the future, which can lead to results far from the actual case in certain cases. The business as usual model in the electricity market aims to satisfy the total demand with minimum cost. If the electricity market will handle the EVs together with the conventional demand and continue with business as usual model, the EVs' net impacts will directly depend on the marginal electricity generators that are put into operation when the EVs are introduced. There are some studies which use this approach and they also proved that the difference is significant. The limited number of studies which use mathematical modelling and optimization methods has always used a single objective function which minimizes total costs of the system and proposes policies that minimize costs. In general, cheaper generators in the electricity market such as coal generators generate more emissions than costly generators like hydro power and natural gas plants. Therefore, single objective models would lead to undesirable results regarding emissions in regions where cheap electricity is generated from carbon intensive energy sources. As stated above, the cost and the environmental performance of the electricity market are two conflicting objectives, which can be handled by the methods in bi-objective decision making. Using bi-objective decision tools may lead to generation of all efficient solutions for a region which can enable policy makers to choose among different options depending on their preferences of being more cost or emissions oriented. Another major gap in the studies using optimization methods was the use of scenarios for representing charging demand. Charging patterns are given as inputs to the model and results from different scenarios are compared without finding optimal charging hours from different regions and periods of the year. This approach limits the ability of the model to optimize performance of the EVs. Therefore, charging hours should be defined as decision variables to determine the most appropriate charging hours. The last gap addressed in this work is the lack of research about Turkey. There are no studies in the literature that analyze the impacts of a possible introduction of the EVs into the Turkish electricity market. The methodology in this thesis is an attempt to fill these gaps in the literature.

Chapter 3

A METHODOLOGY TO ANALYZE THE IMPACTS OF ELECTRIC VEHICLE CHARGING

3.1 Problem Definition

The common result reached in the studies that analyze the environmental and economic impacts of the EVs is that the impacts depend on magnitude, timing and location of battery charging. This means that the EV's impacts are going to show different behaviours in different markets and regions. Since the EV technology is beginning to be commercialized in the mass market in the developed countries, the decision makers need to get a clear understanding of its net impacts in their own region and make appropriate policy recommendations to get the best benefits from the technology. Therefore, a significant number of studies have proposed methods to analyze the impacts of introduction of EVs and this thesis is believed to make a contribution to the research in the area by filling the gaps in the literature.

As discussed in Chapter 2, there are three major methodological gaps that are targeted to be filled by this study. First gap is related to determining where the electricity that is used to charge the EVs is generated. In interconnected grids, it is a cumbersome effort to try to assign certain electrons to predetermined end users; hence, researchers have focused on higher levels of analysis to determine the energy mix used to charge the EVs. Most of the studies have based their calculations either on predetermined energy mix scenarios or average electricity mix of regions. There are problems with these two approaches.

In the first years of the introduction of electric vehicles, the electricity generation sector is not expected to react fast enough to add generation capacity equal to the demand coming from the EVs which are charged from the grid [20]. In addition to the slowness of the reaction, the uncertainties related to customers' charging behaviours are going to make it very difficult to determine timing and magnitude of new capacity decisions for EV charging. Therefore, in the short term, it is not possible to assign certain types of generators to the EV charging and conduct environmental and economic analysis depending on predetermined technologies. Studies using this approach are going to be misleading the results about the impacts of the EVs. Another method that is being used widely is assuming that the EV charging will be equivalent to average energy mix which is used by the conventional electricity demand. The emissions released to the atmosphere during the supply of the conventional demand, will keep on being emitted whilst the EVs are charged. But when the EVs are added to the conventional demand, new generators will start running to supply the increased demand and the amount of total generation will change alongside the shares of primary energy sources. No matter if the electricity which runs through the battery chargers of the EVs are coming from these new generators or not, the net emissions increase will be equal to the amount of GHGs emitted by the new generators. Since EVs are the only root cause of this increase, the energy mix related to the charging of them cannot be determined by the average mix. Calculations based on the average mix can be different from the actual case if the new generators running have a different mix then the average mix. Before the electricity market takes the EV charging demand into account during the capacity expansion decisions in the long term, the EV charging must be treated as a marginal demand that will be added to the conventional electricity demand. The models used in the methodology proposed in this study are created to determine the marginal electricity mix under different market penetration and charging scenarios and base impact calculations on the marginal effects of EV charging.

Another important gap in the literature is about determining the effects of charging hours. All the studies in the literature which have taken charging hours' effects into account have conducted the calculations based on predetermined scenarios and compared the environmental and economic results of these scenarios. Despite the fact that the number of different scenarios analyzed are sufficient to provide insight to policy makers, the scenario analysis approach limits the analysis to a certain number of cases and inhibits the studies from determining which charging patterns would be the most beneficial for the region to charge the EVs. By adding the charging pattern optimization dimension to the system, it becomes possible to see if there are better charging patterns than predetermined scenarios. The multiple-stage methodology proposed in this study enable defining charging hours as decision variables to find the best patterns alongside conducting scenario analysis.

The third gap targeted to be filled with the proposed methodology is the lack of application of bi-objective decision tools to shape policy recommendations about the charging hours and marginal generators of the EVs. In order to get a better understanding about why this is important, the way electricity markets operate will be explained briefly. As expected, the electricity supply chains, aim to supply the electricity demand with the minimum cost possible without violating technical constraints of the generation, transmission and distribution systems. The generators which are going to be operating to supply the electricity demand are determined by a merit-order decision process in which the bids from generators are accepted starting from the lowest possible cost until the demand is met. Generators operating at lower costs are generally thermal generators such as coal and lignite power plants which use the chemical energy contained in fossil fuels to generate electricity. These generators are emitting higher levels of GHGs than those generators which are more costly to operate such as natural gas and hydroelectric power plants. Therefore, the single objective methods which recommend EVs to be charged at the lowest cost hours are forcing EVs to emit more GHGs at the same time. This conflicting relation between the costs and the emissions provide a perfect application area for bi-objective optimization. To the best of the author's knowledge, none of the studies have used a bi-objective model to analyze impacts of the EVs. By optimizing the cost and emissions objectives together, the proposed methodology enables decision makers to see all possible alternatives in their electricity markets and base their supporting policies on these alternative results rather than being only cost oriented. Increased number of alternatives will make it possible to choose among more environmental or more economic policies for the charging hours and electricity markets.

Since the policies regarding the EVs are dependent on the net impacts on the environment and the economy, they should be understood well before the introduction takes place. The systems affected by the introduction of the EVs are too large to be analyzed by a real experiment; therefore, mathematical modelling and solution methods of operations research are the tools that have been used in the methodology proposed in this thesis. Briefly, the methodology presented in this chapter consists of four steps. For a number of market introduction scenarios, on which no agreement is present in the literature, the number of battery electric vehicles (BEV) and plug-in hybrid electric vehicles (PHEV) that are going to be introduced are determined. In the first step, for the same number of gasoline and diesel conventional vehicles, annual GHG emissions, primary energy consumption and energy costs are calculated. For further steps, a bi-objective MILP model to represent the day-ahead electricity market is created which determines the marginal generators. The next step, assumes that the EVs are charged from the electricity grid depending on the business as usual scenario, in which the lowest cost generators are added to the conventional supply, and uses the single objective version of the MILP model to determine the marginal generators. Charging patterns are assumed as fixed scenarios in this step. Environmental and economic impacts of the EVs are calculated depending on the results of the model. In the third step, the model is run as a bi-objective model which determines a number of sets of marginal generators that can be used to supply the additional electricity demand coming from the EVs. The last step defines the charging hours as decision variables rather than fixed scenarios and determines the most economic and environmental charging hours and marginal generators to optimize the benefits of the EVs. Steps 2, 3 and 4 are conducted for different days in a year to represent the average behaviour in a year the annual results are compared with the emissions, cost and energy consumption figures of the conventional vehicles. Remaining subsections of this chapter are organized as follows. First the experimental design is explained in detail. This is followed by the mathematical models created to represent the electricity day ahead market. The last subsection gives brief information about the solution methods used to solve the bi-objective MILP model.

3.2 Step 1: Conventional Vehicles' Impacts

The EV technology is the substitute of the internal combustion engine vehicles which are powered by gasoline or diesel fuels. If the EVs are to be successful in the mass market, they need to perform better than ICEVs in the means of GHG emissions, primary energy consumption and energy costs. Therefore, the performance of conventional vehicles must be understood well to set a reference point to the EVs. In the first step of the impact analysis of the EVs, conventional vehicles' annual performance will be calculated based on simplifying assumptions about market penetration scenarios, vehicle specifications and customer behaviour.

3.2.1. Market Penetration Scenarios

The first assumption that is needed to be set is the market penetration levels of the BEVs and PHEVs but the prediction of market scenarios includes great uncertainties and depends on numerous factors that cannot be foreseen easily. Despite the fact that the automotive industry professionals and environmentalist agree that the electric vehicles will be on the roads before 2020, the magnitude and speed of penetration is a wide topic of debate. Every country will have its own acceptance rate based on the supports of the governments and customer behaviours; therefore, there is no agreement on an internationally accepted prediction about the penetration levels. The way followed to overcome the uncertainties that was used frequently in the literature is to assume different scenarios of penetration levels and conduct analysis for all of them to analyze behaviour of the system under varying parameters.

In the literature, scenarios span over a large scope from very pessimistic to very optimistic market projections. According to International Energy Agency's Energy Technology Perspectives 2008 report, which is an optimistic estimation that includes 3 different scenarios, the penetration of EVs range from 5 to 50% by 2030 [41]. However a revision was issued by IEA after the global economic crisis which is a more pessimistic estimation that assumes average global sale rates to reach 2.5% for BEV and 6.1% for PHEVs with a maximum share of 10% in lead markets by 2020 [2]. United Kingdom Department of Business, Enterprise and Regulatory Reform has made an analysis of the market to shape UK's policies forward and ended in 3 scenarios. This study assumes that by 2020 2.5%, 4.9% and 10% of all cars on the road will be EV for mid-range, high-range and extreme-range scenarios respectively [42]. Another governmental attempt to predict and target penetration rates for EVs was done by Germany, which announced a target of 2.1% market share by 2020 and 10.4% market share by 2030 [43]. Another study conducted in Germany expects a market share of 1% for BEVs 2% for PHEVs by 2015 and expects an increase to 2% and 5% respectively for EVs and PHEVs by 2020 [2]. Consulting companies also had some work to predict the market penetration scenarios. The Boston Consultancy Group predicts vehicles with alternative propulsion technologies to reach 12% to 45% market share by 2020 [20]. In a study by McKinsey, two scenarios are used to analyze the impacts. In the lower penetration scenario BEVs and PHEVs reach respective shares of 1% and 5% by 2020, whereas in the medium scenario these increase to 2% and 6% [44]. Some articles that have analyzed impacts of EVs also used scenarios to reach a solution. Brady and O'Mahony have used 3 scenarios named low, medium and high scenarios and estimated that PHEVs would reach 10% in low case, 15% in medium case and 20% in high case [45]. Hadley and Tsvetkova, estimated that PHEVs will achieve a constant 25% market share by the year 2020 [46]. There are also other approaches different than just assuming numbers, like Perujo and Ciuffo who based their penetration estimation on LPG vehicle sales in Italy by arguing that EV technology and LPG vehicles attract the interest of same customer groups, thus they will follow similar trends [22].

As a result of the literature review on market scenarios, it is decided to assume three different scenarios and compare their results to analyze varying behaviour of the system in this unpredictable environment. The scenarios are named as low, medium and high market scenarios. In the past, new technologies like LPG powered vehicles have penetrated into the market between 10 to 20 years after introduction; therefore, it assumed that at least 10 years are needed for EV technology to have significant market share but the speed of penetration is highly dependent on the policy incentives and governmental regulations [2]. According to this information, the year for EVs to have a share in market that will be enough to conduct a meaningful analysis on the impacts in assumed to be the end of this decade and all the market penetration scenarios used in this study are set to cover years from 2012 to 2020.

The low scenario is the most likely scenario that is expected to be reached by 2020; because, the customer acceptance and the production levels are expected to be a barrier on fast market penetration of the EVs in the coming decade [21]. The low scenario assumes that BEVs reach 2% and PHEVs reach 5% share in passenger car market in 10 years. In the medium scenario, the shares increase to 5% for BEVs and 11% for PHEVs. This scenario is selected to see the effects of a wider acceptance level of the EV technology. The last scenario, which is named as the high scenario, is the most optimistic scenario and it is conducted to see the effects of an unexpected level of market penetration taking place in a relatively short period of time for the electricity market to react and increase capacity. In the high scenario, the BEVs take 10% and PHEVs take 25% share in passenger car market by 2020, which makes this scenario very unlikely to happen. The year by year market shares of the scenarios are given in table 3.1.

Table 3.1: Assumed Market Shares of the EVs in Passenger Car Market from 2011 to 2020

		Year									
Scenario	**Car Type**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**	**2019**	**2020**
Low	**BEV**	0.10%	0.20%	0.30%	0.40%	0.50%	0.75%	1.00%	1.30%	1.70%	2.00%
	PHEV	0.10%	0.15%	0.25%	0.50%	0.75%	1.50%	2.50%	3.50%	4.50%	5.00%
Medium	**BEV**	0.25%	0.45%	0.50%	0.75%	1.25%	1.75%	2.50%	3.00%	4.00%	5.00%
	PHEV	0.10%	0.30%	0.50%	1.00%	1.50%	3.00%	5.00%	7.00%	9.00%	11.00%
High	**BEV**	0.25%	0.75%	1.25%	3.00%	4.00%	5.00%	6.00%	7.50%	9.00%	10.00%
	PHEV	0.10%	0.60%	1.00%	2.00%	3.00%	6.00%	10.00%	14.00%	18.00%	25.00%

For every market penetration scenario, the number of conventional vehicles that are expected to be replaced by the EVs can be found by applying these sale shares to regional passenger car market predictions until 2020. These numbers will be equal to number of conventional vehicles replaced. Gasoline and diesel vehicles have different efficiency and emission rates; therefore, determining the numbers of gasoline and diesel vehicles that are expected to be replaced by the EVs is important. In EU-27 passenger car markets, diesel vehicle sales have passed gasoline vehicle sales in 2005 [47] and still remain over 50% in 2011 [48]. In countries like Belgium and Spain, diesel shares climbed up to 80% in 2008 [48]. Looking at the trend in sales it is concluded that the sale shares trends will continue to climb slightly in the next decade with wider acceptance of diesel technology. Therefore, it is assumed that 60% of the EVs are going to replace diesel and 40% of them are going to replace gasoline vehicles.

3.2.2. Performance Measures

As discussed in chapter 2, the major problems related to the ICEVs are energy inefficiency, high levels of GHG emissions and increasing energy costs. In order to compare the performance of the EVs in these fields, annual energy consumption, GHG emissions and cost of operation of conventional vehicles must be calculated.

3.2.2.1. Annual Primary Energy Consumption

Annual primary energy consumption (APEC) of a conventional vehicle is calculated using the following formula:

$$APEC = fc_{vehicle} \times e_{fuel} \times d \times {}^{1}/_{\theta} \qquad (3.1.)$$

In the formula above, $fc_{vehicle}$ is the fuel consumption of the vehicle which depends on the vehicle type (gasoline or diesel), given in litre/km, e_{fuel} is the energy content of the fuel used by the car, given in kWh/litre, d is annual kilometres driven under urban conditions and θ is the energy efficiency of well-to-tank operations carried out to fill the tank of a car.

In order to calculate the energy consumption of the conventional vehicles, first data needed is the fuel consumption of vehicles. The first customers of the EVs are expected to be people living in big cities who use their cars for commuting. Commuting is defined as the action of transportation between one's place of residence and place of work or study. Since this activity takes place under urban conditions, the comparison of the EVs will be made with urban consumption values of the conventional vehicles. However, as the vehicles sold in every market and average fuel consumption rate, $fc_{vehicle}$, is going to differ from country to country, it is not possible to give a universal fuel consumption figure here (Data used in Turkish Application is given and referenced in Section 4.1.). Second data which is a universal figure is the energy density of commercially sold gasoline and diesel fuels. Every litre of gasoline contains 34.2 MJ of energy and every litre of diesel fuel contains 38.6 MJ of energy [14]. Using the conversion factor of 0.277 from MJ to kWh, e_{fuel} is equal to 9.5 kWh / litre for gasoline and 10.72 kWh / litre for diesel.

The third necessary data is the annual average kilometres driven by the drivers. Despite the fact that the driving habits change from region to region, surveys from different regions enables to make assumptions about the distances travelled. According to the U.S. Environmental Protection Agency passenger cars in the US travel an average of 12,000 miles per year [50]. This average mileage is approximately equal to 52 kilometres per day. For studies conducted in the U.S., d can be assumed as 19,000 km/year. In the European Union driving distances are shorter than the U.S. According to the Panorama of Transport report published by the European Commission, average distances travelled on road ranged between 16 km and 43 km and the average daily passenger vehicle kilometres travelled is 27 km for EU-25 countries [17]. According to Toyota, average weekday kilometre driven by passenger cars is approximately 30 kilometres [51]. Based on these assumptions, d can set equal to 10,000-11,000 km/year for countries where driving habits are similar to Europe and Japan.

The data introduced above is only sufficient to calculate the final energy consumption. In order to find the primary energy consumption, well-to-tank energy conversion efficiency must be known. Well-to-tank steps of the supply chain of conventional road transportation vehicle, extraction of crude oil, distillation processes and transportation of fuels to end users. In the studies explored, energy efficiency of well-to-tank processes is assumed to be 83% [3],[5],[8],[14]. This means that for every unit of final energy consumed in the ICE, 0.17 units of primary energy is consumed in well-to-tank processes. For this reason, final energy consumption in the conventional cars is divided by the efficiency coefficient θ, which is set equal to 0.83 throughout the study, to find the primary energy consumption of the conventional vehicles.

3.2.2.2. Annual GHG Emissions

Annual GHG emission (AGHG) of a conventional is calculated using the following formula:

$$AGHG = fc_{vehicle} \times cc_{fuel} \times d \times \gamma \qquad (3.2.)$$

In the formula (3.2.) $fc_{vehicle}$ and d values have the same use in formula (3.1.). In the formula above, cc_{fuel} is the amount of GHGs emitted when a litre of fuel is combusted, given in g/litre and γ is the GHG emission coefficient of well-to-tank processes. Since the amount of carbon in a litre of gasoline and diesel is known, the amount of CO_2 emitted into the atmosphere can be calculated easily. According to the fuel emissions data used by the U.S. Environmental Protection Agency, every litre of gasoline contains 639.5 grams of carbon and every litre of diesel fuel contains 733.8 grams of carbon [48]. Since there is one atom of carbon in every CO_2 molecule, the amount of CO_2 emitted during the combustion of liquid fuels can be found by multiplying the amount of carbon to the ratio of molecular weight of CO_2 and carbon, which is 44/12. Using this ratio, one litre of gasoline is found to emit approximately 2,350 grams of CO_2 and one litre of diesel is found to emit 2,690 grams of CO_2. In addition to the vehicle emissions, well-to-tank emissions must be taken into account to make a GHG comparison with the EVs. The reason is the GHGs emitted during the extraction, distillation and transportation processes of the energy supply chain. Well-to-tank emissions are calculated in a similar way to primary energy consumption. According to the European Association for Battery Electric Vehicles, in order to find well-to-wheels emissions, tank-to-wheels emissions must be increased by 17% [47]. Therefore γ is set equal to 1.17 for the rest of the calculations in the study.

3.2.2.3. Annual Energy Costs

Annual energy costs (AOC) of a conventional is calculated using the following formula:

$$AOC = fc_{vehicle} \times c_{fuel} \times d \tag{3.3.}$$

In (3.3.), $fc_{vehicle}$ and d are defined as the same as they were defined for formulas (3.1.) and (3.2.). The only necessary data needed to calculate annual energy costs is the cost of the fuel, which is defined as c_{fuel} and given in \$/litre. c_{fuel} value changes for different stakeholders in the problem. If the energy costs are going to be calculated for the owners of the vehicles, than c_{fuel} is equal to the retail pump price of the fuel. Otherwise, to calculate the energy costs for the sector c_{fuel} is set equal to the refinery cost of the fuel itself, excluding the taxes, transportation costs and the profits of the stakeholders in the supply chain. Since these costs change significantly from region to region (up to 67% in Turkey according to PETDER's report on sector performance in 2010 [49], there is no general assumption for energy cost of fuels. It should be found before the application of the methodology.

At the end of the first step, the decision makers know the approximate primary energy consumption, GHG emissions and energy costs of conventional vehicles by using the formulas described above. After finding the performance of the EVs for the same measures, competing technologies of ICEVs and EVs can be compared clearly.

3.3 Step 2: EVs' Impacts with Business as Usual Generation Decisions

The purpose of the second step in the proposed methodology is to calculate the annual primary energy consumption, GHG emissions and energy costs of the EVs under business as usual generation decisions. In this subsection, model and data that are used to determine the impacts are introduced.

The energy consumption, emissions and cost performance of the vehicles depend on which primary energy source supplies the energy that runs the vehicles. For ICEVs, the energy supply chains are relatively easier to analyze than that of the EVs because the primary energy source that runs the internal combustion engine, does not show significant variance as the region, time and magnitude of the demand changes. On the other hand, the primary energy source that generates the electricity to charge the EVs differs from region to region, time to time and shows variance as the magnitude of charging changes, which makes it difficult to calculate the impacts of the EVs. Therefore, it is necessary to find a methodology that can determine the sources of energy that generate electricity to charge the EVs and calculate the net impacts of the technology in different regions.

As stated in the second section, one of the main gaps in the literature is the calculation of impacts by using predetermined energy mix scenarios or average mixes. The methodology proposed in this step, aims to fill this gap by focusing on the marginal electricity generation. After the introduction of the EVs, the conventional electricity load profile in cities will change because of the charging activity. The conventional load profile on 19/07/2012 at Adapazarı region which also covers demand of Istanbul is given in blue bars in figure 3.1. [52]. To the top of the conventional demand, an estimated charge demand for 200,000 PHEVs being charged at peak hours are added and marked in red.

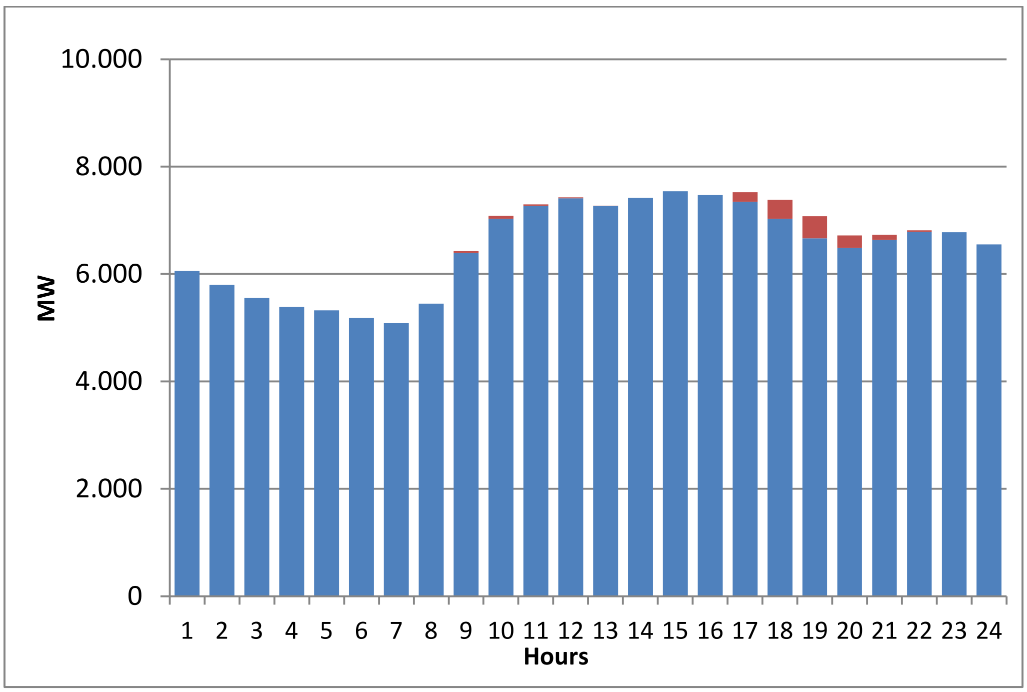

Figure 3.1.: Marginal load representation on 19/07/2012 for Adapazarı Region

This visualizes the amount of extra demand that needs to be supplied by the electricity network when EVs need to be charged. It is for sure that either existing generators will increase production or new generators, named as the marginal generators will be put in operation to satisfy the increasing demand. The idea behind the methodology that focuses on marginal electricity generation is that, no matter if the electricity generated in these marginal generators are used to charge the batteries or not, primary energy consumption, GHG emissions and energy costs of the system will increase as new generators are put in operation. Since the EVs are the only root cause of the marginal increase, the net impacts of the EVs are equal to the amount of increase in the primary energy consumption, emissions and costs due to new generation. Therefore, it is necessary to find a method to determine the set of marginal generators that are put in operation when the EVs are added to the conventional electricity demand.

The aim of the second step of the experiment is to find how the equal number of EVs to ICEVs performs for the same mileage in a region under business as usual electricity market operations. In order to accomplish this, a number of EVs found by market penetration scenarios are assumed to be charged from the electricity grid as a new demand and the effects on the electricity market are found. The following paragraphs give detailed information about the assumptions in the study. Some readers may find the assumptions too simplifying or unrealistic but the lack of real-world data and abundance of uncertainties force the study to be carried under many assumptions for this new technology.

3.3.1. EV Fleet and Models

In order to compare the performance of EVs to an ICEV fleet, technical data about the vehicles to be used must be known clearly. Since there are not any widely available EVs in the market, the vehicles to be used for technical data cannot be determined with a similar method to ICEVs by creating a representative fleet. The vehicles to be used have been chosen among vehicles of comparable size and performance, which have been announced to be produced in short term by major automobile manufacturers. Another criterion for selection of vehicles was the availability and reliability of technical data, which is very important for the reliability of the results. The details for some of the most recent EVs announced by manufacturers were given in Chapter 2.

For the BEV to be used throughout the study, Renault's Fluence Z.E. model has been chosen which has started to be produced in Renault's Bursa plant in 2011. The PHEV to be used throughout the study is Toyota's Prius PHEV model. Detailed technical data about these two vehicles about their energy consumption data are given briefly in Table 3.2.

Table 3.2.: Summary of BEV and PHEV Data Used in the Study

Manufacturer	Renault	Toyota
Model	Fluence Z.E.	Prius
Characteristic	BEV	PHEV
Production	Started in 2011	2012
Electric Motor Power	70 kW	60 kW
Battery capacity	22 kWh	5.2 kWh
All-electric range	160 km	23.4 km
Fuel consumption	-	3.27 lt/100 km
Electricity consumption (Tank to Wheels)	0.18 kWh/km	0.152 kWh/km

3.3.2. Daily Energy Need and Charging Data

Both of the models are assumed to be driven for 40 kilometres every day for commuting, similar to ICEVs in Step 1. The vehicles are than assumed to be plugged in to a regular EV charger which is powered by a conventional plug. Since the duration of charging changes from charger to charger, a charger model is assumed to be used for charging the vehicles to fill the battery that has been depleted during the 40 kilometres. Coulomb Technology holds a significant share of EV charging service providing market and has signed agreements with many countries in Europe, including Turkey [53]. The company's CT1500 charging stations provide 3.7 kW (230V at 16 A) charging and are applicable to standard plugs to provide regular charging service to EVs [54]. The efficiency of the CT 1500 charger is assumed to be 85% throughout the study, which is found to match the charger efficiency assumptions in similar studies [55].

During the constant current phase the charger transfers the maximum capacity allowed by the power coming from the plug, but as the battery voltage saturates, the transfer slows down [18]. To show this effect, the amount of power needed by the charger is assumed to change from hour to hour, decreasing in time. For Renault Fluence which depletes 7.2 kWh of its battery capacity by travelling 40 kilometres a day, the total amount of energy demand increases to 8.7 kWh when charger efficiency of 85% is taken into account. As explained in the charger specifications used in the study, charger is able to load 3.7 kWh in one hour. This value decreases as the battery saturates and full charge is reached after 4 hours. This is aligned with the technical specifications announced by the manufacturer [56]. With the same reason, 3.56 kWh demand of Toyota Prius for 23 kilometres, which is the limit on full EV drive, increases to 4.2 kWh. With the assumed charger capacity of 3.7 kW, this amount is charged in approximately 100 minutes to full charge. This information is also aligned with the data taken from the manufacturer [57]. Figure 3.2. gives the amount of energy needed during the charging process by two vehicles and these values are used throughout the study to create the marginal demand estimations.

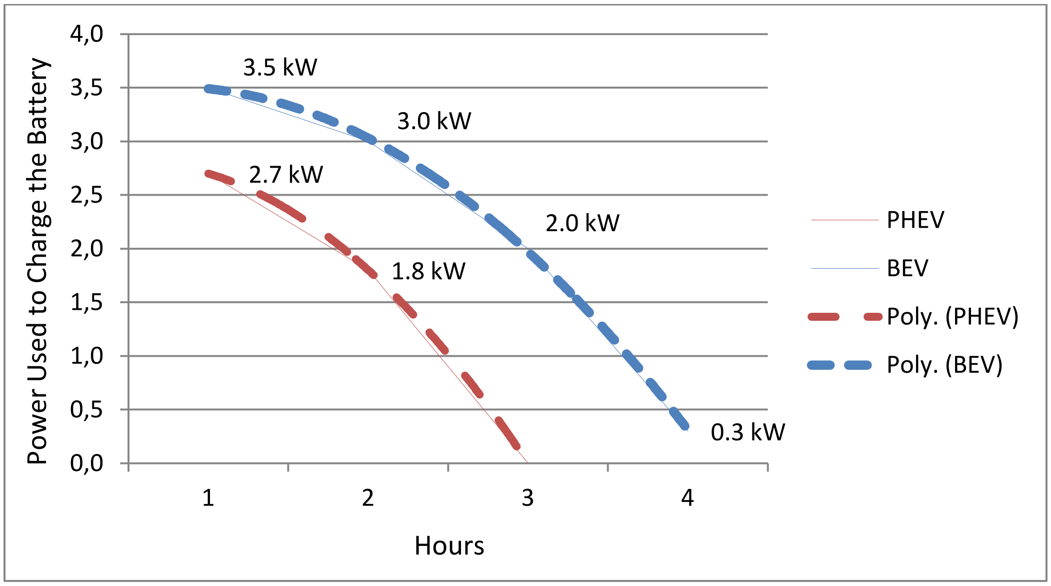

Figure 3.2.: Charge profiles of BEV and PHEV Batteries

3.3.3. Charging Scenarios

The energy demand of ICEVs considered in this study is supplied by liquid hydrocarbons. The amount of primary energy used to produce the fuel and the amount of GHG particles emitted per litre are independent of the time of refilling. On the other hand, the energy mix of electricity generation changes from hour to hour, thus primary energy consumption and environmental performance of the energy source alters. In Figure 3.3., the energy mix of the Turkish electricity market from a representative day reported by TEİAŞ is shown. Early morning hours have a higher share of fossil fuels whereas peak hours have a more clean energy mix as the share of hydro generators increase. Therefore, the hour of battery charging has an impact on the performance measures of the EVs and it is very important for the decision makers to determine which hours are the most suitable for costs and environmental performance. Since there is lack of real world data about customer charging behaviour, before going into optimization efforts, assuming charge scenarios has been determined as the best way of modelling the impacts of the EVs.

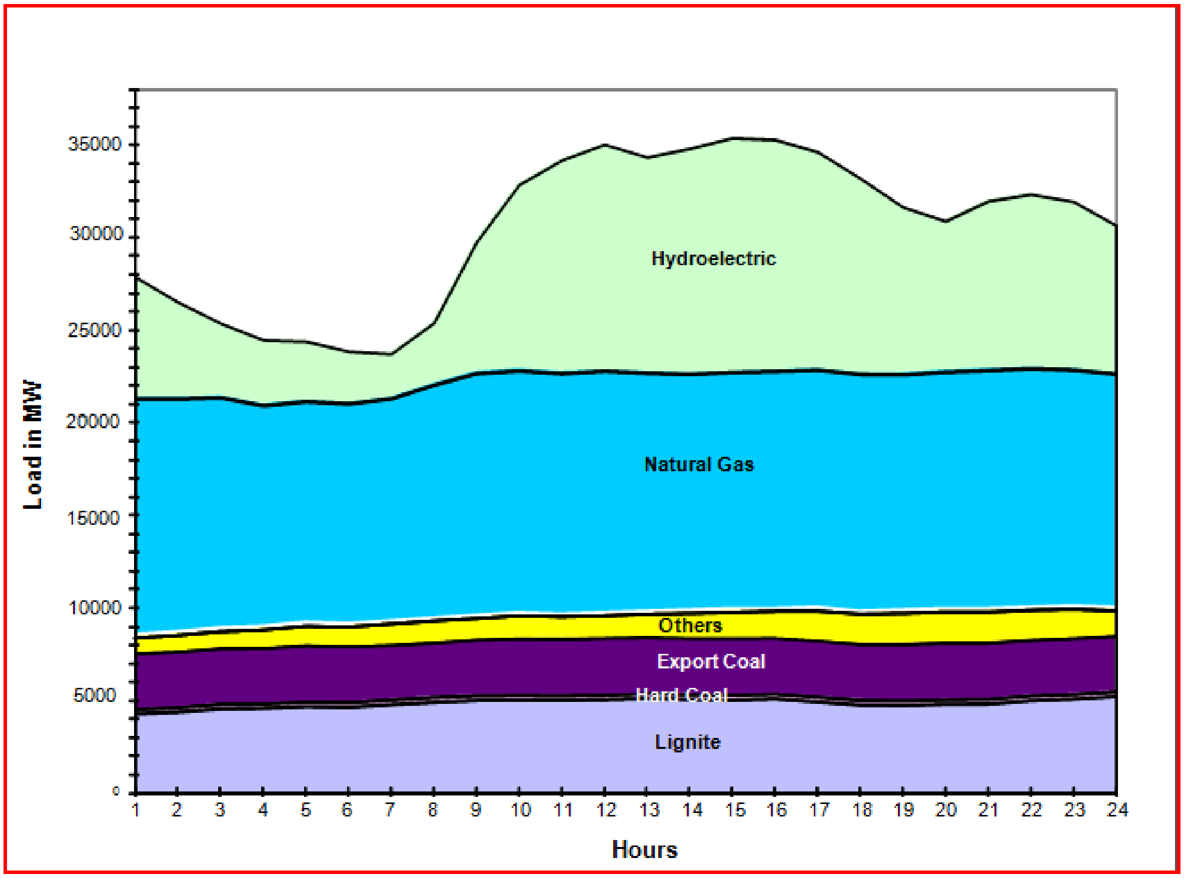

Figure 3.3.: Primary Energy Sources of Generation on 23 July 2011 in Turkey

In the second step, the EV fleet is assumed to be charged according to predetermined charging scenarios. Charging scenarios show what percentage of vehicles start charging in every hour of the day. In the literature related to the impacts of the EVs, some charging scenarios have gained wider acceptance than others. First and the most accepted scenario is the uncontrolled charging scenario in which authorities has no influence on customers' charging decision. In such a case, customers are expected to plug-in their vehicles when it is most convenient for them, especially at the end of each trip. Since the EV projects in the short term target commuters, the biggest percentage of charging will occur after customers turn back their homes after work, during peak hours of electricity use [39],[58]. This scenario is worth analyzing because it is the most likely scenario to occur unless authorities install necessary promoting regulations to shift charging to early morning hours where the conventional electricity demand is lower. The percentage of vehicles plugged in for charging at each hour according to uncontrolled scenario is given in Figure 3.4.

The second charging scenario, which is named as delayed charging, is also considered as an option in the literature [34],[35]. In this scenario, it is assumed that the customers are encouraged to plug-in by themselves without any advanced technology like smart applications in hours where conventional load is less than peak hours in the evening. The vehicles are distributed evenly to hours between 20:00 and 01.00. This scenario gives the analyzers a chance to compare the results of a charge hour regulation policy with the expected case of uncontrolled charging. The percentage of vehicles charged in the delayed charging scenario is given in Figure 3.4.

The overall effect of EV charging can be better understood when the power demand of battery chargers and the charging scenarios are combined. In Figure 3.5. and 3.6., the electricity demand coming from the EVs under two different charging scenarios are given for the low market penetration case. As expected, in the uncontrolled charging case, the charging demand peaks during evening hours where the conventional demand is also very high whereas the delayed charging case better fills the valley of low demand hours by shifting the charging demand to late night hours. The medium and high penetration scenarios show the same distribution with higher values. Comparing results of these two different situations is expected to give valued insights to decision makers to support charging hour policies or not.

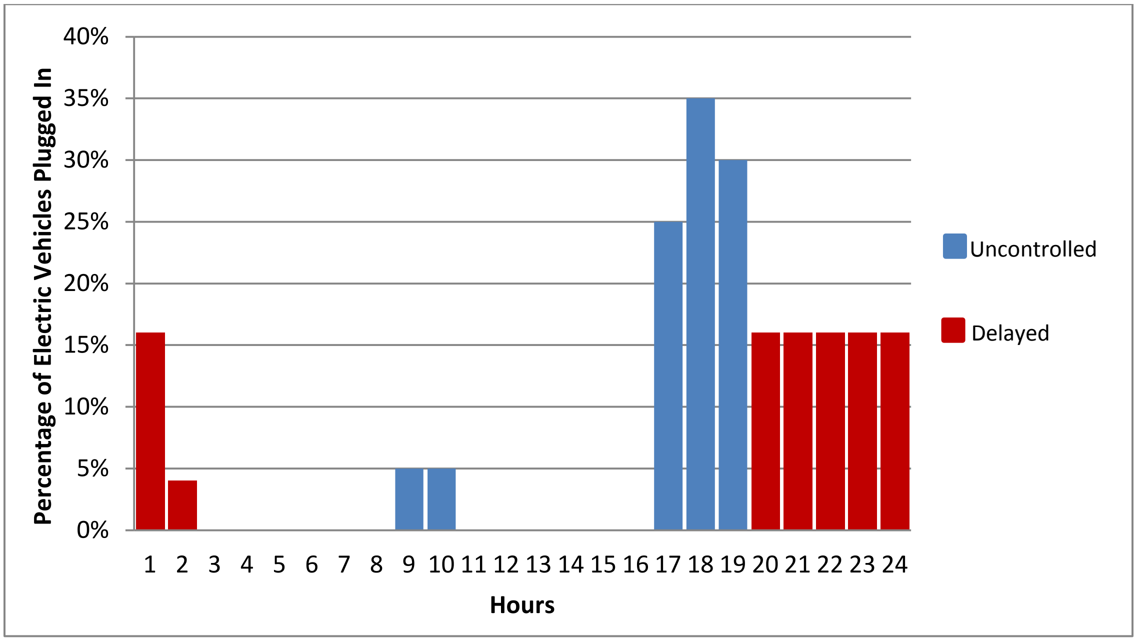

Figure 3.4: Percentage of Electric Vehicles Plugged in According to Two Scenarios

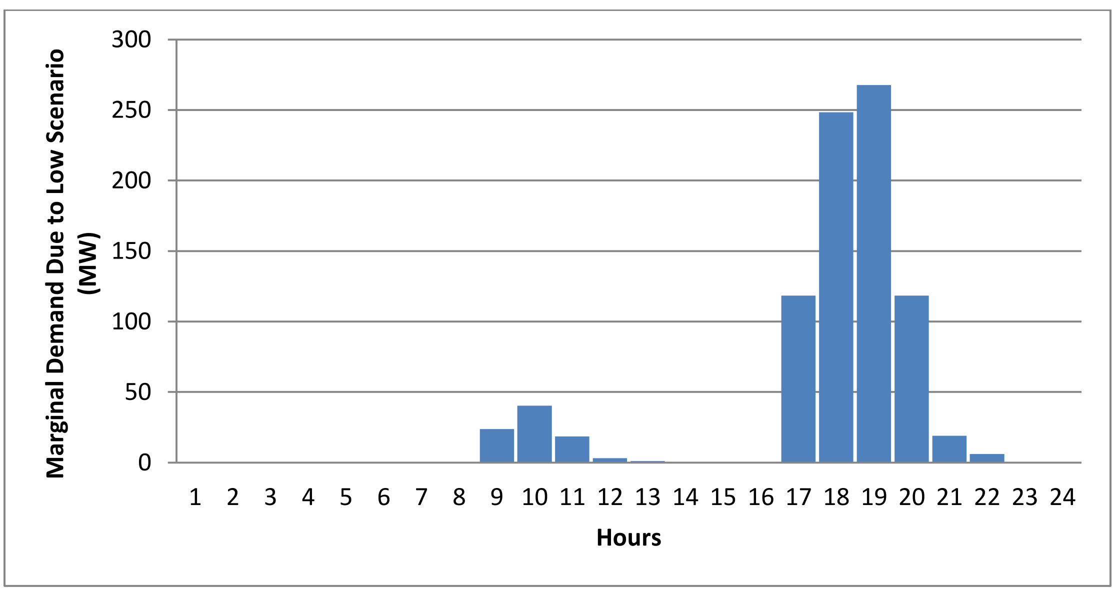

Figure 3.5.: Marginal Load Profile Due to Uncontrolled Charging

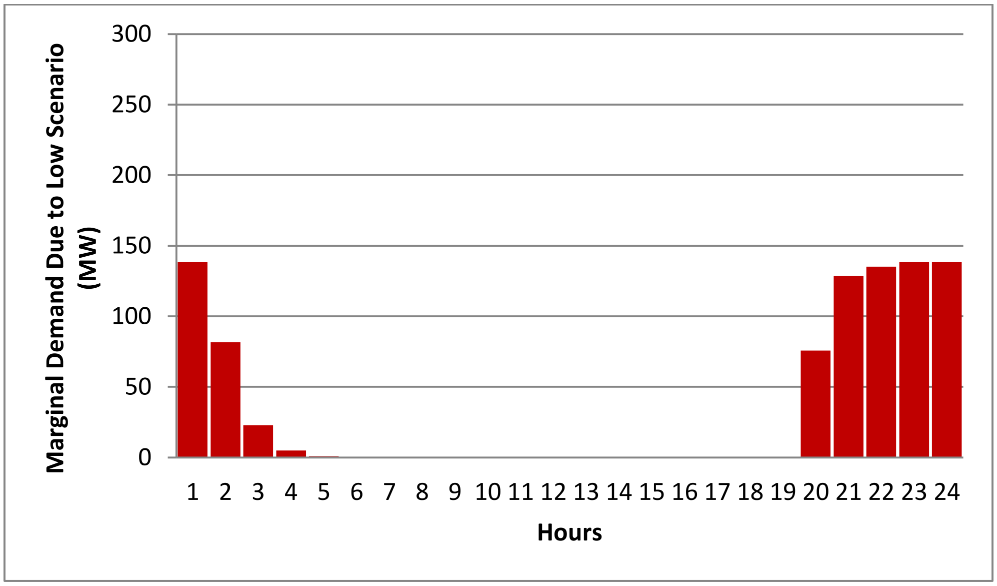

Figure 3.6.: Marginal Load Profile Due to Delayed Charging

3.3.4. Electricity Market Assumptions

The electricity market settings, under which the EVs will be charged, need to be considered carefully before modelling the charging impacts on the network. In this study, the regions in which the EVs are charged are divided according to the electricity market operation borders. In each region, the EVs charged in cities increase the electricity demand and this increased demand is supplied by the generators which are decided by the region's electricity market operations. EV fleets in different regions will be charged according to the same charging scenarios but the energy mix they will be charged will change from region to region. The regions can also import electricity from neighbouring regions if it is economical to do so. The best example to such a market structure is the United States where the states are shared among different distribution companies operating their own daily market operations. By doing so, the electricity trade among different regions can be taken into account thus better charging results can be achieved by utilizing a larger set of generators.

Independent from the number of regions, all electricity markets considered in this study are day–ahead electricity markets, where the system regulator announces a demand forecast for 24 hours and collects bids from generators from different regions for every hour of the day. The dispatch algorithms used by the system regulators list those bids in increasing order of cost and dispatches the maximum amount possible to cheapest generators without violating technical constraints until the demand is satisfied for every hour. This method is called merit-order dispatch and the model used in this step of the methodology is built to represent this market structure. In this step of the methodology, the market is assumed to operate a merit order dispatch rule, therefore the step is named as the "Business as Usual Case".

In this step of the methodology, the EV charging demand is added to conventional demand of regions. The bid data taken from the regional market operators are used in a mathematical model and the marginal generators which satisfy the increased demand coming from the EVs are determined under technical considerations described below. Availability of bid data from market operator is crucial at this step.

The most important bid specification that shapes the behaviour of the system is the price of the bid per MWh electricity produced for each hour for each region and the upper bound of generation. The generators are allowed to give more than one bid to the market operator and increase the cost of electricity as the amount of generation increases. Generators are divided into two groups depending on their bid durations: hourly bids and block bids. Hourly bids can be accepted without any obligation to accept the bids from the same generators for the following hours, whereas block bids are either accepted for every hour or rejected completely. It is not possible to partially accept a block bid, therefore accepting one hour means accepting all the remaining hours of the block bid given by the generator.

3.3.5. Technical Considerations

Hourly bids are separated into two groups according to their generator's technology. Generators using fossil fuels such as coal, lignite, natural gas, fuel-oil and petroleum, and other thermal operating generators such as bio-fuel generators are named as thermal generators. These generators operate under very strict operation rules and change the generation level by switching generation units on or off with limited flexibility. Therefore, it is not possible to partially accept an hourly bid from a thermal generator. They are either accepted as a whole or rejected. The second group of generators consists of generators using renewable sources of primary energy such as hydro power, wind power or solar power. Since it is possible to adjust the amount of generation by changing the amount of primary energy intake, renewable generators operate more flexibly. Thus, bids coming from renewable generators are assumed to have the option to be accepted partially. For block generators all bids are accepted as a whole or rejected independent of their generation technology. Renewable generators are allowed to give a lower bound for generation to the market operator in order to avoid uneconomical production volumes.

There are ramp-up and ramp-down constraints especially in thermal generators. The increases and decreases in generation amounts must be within these limits to sustain safe operation of the generators. Therefore, the model in this step considers these limits. ,

Another technical consideration taken into account in this study is the amount of transmission and distribution losses. As the electricity travels in high voltage transmission lines and distributed in low voltage distribution lines, some of the electricity is lost due to technical and non-technical reason. Technical losses are mainly caused by the heating in high voltage wires and the amount of loss increases as the distance travelled by the electricity increases. Therefore, generating electricity in generators that are geographically closer to the demand points is more efficient than generating electricity in remote regions, assuming that the generation and transmission technologies are identical. In the OECD countries an average of 6.5% of annual electricity generation is lost in transmission and distribution lines. The world average is higher than the OECD countries with a loss of 8.7%. Turkey possesses one of the most inefficient transmission and distribution systems with an annual loss of 18.6%. [59]. These losses are too big to be neglected in the model therefore the model proposed for the second step, takes transmission losses into account in a simple way. Calculation of net transmission losses for every generator and load is out of the reach of industrial engineering education. Therefore, every generator is assigned a predetermined loss coefficient which changes according to the region the bid is offered for. The loss coefficients are set equal to the average transmission and distribution loss levels in the region unless more detailed data is available. For example a coal power plant in Turkey is assumed to transmit and distribute electricity with an efficiency of 81.4% in 2012 [59]. Since the trends show that the losses are decreasing every year, the average losses in 2020 may be slightly lower than today's levels.

The second technical consideration about the transmission system is the transmission line capacities. Having enough generation capacity in a region may not be enough to be utilize the generators there because transmission lines have a capacity for electricity that can be carried through the wires in a certain period of time. The model in this step takes transmission line capacities into account and ensures that the transmission lines are not overloaded by the marginal electricity generators that are utilized to supply the EV charging demand. It is assumed that the generators and the generation levels that satisfy the conventional electricity demand are known prior to EV demand. By knowing the conventional generator and transmission line loads, the spare generation and transmission capacities are known and the dispatch algorithm can output feasible results without violating transmission constraints.

3.3.6. Business as Usual Mathematical Model

According to the assumptions and technical considerations described above a mathematical model has been created to determine the set of marginal generators. For a predetermined market penetration and charging scenario the model satisfies the marginal demand coming from the EV charging with minimum cost without violating the technical constraints in a day-ahead electricity market applying a merit-order dispatch rule.

3.3.6.1. Demand Balance Constraints

The first constraint group in the model is the demand balance constraints. The constraints ensure that the conventional generation plus the marginal electricity that has been generated for the EVs are enough to supply the conventional electricity demand and the charging demand of the electric vehicles for every region and time period.

$$\sum_{i\in G}\sum_{b\in B_{int}}(\beta_{in}x_{intb}) + \sum_{i\in G'} g_{int} \geq d_{nt} + \sum_{s=1}^{4}(\delta_s^{BEV}\ BEV_{n,t-s+1}) + \sum_{s=1}^{2}(\delta_s^{PHEV}\ PHEV_{n,t-s+1}) \qquad \forall\ n,t \qquad (3.4)$$

The decision variable used throughout the model is x_{intb}, which is defined as the amount of marginal electricity generated at generator i, for region n, at time t according to the bid b of generator i. The variable can take any positive value. Time periods in this model correspond to hours of the day. Here G is the set of marginal generators which can submit bids to generate electricity for the increased demand. B_{int} is the set of bids submitted by generator i for region n at time period t. β_{in} is the loss coefficient assigned to each generator-region pair which takes a value between 0 and 1. The loss coefficients are independent of the time of the day and the bid number and they are assumed to be equal to the average transmission and distribution losses in a region, unless more detailed loss data is available. g_{int} is the amount of conventional electricity generated at generator i for region n at time period t. The set of conventional generators which do not submit bids for the increased demand is symbolized by G'. Summation for these two generator groups make up the total electricity supply for region n at time t. The supply must be greater than or equal to the electricity demand.

The conventional electricity demand of region n at time t is known and it is symbolized by d_{nt}. The EV charging demand is separated into two parts as the demand coming from BEVs and PHEVs. As stated above, BEVs are assumed to be plugged in for 4 hours and PHEVs are assumed to be plugged in for 2 hours. Therefore at time t, the charging demand of BEVs is the sum of the demand of vehicles plugged-in at t, $t-1$, $t-2$ and $t-3$ and the charging demand of PHEVs is the sum of the of the demand of vehicles plugged-in at t and $t-1$. In this constraint s is the indicator which shows the number of hours that the vehicle has been plugged in for. For example, a vehicle that has just been plugged-in is in the first hour of charging and s is equal to 1. δ_s^{BEV} and δ_s^{PHEV} are the amount of power needed by the charger at charge state s by BEVs and PHEVs respectively. BEV_{nt} and $PHEV_{nt}$ are the numbers of battery electric vehicles and plug-in hybrid electric vehicles plugged in at time t at region n respectively. Equation (3.4.) ensures that the electricity generation is greater than or equal to the electricity demand for every region and time period.

3.3.6.2. Generation Bound Constraints

Every bid submitted by the generators has lower and upper bounds of operation for a certain price interval. Since the amount of electricity generated in every generator should obey these bounds, a group of generation bound constraints are added to the model.

$$x_{intb} = U_{intb}Y_{intb} \qquad \forall\, i,t,b \quad i \in G_{thermal} \quad b \in B_{int} \qquad (3.5)$$

$$x_{intb} \leq U_{intb}Y_{intb} \qquad \forall\, i,t,b \quad i \in G_{renewable} \quad b \in B_{int} \qquad (3.6)$$

$$x_{intb} \geq L_{intb}Y_{intb} \qquad \forall\, i,t,b \quad i \in G_{renewable} \quad b \in B_{int} \qquad (3.7)$$

The decision variable used to represent the bound of generation is Y_{itb}, which is a binary variable taking 1 when the bid b of generator i is accepted at time t. For thermal generators, accepting a bid means that all of the available power capacity must be utilized. Therefore in equation (3.5) the amount of generation is set equal to the upper bound of the bid b submitted by generator i for region n at time t, symbolized by U_{intb}. For renewable generators, it is assumed that partially accepting a bid is possible. Therefore, the generation is bounded by inequality (3.6). It is possible for renewable generators to submit bids with lower bounds to ensure economical production. This lower bound relation is modelled with inequality (3.7).

3.3.6.3. Ramp-Up and Ramp-Down Constraints

It is not possible to immediately start and stop operations of large generators due to technical reasons such as heating and cooling times of boilers, mandatory acceleration and deceleration times of generator coils. Therefore, ramp-up and ramp-down constraints are added to the model to ensure that the difference of generation between one hour and the consequent hour is within secure limits of operation.

$$\sum_{n\in N}\sum_{b\in B_{int}}(x_{intb} - x_{in(t-1)b}) \quad \leq R_i^+ \qquad \forall\, i,t \quad (3.8)$$

$$\sum_{n\in N}\sum_{b\in B_{int}}(x_{in(t-1)b} - x_{intb}) \quad \leq R_i^- \qquad \forall\, i,t \quad (3.9)$$

For every generator, inequality (3.8) ensures that the difference of generation amount between time period t and $t-1$ is less than or equal to the ramp-up limit symbolized by R_i^+.Similarly, inequality (3.9) ensures that the difference of generation amount between time period $t-1$ and t is less than or equal to the ramp-down limit symbolized by R_i^-.

3.3.6.4. Transmission Constraints

The transmission lines may be the limiting factor in an electricity grid, where the demand is increasing. In order to ensure the feasibility of solutions for the transmission infrastructure, transmission constraints have been added to the model.

$$\sum_{i\in G}\sum_{n\in N}\sum_{b\in B_{int}} e_{hin}x_{intb} \quad + \sum_{i\in G'}\sum_{n\in N} e_{hin}g_{int} \leq T_h \qquad \forall\, h,t \qquad (3.10)$$

In inequality (3.10), the set of transmission lines is represented with set H. For every transmission line h at every time period t, the amount of electricity passing through the line must not be greater than the thermal capacity, T_h. In order to relate the generated electricity with the relevant transmission lines, a binary data symbolized by e_{hin} is defined. Value of e_{hin} is equal to 1 if the electricity generated at generator i must pass through transmission line h to be transferred to region n and 0 otherwise. Multiplying the transmission binary data with the amount of marginal and conventional generation, gives the total amount of electricity passing through line h, which must be less than the thermal capacity.

3.3.6.5. Objective Function

The objective of the model represents the assumptions about the electricity market and minimizes the total cost of marginal generation that occurred as a result of EV charging.

$$\min \quad z_1 = \sum_{i \in G} \sum_{n \in N} \sum_{t \in T} \sum_{b \in B_{int}} P_{itb}\, x_{intb} \tag{3.11}$$

Every bid submitted by generators has a price per MW of generation capacity utilized, which is symbolized by P_{itb}. The objective function minimizes the cost of marginal electricity under the technical constraints described above.

3.3.7. Performance Measures

In a similar manner to the first step, performance measures of the EVs must be identified to compare the technology with conventional vehicles technologies. The outputs of the mathematical model presented above, enable the calculation of primary energy consumption, GHG emissions and energy costs.

3.3.7.1. Primary Energy Consumption

Due to the losses in the energy supply chain, there is a difference between final energy consumption and primary energy consumption of road transportation vehicles. For conventional vehicles, the losses occur during the conversion of crude oil to fuel products, in which approximately 13% of primary energy stored in crude oil is lost. For the electricity supply chain the main source of losses is the electricity generation and transmission process. Each generation technology has a different efficiency rate which is equal to the amount of electricity energy generated divided by the energy of primary energy sources consumed to generate electricity. For example, coal power plants consume 100 units of primary energy stored in coal to produce 30-35 units of electric energy, which is equal to an efficiency of 30-35% [60]. Since the outputs of the model provide the amount of electricity generated by each generator, it is easy to calculate the primary energy consumed by dividing the electricity generated to the efficiency of the generation technology used by the generator. The efficiencies of the generation technologies might change from country to country therefore this data should be collected before the application rather than giving a universal assumption (Data used in Turkish Application is given and referenced in section 4.1.). The formula below is used to determine the amount of primary energy consumption of battery charging in a day.

$$DPEBC = \sum_{i\in G}\sum_{n\in N}\sum_{t=1}^{24}\sum_{b\in B_{int}} x_{intb} \times {}^{1}/_{\mu_i} \qquad (3.12)$$

In the formula above x_{intb} the amount of marginal electricity generated at generator i, for region n, at time t according to the bid b of generator i. The efficiency of generator i is symbolized by μ_i. The formula gives the amount of primary energy consumed by battery charging in a day. Since the PHEVs consume gasoline when the battery depletes, the total primary energy consumption is calculated by the formula below.

$$DPEC = DPEBC + fc_{PHEV} \times e_{fuel} \times d \times {}^{1}/_{\theta} \qquad (3.13)$$

The second part of the formula gives the primary energy consumption of PHEVs as a result of gasoline combustion in their internal combustion engines. In formula (3.13) d represents the daily kilometres driven by PHEVs. (The details of the formula can be found under subsection 3.2.2.1.). Calculation of the annual energy consumption depends on the availability of data and number of days the model is run for. In order to shorten the time of analysis, one day from each month or season to represent the general behaviour of the system in different times can be chosen as if all days in that month or season gives the same results and annual energy consumption can be calculated.

3.3.7.2. GHG Emissions

The second performance measure to be calculated for EVs is the amount of GHG emissions. Despite the fact that the BEVs have zero direct emissions, the net emissions depend on where the electricity that is used for battery charging is generated. Therefore, the GHG emissions of marginal electricity generation must be calculated. Each generation technology has a different GHG emission effect. In this study, life cycle emissions of different generation technologies have been taken into account to reach comparable results with conventional vehicles.

Most of the emissions related to electricity generation occur during the generation process itself. For thermal generators, combustion of fossil fuels is biggest contributor to GHG emissions. Since the carbon content of fossil fuels are high, thermal generators such as coal, natural gas and fuel-oil generators emit more GHG particles than other sources. Emissions related to renewable energy sources are generally a result of construction, manufacturing and maintenance steps of the generation. Therefore, every generator has a life cycle emission per unit of electricity generated. GHG emission also show variance from location to location based on the technologies used. Therefore, a universal assumption for emission cannot be done (Data used in Turkish Application is given and referenced in Section 4.1.). According to the emission data, the amount of daily GHG emissions of marginal electricity is calculated as follows.

$$DGHGBC = \sum_{i \in G} \sum_{n \in N} \sum_{t=1}^{24} \sum_{b \in B_{int}} C_i \, x_{intb} \tag{3.14}$$

In (3.14), C_{itb} gives the amount of life-cycle GHG emissions for generator i per unit electricity generated. Since the PHEVs emit GHG while operating on the internal combustion engine, the total GHG emissions of the electrified road transportation is equal to the sum of the GHG related to electricity generation and vehicles emissions of PHEVs given by the formula below:

$$DGHG = DGHGBC + fc_{vehicle} \times cc_{fuel} \times d \times \gamma \tag{3.15}$$

In (3.15), the emissions of PHEVs are given in the second term of the summation, where d is equal to the kilometres driven by the PHEVs every day on internal combustion engines. If it is not possible to run the model for 365 days, one day from every month or season can be chosen to run the model for, and reach annual results.

3.3.7.3. Energy Costs

Energy costs related to electrification of the road transport is separated into two parts. First is the cost reflected to the customers directly and the second is the energy cost to the energy supply chain. For conventional vehicles, the cost of gasoline and diesel at the pump is the cost reflected to customers and the refinery cost of gasoline is the cost to the energy supply chain. Similarly, retail price of electricity at the hour of charging is the cost reflected to the customer and the bid price given by the generator is the cost to the energy supply chain. The marginal electricity cost of battery charging is given in the objective function of the business as usual mathematical model. Since PHEVs consume gasoline, the refinery price of gasoline must be added to the objective function value in order to find the total daily energy cost of EVs to the energy supply chain. The related formula is given below:

$$DEC^1 = \sum_{i \in G} \sum_{n \in N} \sum_{t \in T} \sum_{b \in B_{int}} P_{itb}\, x_{intb} + fc_{PHEV} \times c_{gasoline} \times d \tag{3.16}$$

In (3.16), d is the average daily kilometres driven by PHEVs on internal combustion engines and . $c_{gasoline}$ is the refinery price of gasoline. The cost of electric transport to the customers is calculated by using the formula below:

$$DEC^2 = \sum_{i \in G} \sum_{n \in N} \sum_{t \in T} \sum_{b \in B_{int}} RP_t\, x_{intb} + fc_{PHEV} \times c_{gasoline} \times d \tag{3.17}$$

In (3.17), RP_t is the retail price of electricity at tth hour of the day. The first part gives the amount paid to the electricity consumed to charge the vehicles and the second part, in which $c_{gasoline}$ is the retail price of gasoline, gives the amount paid to gas stations.

3.3.8. Comparison with Previous Steps

The outputs of the business as usual model and calculation of the performance measures enable the decision makers to compare the conventional vehicle fleet with the EV fleet. Depending on the preferences of the stakeholders such as the governments, electric utilities, environmental agencies, the decisions to support introduction of EVs or not can be based on the economic, environmental or efficiency performance of the vehicle fleet. The outputs also enable comparison of different charging patterns. If there is significant difference in the performance of EVs between charging patterns, the decision makers can take necessary precautions to promote charging of the EVs according to the charging pattern that are more economical and/or more environmental.

3.4. Step 3: EVs' Impacts with Bi-Objective Generation Decisions

The purpose of the third step in the proposed methodology is to calculate the performance measures of the EVs under environmentally conscious electricity market decisions. In the second step, the market structure was assumed to follow the rules of merit-order dispatch and satisfy electricity demand with minimum cost possible. However, the benefits of the introduction of EVs might be very attractive for governments or regional authorities since they can secure the energy supply, increase energy efficiency, decrease GHG emissions or remove air pollution in urban areas, so that decision makers may be willing to pay an economic offset to make use of these opportunities. One of the biggest opportunities offered by the electrification of the road transportation is the GHG emission reduction. The governments are under pressure from international agreements such as the Kyoto Protocol and emissions over limits are subject to penalties. Hence, EVs might be an efficient way of decreasing emissions. For example, a regional authority that has to decrease the GHG emissions of the region would be willing to pay for the expensive electricity produced at renewable power plants that charge the electric vehicles to decrease GHG emissions of the transportation sector. Therefore, it is important for the decision makers to see a group of solutions, which perform better in the environmental performance with a higher cost than the merit-order solution.

In order to reach comparable results with the first two steps, the assumptions of the EV penetration levels, technical data and charging patterns remain unchanged in the third step. The changes in the market structure, which are explained above, are introduced to the methodology by making slight modifications in the mathematical model.

3.4.1. Modifications in the Model

The only difference with the business-as-usual mathematical model is the introduction of the second objective function. The second objective function in the model aims to minimize the amount of GHG emissions resulting from the marginal electricity generation. Introduction of this second objective function enables the model to output the set of efficient feasible solutions for marginal generator mix, among which the decision makers can choose to reach more economical or environmental solutions. The second objective function is as follows:

$$\min \qquad z_2 = \sum_{i \in G} \sum_{n \in N} \sum_{t \in T} \sum_{b \in B_{int}} C_i \, x_{intb} \qquad (3.18)$$

The decision variable in (3.18) is the same decision variable used in the business-as-usual model. The amount of GHG emissions emitted by generator i per unit of electricity generated is represented as C_i. The objective function sums the amount of GHG emissions resulting from marginal electricity. The constraints, decision variable definitions and the first objective function remain unchanged in the third step.

3.4.2. Comparison with Previous Steps

The output of the bi-objective model includes more than one solution set. The solution method used, brings out all the efficient solutions of the system and construct the efficient frontier of the problem. In Figure 3.7., an example of efficient frontier is given.

Every solution in the efficient frontier gives a different cost and emissions result. The cheapest solution in the efficient frontier is equivalent to the solution found by the business-as-usual model, whereas the most expensive and the least polluting solution is equivalent to the solution that could have been found when the model was run with the emission objective (z_2) only. The solutions between these two extreme solutions are also efficient and create a set of compromising solutions between two objectives. In order to compare the performance of the solutions, performance measures must be calculated as shown for the second step and the decision makers must choose among the listed solutions depending on their preferences of being more economical or environmentally conscious.

Since the model represents the behaviour of the model in one day, it is not possible to reach annual efficient solutions. The analysis must be carried out for as many days as possible to understand the behaviour of the region's electricity market. For example, the electricity market for which the efficient frontier is given in Figure 3.7., it is possible to reach significant reductions in GHG emissions while the cost objective remains more stable in the region shown as region A in the figure. This is the result of the abundance of clean energy sources which has compatible price with more polluting sources of generation.

As opposed to region A, in region B no matter how much the cost increases the reductions in GHG emissions remain insignificant. This might be a result of the existence of expensive sources which bring small reductions in emissions. These frontier behaviours change from region to region and from time to time. Therefore, it is not possible to reach general conclusions by calculating annual performance measures as in the second step. Increasing the number of days analyzed would improve the success of the methodology to generate recommendations about the electricity market.

3.5. Step 4: EVs' Impacts under Optimal Charging Patterns

The fourth and the last step of the proposed methodology to analyze the impacts of EVs, includes optimization of charging hours under environmentally conscious market operations. As stated in the literature review, one of the main gaps in the literature about the EV impact analyses is that none of the studies proposes a method to find the optimal - in this case cheapest and the least polluting- charging hours. Instead of optimizing the charging hours, the methods use predetermined charging scenarios to distribute the charging demand to hours of the day. Despite being a valid approach, using predetermined scenarios inhibit the opportunities to further reduce marginal generation costs and GHG emissions. In addition to the predetermined scenarios used in the second and third steps, the fourth step defines charging hours as new decision variables and enables the model to find the most suitable hours for EV charging.

3.5.1. Modifications in the Model

Optimization of charging hours requires a new decision variable to be introduced to the bi-objective mathematical model. Until this step, the number of vehicles being charged was given as an input to the model at the demand balance constraints but in this step the number of vehicles is determined by the model. In order to sustain the assumptions of linear programming the new decision variable is defined as the percentage of EVs being plugged in at region n and at time period t. The new decision variable is represented as PEV_{nt} and the new demand balance constraint is defined as follows.

$$\sum_{i\in G}\sum_{b\in B_{int}}(\beta_{in}x_{intb}) + \sum_{i\in G'} g_{int} \geq d_{nt} + \sum_{s=1}^{4}(\delta_s^{BEV} PEV_{nt} NBEV_n) + \sum_{s=1}^{2}(\delta_s^{PHEV} PEV_{nt} NPHEV_n) \quad \forall\, n,t \qquad (3.19)$$

In (3.19), the supply side remains unchanged whereas the new decision variable changes the demand side of the inequality. Instead of a predetermined number of vehicles in region n plugged-in at time t represented by BEV_{nt} and $PHEV_{nt}$ in inequality (3.4), the number of BEVs is determined by multiplying the new decision variable PEV_{nt} by the total number of BEVs to be charged in region n represented by $NBEV_n$. The demand of PHEVs is found by using the same decision variable and multiplying it by $NPHEV_n$ which is equal to the number of PHEVs to be charged in region n. In order to ensure that all vehicles are charged, the following constraint is added to the model

$$\sum_{t=1}^{24} PEV_{nt} = 1 \tag{3.20}$$

Equation (3.20) sums the decision variables for 24 hours of the day and sets the sum equal to 1, in order to ensure that all vehicles in the region are plugged-in during the day. In addition to (3.20) it is possible to introduce upper bounds on the new decision variable to prevent the model from reaching unrealistic solutions such as plugging-in all the vehicles during rush hours while the vehicles are on the roads and unable to be charged. These upper bounds depend on the driving behaviour of the drivers in the region and need intensive data collection to be identified before being used in the model. Upper bounds can be used in the model by introducing the following group of constraints.

$$PEV_{nt} \leq p_{nt} \tag{3.21}$$

In (3.21), p_{nt} is the maximum percentage of vehicles in region n that can be plugged-in at time t.

3.5.2. Comparison with Previous Steps

Since the charging hours of EVs are defined as decision variables, the results of this step of the experiment will clarify the set of efficient solutions for charging hours. The results will give all the solutions between the cheapest and the least polluting charging options for EVs in a region. In order to compare the performance of the solutions, performance measures must be calculated as shown for previous steps and the decision makers must choose among the listed solutions depending on their preferences of being more economical or environmentally conscious. The decision makers can compare the results of this step with predefined charging scenarios and see how much the cost and emissions will differ. If the optimal charging hours are convenient (different than rush hours) for charging the EVs the regional policy makers must install necessary regulations to encourage the charging of EVs at optimal hours. The difference between predefined charging scenarios and optimal hour scenario shows how beneficial it can be to determine the optimal charging hours.

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3.6 Solution Method

The problem addressed in this thesis is one of many real world problems, in which more than one objective affects the decision making process. Branch of operations research that deals with problems where there is more than one objective is called multi-objective optimization. The model proposed in this thesis represents a special case of multi-objective optimization as it has two objective functions: one for minimization of the total electricity bid costs and one for minimizing the emissions released from marginal generators. Problem that deals with precisely two objective functions are called bi-objective optimization problems. Another special case of the model is that it includes both continuous and discrete decision variables.

Before going into the application of the related bi-objective optimization techniques on the proposed model, some basic definitions about bi-objective optimization are given. The model created in this thesis can be stated as:

$$\begin{aligned} \text{P1} \qquad & \min \quad (f_1(x,y), f_2(x,y)) \\ & s.t. \quad x, y \in X \end{aligned} \tag{3.22}$$

where x and y consists of discrete and continuous variables, respectively. X is the feasible set and $f :\rightarrow Z^2$ is a vector valued objective function. In order to connect the definitions with the model proposed, readers can assume that x is representing x_{intb} and y is representing Y_{intb} as well as two objectives are z_1 and z_2 given in Eq. (3.11) and Eq. (3.18) respectively.

Definition 1. Let x and x' be two solutions of X. (x, y) weakly dominates (x', y'), if $f_j(x,y) < f_j(x',y')\ \forall j$, similarly (x, y) dominates (x', y') if $f_j(x,y) \leq f_j(x',y')\ \forall j$ and $f_j(x,y) \neq f_j(x',y')\ \exists\, j$, $j = 1,2$

Definition 2. A solution $x^* \in X$ of P is called weakly efficient if there does not exist any other feasible solution $(x, y) \in X$ such that (x, y) weakly dominates(x^*, y^*).

Definition 3. A solution $x^* \in X$ of P is called efficient or non-dominated point if there does not exist any other feasible solution $(x, y) \in X$ such that (x, y) dominates(x^*, y^*).

In general, multi-objective optimization tools try to develop procedures that generate efficient solutions that have the property that no improvement on any objective is possible without sacrificing on the other objective. Specifically speaking for this study, the procedure that is used should search for solutions where it is not possible to decrease emissions further without sacrificing the financial objective and getting an increase in the marginal electricity costs. Once the efficient solutions are known the decision makers are able to choose among them based on their preferences or being more cost oriented or environmentally conscious. One important concept that is useful in these decision processes is the efficient frontier which can be defined as the set of all efficient solutions. As the nature of the problem studied in this thesis includes a compromise between costs and emissions it is important to create the efficient frontier and provide all possible solutions to decision makers.

One of the most widely used solution approaches to multi-objective optimization is scalarization. Scalarization technique involves creating a single objective optimization problem that represents the multi-objective problem and enabling a solution procedure without disregarding the constraints of the original problem [65]. Weighted sum method is one of the simplest scalarization techniques; however in non-convex cases like the model in this study, it may fail to generate efficient solutions [65]. Hence, another popular multi-objective optimization method, namely ε-constraint method, has been used in this study to generate the efficient solutions for the problem. As stated in the introduction, this study is not an attempt to improve any solution procedure in the literature or to suggest a new one rather it is an application study that uses the available solution methods in the literature. Therefore, only general concepts of the ε-constraint method will be given as a reference to clarify the solution approach applied.

The ε-constraint method is a widely accepted technique to solve multi-objective optimization problems. In summary the procedure optimizes only one of the objectives at a time and transforms the rest of objective functions to constraints of the problem. In bi-objective problems like the model in this study, this is equal to solving the problem for one of the objectives at a time while the other objective is defined as a constraint to the new single objective optimization problem. The method was introduced by Haimes et al. [66]. Detailed discussion of the formula can be found in Chankong and Haimes [67]. With this method the bi-objective optimization problem can stated as follows:

$$\begin{aligned} \text{P2} \qquad & \min_{x \in X} \ f_1(x) \\ & s.t. \quad f_2(x) \leq \varepsilon \end{aligned} \tag{3.23}$$

where $\varepsilon \in R$. To justify the approach it is shown that optimal solutions of (3.23) are at least weekly efficient.

Proposition 1. Let x^* be an optimal solution of (3.23) for $f_1(x)$. Then is x^* weakly efficient.

Proof. Assume $x^* \notin X_{wE}$. Then there is an $x \in X$ such that, $f_k(x) < f_k(x^*)$ for *k*=1,2 and in particular $f_1(x) < f_1(x^*)$. Since $f_2(x) < f_2(x^*) <$, the solution x is feasible for (3.23). This is a contradiction to x^* being an optimal solution. Therefore x^* must be weekly efficient. [65]

In order to strengthen Proposition 4.3 to obtain efficiency we require the optimal solution of (4.3) to be unique.

Proposition 2. Let x^* be a unique optimal solution of (3.23) for $\mathrm{f}_1(\mathrm{x})$. Then $x^* \in X_{sE}$

Proof: Assume there is some $x \in X$ with $f_2(x) < f_2(x^*) < \varepsilon$. If in addition $f_1(x) \le f_1(x^*)$ we must have $f_1(x) = f_1(x^*)$ because x^* is an optimal solution for (3.23).Thus uniqueness of the optimal solution implies $x = x*$ and $x^* \in X_E$[65]

Efficiency of x^* is related to x^* being an optimal solution to (3.23) so if the optimality of x^* could be proven, it is also proved that by solving a sequence of ε-constraint models efficient frontier can be found. This is given in Theorem 1.

Theorem 1. The feasible solution $x^* \in X$ is efficient if and only if there exists an $\varepsilon \in R$ such that x^* is an optimal solution of (3.23)

Proof: => Let $\varepsilon' = f(x^*)$. Assume that x^* is not an optimal solution of (3.23). Then there must be some $x \in X$ with $f_1(x) < f_1(x^*)$ and $f_2(x) \le \varepsilon' = f_2(x^*)$, that is $x^* \notin X_E$

<= Suppose $x^* \notin X_E$ Then there is a feasible solution $x \in X$ such that $f_1(x) < f_1(x^*)$ and $f_2(x) \le f_2(x^*)$. Therefore x^* cannot be an optimal solution of (3.23) for any ε for which it is feasible. Note that any such ε must have $f_2(x^*) \le \varepsilon$. [65]

This proof shows that with appropriate choices of ε all efficient solutions can be found and efficient frontier can be constructed by using this set of solutions in cases where the optimal solution is unique. As this cannot be guaranteed before solving the model, to deal with weakly efficient solutions a slight modification has been done in the solution method. As proposed in the work of Özlen and Azizoğlu [72] and similarly by Mavrotas [73], the formulation of bi-objective ε-constraint method can modified as follows to ensure that every solution gives an efficient solution:

$$\text{P3} \qquad \min_{x \in X} \; f_1(x) + \psi\, f_2(x)$$
$$s.t. \quad f_2(x) \le \varepsilon \tag{3.24}$$

Theorem 2. For $\varepsilon \in R$ and $\varphi > 0$ optimal solution $x^* \in X$ of P3 also an efficient solution

Proof: Let $x^* \in X$ be the optimal solution of P3. Suppose that x^* is not efficient. Than there exists a $x' \in X$ such that $f_1(x') \leq f_1(x^*)$ and $f_2(x') \leq f_2(x^*)$. There also exists an i for which $f_i(x') < f_i(x^*)$. This implies feasibility of x'. Taking summation in both sides and multiplying one side with ψ implies that $f_1(x') + \psi f_2(x') \leq f_1(x^*) + \psi f_2(x^*)$ which contradicts optimality of x^* .Therefore x^* must be efficient.

Using this argument, an algorithm that sets ψ to a small positive value is created. The algorithm starts by setting ε to positive infinity and iteratively decreases ε to obtain the efficient frontier. Details of the algorithm which has been written by C++ modeling language and solved with the help of CPLEX solvers can be found in Appendix B.

By creating the efficient frontier, it is possible to visualize the general trends in cost-emission relation and see areas where it is very cost effective to decrease emissions or where it is very difficult to further decrease costs. A representative figure of efficient frontier for this study is given in Figure 3.7. As stated above it is possible to reach significant reductions in GHG emissions while the cost objective remains more stable in the region shown as region A in the figure. This is a result of the abundance of clean energy sources which has compatible price with more polluting sources of generation. As opposed to region A, in region B no matter how much the cost increases the reductions in GHG emissions remain insignificant. This might be a result of the existence of expensive sources which bring small reductions in emissions. These frontier behaviours change from region to region and from time to time. Therefore, it is not possible to reach general conclusions by calculating annual performance measures as in the second step. Increasing the number of days analyzed improve the success of the methodology to generate recommendations about the electricity market.

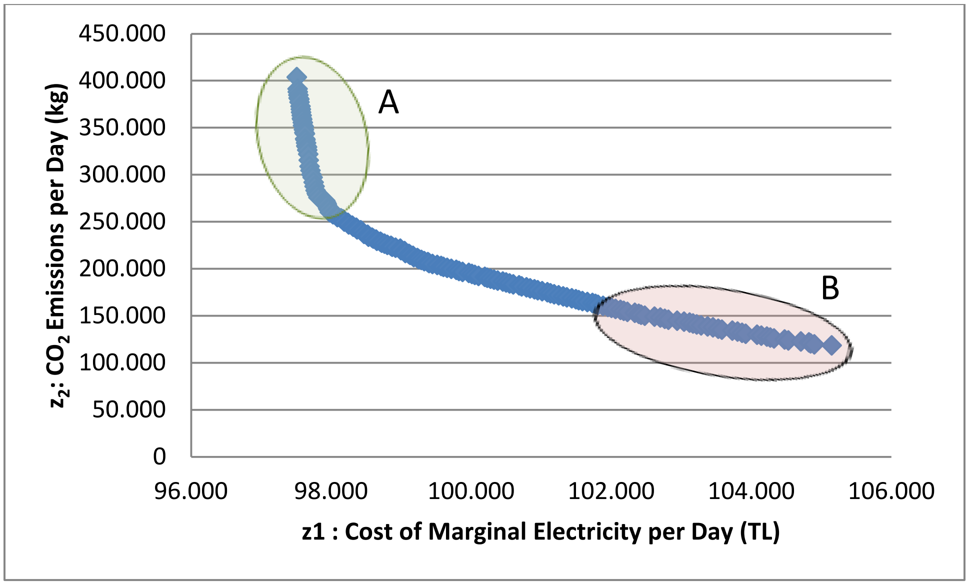

Figure 3.7.: An Example Efficient Frontier Obtained at the End of Step 3

Chapter 4

APPLICATION OF THE METHODOLOGY IN TURKEY

In this chapter the methodology and solution method that has been provided in the previous chapter is applied to the Turkish electricity market with real market bid data taken from Turkish Electricity Transmission Company (TEIAS) assuming a 10 year penetration period for electric vehicles in Turkish passenger car market. Results of two different scenarios have been analyzed in detail. This section starts with explaining the assumptions and providing references for the data used in the Turkey case, and results for low and medium market scenarios are given in Sections 4.2. and 4.3. respectively. As the high market scenario results only differed in the magnitude, only a short summary and comment was allocated to the scenario in Section 4.4.

4.1. Assumptions and Setting of Turkey Case

4.1.1. Electricity Sector Data

As the methodology is created based on the operations of day-ahead electricity market, a brief introduction to day electricity market in Turkey will be made and data that is used in the application will be referenced in this section.

Day-ahead electricity market is defined as the organized market structure where the suppliers (generators) of next day's electricity energy demand is decided [1]. In Turkey, day ahead market is operated from Ankara by Piyasa Mali Uzlaştırma Merkezi (PMUM) which is a governmental entity linked to TEIAS and centred in the headquarters of TEIAS. Turkish day ahead market operates as follows: Based on statistical models and market expertise, PMUM estimates the electricity demand per hour in Turkey for the next day. Output of this stage is the hour by hour electricity demand expectation in MWh. Once the production that is fixed by long term contracts, exports and import generations are subtracted from this demand PMUM announces the electricity demand that must be balanced by the generators in the market for each hour. At this step, every day electricity generation companies that are registered to the market inform their technical parameters (minimum and maximum operation capacities by hours, load increase rate, load decrease rate, start up time) and place their bids for the coming day's electricity supply to PMUM for each of their generators until 10:30 am. PMUM takes all those bids and inputs these bids to a detailed electricity market optimization tool that takes the technical constraints into account and runs the model between 11:00-13:00 to determine next day's supply. The model operates by merit order dispatch, which means that the cheapest bid in row is accepted until the demand estimated by PMUM is satisfied and the final bid that is accepted is announced as unconstrained market exchange rate (KPTF). After this step the planning tools compare the supply plan to transmission constraints and makes necessary adjustments. If no constraints are violated, KPTF is announced as the final market exchange rate (NPTF) or the new highest bid after making changes in the supply plan is set as the NPTF. (As the location information of the generators were not made available by PMUM data data collection stage for this application and the location of electricity demand due to electric vehicle charging is unclear, the methodology assumed that the marginal dispatch model operates under no transmission constraints and the final bid accepted will be equal to KPTF.) Once final price is set, PMUM announces the generators the production plan for next day. Balancing acts during the day are not managed by PMUM. These operations are managed by National Load Dispatch Centre (Milli Yük Tevzi Merkezi-

MYTM) from operational centres at each regional in Turkey. MYTM controls if the generators are operating according to the plan decided by the day ahead market and gives orders to increase or decrease load based on the ramp ups and downs in the system.

Most important data to be able to run the methodology is the day ahead market bids placed by generators. By having these data it is possible to run the model proposed in Section 3 and to determine the set of generators that would have been accepted to supply electricity which is the key driver of EV's performance measures. In this application it was assumed that no matter if electric vehicles were in the system or not conventional demand (any other electricity demand other than EV charging) would have been supplied by the same set of generators as it was supplied on the same day so the necessary bid pool that should be taken into account consist of the bids that are more expensive than the final bid that was accepted. A limit of 2000 MW extra load was decided which covers all the market scenarios that has been analyzed in this application. In order to decrease the amount of time required from PMUM to prepare the data without losing the ability to have a good estimation of the annual performance it has been decided to use data from 6 representative days from the year 2010. In the reports of Turkish energy sector, second or third Wednesdays of the months are used to present monthly trends. In 2010 where data was available third Wednesdays were national holidays in two months therefore the following second Wednesdays have been chosen to run the model on: December 8th and February 10th to model winter months, April 14th to model spring months, June 9th and August 11th to model summer months and October 13th to model fall months. After communication with PMUM, a meeting had been arranged and at the end of a visit to Ankara, an application according to law of accessibility to information (Bilgi Edinme Kanunu) has been made to get the bid data for the above mentioned days.

As the market data are protected according to law, PMUM was not able to provide all details of the bids like company names and locations, which could be used to model transmission constraints, or detailed technical information that was proposed to be used in the model such as Ramp up and Ramp down limits as these would reveal the company information which is protected by law according to the same law of accessibility to information. The data received was limited to :

- Day and time every bid was valid for
- Upper limit of load that can be generated with the bid (MW)
- Type of the bid (Block or hourly bid)
- Primary energy source of the generator (Coal, Natural gas etc.)
- Cost of bid (TL/MW)

A sample of the bids can be found below.

Table 4.1.: Sample of Day-Ahead Bids Taken from PMUM

Bid No	Primary Energy Source	Date and Time	Type	Upper Limit (MW)	Bid Price (TL/MW)
153875	Natural Gas	10.02.2010	Hourly	240	140.00
153906	Large Hydro Dam	10.02.2010	Hourly	29	141.00
153868	Natural Gas	10.02.2010	Hourly	59	145.00
153797	Hard Coal	10.02.2010	Hourly	40	146.00
153381	Natural Gas	10.02.2010 01:00:00	Hourly	10	130.00
153399	Biogas	10.02.2010 01:00:00	Hourly	13	133.00
153432	Natural Gas	10.02.2010 01:00:00	Block	50	135.00
153386	Natural Gas	10.02.2010 01:00:00	Hourly	33	136.00
153821	Hard Coal	10.02.2010 01:00:00	Hourly	40	140.00
153322	Export Coal	10.02.2010 02:00:00	Hourly	30	130.00
153321	Natural Gas	10.02.2010 02:00:00	Hourly	20	130.00
153408	Natural Gas	10.02.2010 02:00:00	Block	50	135.00
153432	Natural Gas	10.02.2010 02:00:00	Block	50	135.00
153386	Natural Gas	10.02.2010 02:00:00	Hourly	33	136.00
153883	Natural Gas	10.02.2010 02:00:00	Block	95	140.00

This data provides P_{itb} which is the price of bid b placed by generator i at time t per MW of generation capacity and enable to attach technical data like emissions, energy efficiency to each bid according to its primary energy source. These data are explained in detail in the next subsection.

4.1.2. Technical Assumptions for Turkey

First important assumption of the Turkey case is the transmission loss coefficients, which was defined as β_{in} in demand balance constraints in formula (3.4.). As this case assumed there is one single market, a coefficient between 0 and 1 needs to be assigned to each generator. According to 2010 Electricity Distribution and Consumption Statistics report published by Turkey Electricity Distribution Company, transmission losses have accounted for 18.6% of total consumption in Turkey in 2010 [4]. In the eastern cities losses go up to 77%, and the average losses in southeast region are 65%. As this is the region where most of the hydroelectricity capacity is concentrated, these sources are affected more compared to fossil fuel generators in the west. However the decreasing trend between 2000 and 2008 shows that the current high losses might be brought down. This is shown to be achievable by OECD countries which have an average loss rate of 6% according to Electricity Information report published by International Energy Agency [5].
Therefore an optimistic assumption for the transmission losses has been made for 2020 scenario in Turkey and β_{in} was assumed to be 0.93 for all primary energy sources except hydroelectricity sources and 0.9 for all hydroelectricity sources. By setting these coefficients, the demand balance constraints force the model to generate enough electricity that can overcome transmission losses to charge the electric vehicles.

The second objective in the bi-objective model is the minimization of CO_2 emissions resulting from electricity generation, which is dependent on the emission rate of generator, defined as C_i in equation (3.18). Since it was not possible to get generator specific emission data from PMUM, it is assumed that all generators using the same primary energy source has constant emission rate. An extensive literature research has been conducted to find the life cycle emission estimation of generators with different primary energy sources. In Table 4.2 the final assumption of CO_2 emissions per MWh generation based on the average of emission rates taken from the literature [68],[69],[70],[71].

In order to calculate the primary energy consumption, energy efficiency of generators must be estimated. In the literature as there was no specific work dedicated to calculating energy efficiency of Turkish generators a similar approach to emissions is followed and an energy coefficient, which was defined as μ_i in equation (3.12), is assigned to each generator according to its primary energy source. As the application is looking at a 10 year horizon, a slight increase the energy efficiency was assumed for each source compared to the figures found in the literature [16],[6]. Assumptions are given in Table 4.2.

Table 4.2.: Emissions and Energy Efficiency of Generators in Turkish Electricity Network

Generator's Primary Energy Source		**CO_2 Emissions (kg/MWh)**	**Efficiency**
Natural Gas		450	45%
Coal	Lignite	1100	40%
	Hard Coal	1000	40%
Fuel Oil		800	40%
Hydro	Large Dam	15	90%
	Flow of River, Lake	5	90%
Biogas		75	40%

4.1.3. Market Scenarios

Estimation of the number of electric vehicles on the road by 2020 was another challenging step in the application of the methodology. As explained in Section 3.2.1. three market penetration scenarios have been decided to be used to model the behaviour of the system under different charge demand loads. In order to use these percentages, number of passenger car sales until 2020 must be estimated.

First of all, a group of cities has been selected as the first target locations of electric vehicles in Turkey. This selection has been based on the size of passenger car market in recent years and on development of necessary infrastructure for electric vehicle charging and list was limited to 25 cities. The cities are as follows: Istanbul, Ankara, Izmir, Adana, Bursa, Antalya, Eskisehir, Kocaeli, Erzurum, Sakarya, Tekirdağ, Balıkesir, Manisa, Aydın, Denizli, Muğla, Gaziantep, Hatay, İçel, Konya, Kayseri, Samsun, Trabzon, Diyarbakir, and Şanlıurfa. Total of passenger car sales equals 89% of total sales in Turkey in 2010 [2].

According to Automotive Industry Union (OSD) in Turkey, passenger car vehicle sales from 2012 to 2020 will follow the trend given in Table 4.3. This data can be used to estimate the number of BEVs and PHEV that will be on the roads in 2020 in Turkey. Year by year sales and resulting number of vehicles in 2020 can be seen in Table 4.4.

Table 4.3: Passenger Vehicle Sales Estimations from 2012 to 2020

Year	Passenger Car Sales	25 Cities
2012	437,300	389,197
2013	458,600	408,154
2014	473,900	421,771
2015	489,200	435,388
2016	515,625	458,906
2017	531,250	472,813
2018	546,875	486,719
2019	562,500	500,625
2020	581,250	517,313

Table 4.4: 2012-2020 BEV and PHEV Sales Assumptions in Turkey

Scenario	Year	2012	2013	2014	2015	2016	2017	2018	2019	2020
Low	BEV Share in Sales	0.10%	0.20%	0.40%	0.50%	0.75%	1.00%	1.30%	1.70%	2.00%
	Number of BEVs sold	383	818	1,690	2,181	3,448	4,737	6,339	8,527	10,366
	PHEV Share in Sales	0.10%	0.25%	0.50%	0.75%	1.50%	2.50%	3.50%	4.50%	5.00%
	Number of PHEVs sold	383	1,022	2,113	3,272	6,897	11,843	17,068	22,571	25,915
Medium	BEV Share in Sales	0.25%	0.40%	0.75%	1.25%	1.75%	2.50%	3.00%	4.00%	5.00%
	Number of BEVs sold	959	1,636	3,169	5,453	8,046	11,843	14,629	20,063	25,915
	PHEV Share in Sales	0.10%	0.50%	1.00%	1.50%	3.00%	5.00%	7.00%	9.00%	11.00%
	Number of PHEVs sold	383	2,045	4,226	6,543	13,793	23,686	34,135	45,142	57,012
High	BEV Share in Sales	0.25%	1.00%	3.00%	4.00%	5.00%	6.00%	7.50%	9.00%	10.00%
	Number of BEVs sold	959	4,089	12,677	17,449	22,989	28,423	36,573	45,142	51,829
	PHEV Share in Sales	0.10%	1.00%	2.00%	3.00%	6.00%	10.00%	14.00%	18.00%	25.00%
	Number of PHEVs sold	383	4,089	8,451	13,086	27,587	47,371	68,270	90,284	129,574

As EVs will be compared with conventional vehicle fleet it is also necessary to know the percentage of gasoline powered and diesel powered vehicles that will be replaced by EVs. According to Turkish Statistical Institute the percentage of diesel vehicle sales in passenger car sales has increased from 19.5% in 2004 to 53.2% in 2010, which is the first year in history when diesel vehicle sales have exceeded gasoline powered vehicle sales [2]. Taking into account the recent developments in diesel technology it is assumed that this increasing trend will continue and mature at 60% level, similar to European passenger vehicle market. This assumption clarifies the application fleet data as seen in Table 4.5:

Table 4.5: EV and Conventional Fleet Assumptions by 2020

Scenario	**New entries to market**		**Replaced conventional vehicles**		**Total**
	BEV	**PHEV**	**Gasoline**	**Diesel**	
Low	40,000	90,000	52,000	78,000	130,000
Medium	90,000	190,000	112,000	168,000	280,000
High	225,000	400,000	250,000	375,000	625,000

As explained in Section 3.2.2.1, EVs are expected to be used for commuting in the first years of introduction. Therefore, the fuel consumption ($fc_{vehicle}$) that will be used to compare conventional vehicles' performance with EVs is urban consumption figure. According to the distribution of passenger cars by segment in Turkish market a representative fleet of 14 vehicles, including 5 B class, 5 C class, 3 D class passenger cars, and one SUV, has been created for both gasoline and diesel options.

The average fuel consumption is 8.8 litre / 100 km for the gasoline fleet and 6.0 litre / 100 km for the diesel fleet for these representative fleets and these figures have been used as $fc_{vehicle}$ in the Turkish application.

4.1.4. Other Data

In the literature, a study that investigates the average kilometres driven by Turkish drivers was not found. As stated in Section 3.2.2.1., studies suggest that annual distances travelled are 19,000 kilometres in the US and 11,000 kilometres in EU-25 countries. Keeping in mind that the first target customers in Turkey will be commuters in big cities where the distance between commercial and industrial areas and residences are increasing it is assumed that EVs will be travelling higher than EU-25 average but still less than US where driving habits are different than Europe. Therefore, in this study vehicles in Turkey are assumed to travel 40 kilometres per day which is equal to 14,600 kilometres per annum.

Price of gasoline and diesel changes from time to time but at the time of calculation of results of the methodology, barrel price of crude oil was $95 and pump price of gasoline and diesel vehicles in Turkey was 4.3 TL/lt and 3.68 TL/lt respectively. According to PETDER's sector report the tax ratio on the gasoline and diesel pump prices are up to 67% in Turkey [3]. Therefore, in the calculation of cost of energy performance measure, end price to customers was multiplied by 0.4 to reflect an estimation of cost of fuel without taxes.

4.2. Results of Low Market Penetration Scenario

First scenario to be analyzed in the results section is the low market penetration scenario which assumes that BEVs and PHEVs will reach a market share of 2% and 5% respectively. This section focuses on the summary of these outputs from Step 1 to Step 4 for low penetration scenario, which are followed by comments on the results.

4.2.1. Step 1: Conventional Results

According to the assumptions of low market penetration scenario 130,000 passenger vehicles will be subject to comparison, 52,000 of which are gasoline powered vehicles and 68,000 of which are diesel powered vehicles. Four performance measures; annual CO_2 emissions, primary energy consumption, annual cost of energy before taxes and annual purchase cost to end users are calculated as explained in section 3.1. and the summary of results are given in Table 4.6.

Table 4.6: Results of Step 1 for Low Market Penetration Scenario

Performance Measure	Result
Annual Primary Energy Consumption	1,646 GWh
Total Fuel Pathway CO_2 Emissions	393,199 tons
Total Cost of Purchase to End User	538,728,320 TL
Total Energy Costs Before Taxes	215,491,328 TL

4.2.2. Step 2: Uncontrolled and Delayed Charge Results in Business as Usual Market Operations Results

In this subsector, results for the business as usual market operations will be given for two different charging scenarios for the low market penetration scenario. Under business as usual assumptions the marginal demand that occurs due to electric vehicle charging is supplied by accepting the cheapest bids in row at the time of demand and the energy mix and specifications of these marginal generators determine the performance measures of electric vehicle charging. Two scenario's results are given separately below.

4.2.2.1. Uncontrolled Charge Results

In the uncontrolled charge scenario for low market penetration, it is assumed that 40,000 BEV and 90,000 PHEV will be charged without any type of regulation in an uncontrolled environment. Resulting load profiles for the six representative days are given in Figure 4.1. where yellow bars show the conventional electricity load whereas black bars above are the marginal demand that is a result of electric vehicle charging. 130,000 electric vehicles being charged from the grid according to uncontrolled scenarios increases the peak demand and total electricity consumption with the values seen in Table 4.7.

With this scenario on average electricity consumption in Turkey rises by 0.14%, whereas the average peak increases by 0.21% with a maximum increase of 0.82% in December at 18:00. So it can be concluded even if the vehicles are charged in an uncontrolled way even the maximum peak increase does not put the overall electricity supply under threat in low penetration scenario, whereas local distribution affects are not considered in this study.

Table 4.7: Affects of Low / Uncontrolled Charge on Conventional Load and Peak Demand

Month	**Total Conventional Demand (MWh/day)**	**Charging Demand before Transmission Losses (MWh)**	**Increase percentage**	**Peak without Charging (MWh)**	**Peak with Uncontrolled Charging (MWh)**	**Increase in Peak**
February	598,677	864	0.14%	28,472	28,517	0.16%
April	570,353	864	0.15%	26,823	26,826	0.01%
June	566,940	864	0.15%	27,487	27,490	0.01%
August	688,521	864	0.13%	32,926	32,926	-
October	577,895	864	0.15%	27,083	27,151	0.25%
December	619,175	864	0.14%	30,114	30,362	0.82%
Average	**603,594**	**864**	**0.14%**	**28,818**	**28,879**	**0.21%**

In accordance with the daily bid data taken from TEİAŞ the details of the accepted bid pool for six representative days covering all seasons for the business as usual case are given in Table 4.8. At the bottom of the table an average value is also given which is the basis of annual results given at the end of this subsector.

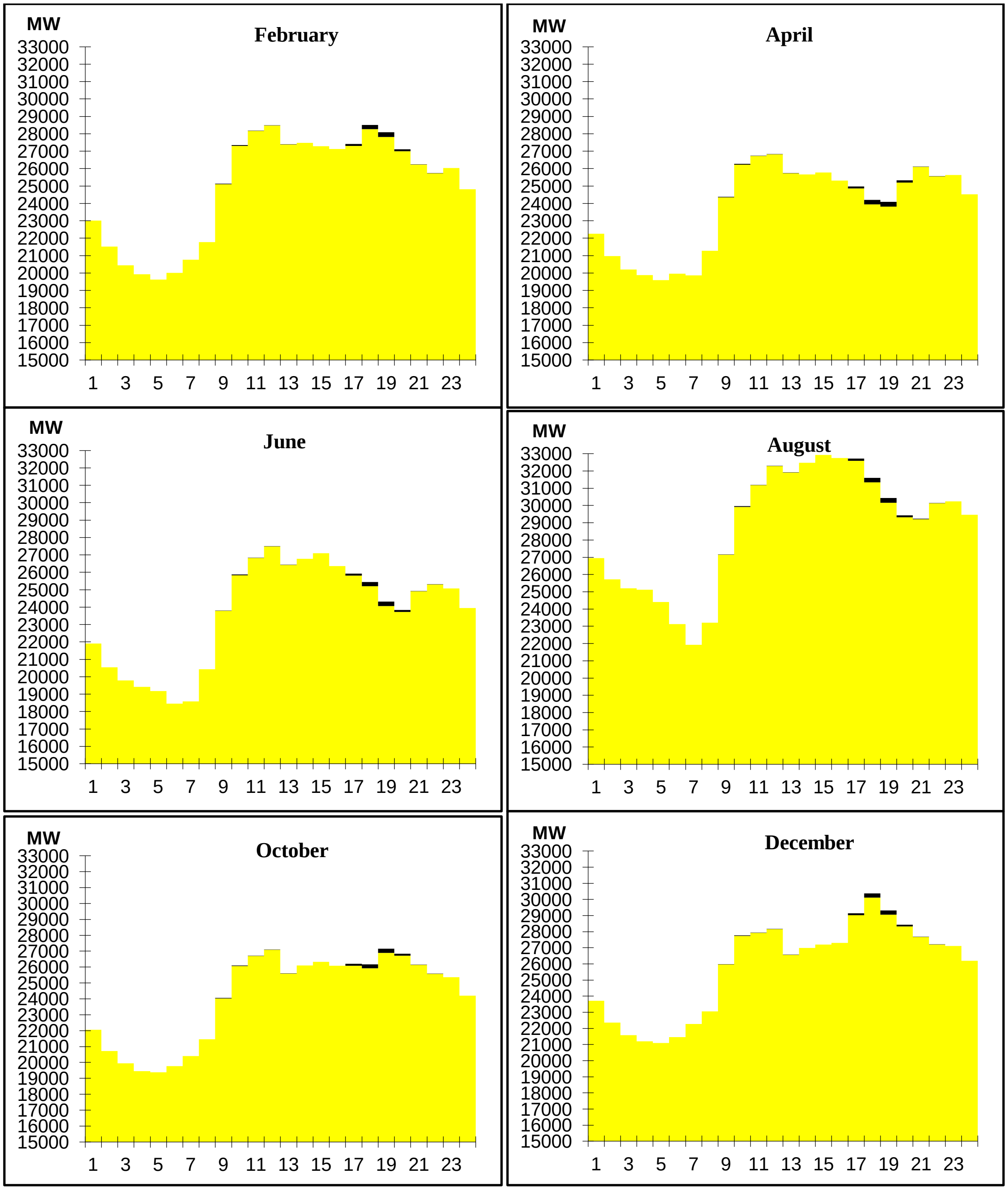

Figure 4.1: Daily Load Profile in 6 Days for Low Market and Uncontrolled Charge Scenario

Table 4.8: Daily Results of Uncontrolled Charging with Low Market Scenario

Month	Cost of Electricity Per Day (TL)	Daily CO2 Emissions (kg)	Daily Electricity (MWh)	Marginal CO2 (g/kWh)	Marginal Bid Costs (TL)	Primary Energy (GWh)
February	158,339	273,608	943	290	161,008	1,621
April	120,182	441,198	934	472	131,086	1,940
June	97,511	403,732	936	431	109,375	1,881
August	169,317	243,017	951	256	171,519	1,437
October	150,774	226,855	945	240	154,344	1,558
December	147,152	168,393	949	177	154,513	1,423
Average	140,546	292,800	943	311	146,974	1,643

In Table 4.9 energy mix for different months are seen. On average there is a balanced use between hydroelectricity sources and natural gas whereas coal takes only a total of 10% on average with help of two peaks in April (due to low cost of hydroelectricity, coal can win the bids only at higher prices) and in August (due to maximum utilization of other clean sources). This enables a low marginal CO_2 emission rate (average 311 g/kWh with a maximum 472 g/kWh in April) and low primary energy consumption as hydroelectricity dams and natural gas powered plants are the most efficient sources in the system. As expected, hydroelectricity's share in marginal supply decreases in April where the hydro capacity reaches its maximum and costs decrease to the lowest level. As the cost of hydroelectricity goes down it is consumed in the base load by the conventional demand and marginal demand is mostly supplied by natural gas plants which are down to the lowest utilization during hydroelectricity's peak. Other sources have negligible contribution to marginal demand generation in low scenario.

Table 4.9: Energy Mix of Marginal Demand for EVs in Low Scenario / Uncontrolled Charge

Month	Large Hydro Dams	River Type Dams	Lake Type Dams	Natural Gas	Hard Coal	Lignite	Export Coal	Fuel Oil	Biogas	Diesel
February	48%	0%	0%	44%	8%	0%	0%	0%	0%	0%
April	16%	2%	0%	63%	17%	0%	0%	2%	0%	0%
June	23%	0%	0%	64%	0%	4%	9%	0%	0%	0%
August	67%	2%	0%	12%	0%	0%	19%	0%	0%	0%
October	51%	2%	0%	45%	0%	3%	0%	0%	0%	0%
December	63%	2%	0%	32%	0%	2%	0%	0%	0%	0%
Average	44%	1%	0%	43%	4%	2%	5%	0%	0%	0%

By using the average figures obtained by taking 6 different representative days in 6 months that spread over the year it is possible to estimate the annual performance of uncontrolled charging scenario in order to compare with annual performance of conventional scenario. Formulas that have been used to calculate the performance measure are given in 3.3.7. Results are given in Table 4.10.

Table 4.10: Results of Step 2 for Low Market Penetration Scenario with Uncontrolled Charge

Performance Measure	Result
Annual Primary Energy Consumption	801 GWh
Total Fuel Pathway CO_2 Emissions	154,977 Tons
Total Cost of Purchase to End User	199,543,605 TL
Total Energy Costs Before Taxes	84,320,190 TL

4.2.2.2. Delayed Charge Results

In the delayed charge scenario for low market penetration, it is assumed that electric vehicles will be charged with a simple delayed approach starting at 22:00 when electricity costs without any type of regulation in an uncontrolled environment. Resulting load profiles for the six representative days are given in Figure 4.2 where yellow bars show the conventional electricity load whereas black bars above are the marginal demand that is a result of electric vehicle charging. Charging with delayed scenario increases the peak demand and total electricity consumption with the values seen in Figure 4.2.

As the total consumption does not change according to the charge scenario average electricity generation increases by 0.14%, similar to uncontrolled case. But delayed charge scenario avoids any peak increase in the system as the demand shifts from peak period to night time. Details can be seen in Table 4.11.

Table 4.11: Affects of Low / Delayed Charge on Conventional Load and Peak Demand

Month	**Total Conventional Demand (MWh/day)**	**Charging Demand before Transmission Losses (MWh)**	**Increase percentage**	**Peak without Charging (MWh)**	**Peak with Uncontrolled Charging (MWh)**	**Increase in Peak**
February	598,677	864	0.14%	28,472	28,472	0.00%
April	570,353	864	0.15%	26,823	26,823	0.00%
June	566,940	864	0.15%	27,487	27,487	0.00%
August	688,521	864	0.13%	32,926	32,926	0.00%
October	577,895	864	0.15%	27,083	27,083	0.00%
December	619,175	864	0.14%	30,114	30,114	0.00%
Average	**603,594**	**864**	**0.14%**	**28,818**	**28,818**	**0.00%**

Details of the accepted bid pool for six representative days with the business as usual case with delayed charging are given in Table 4.12.

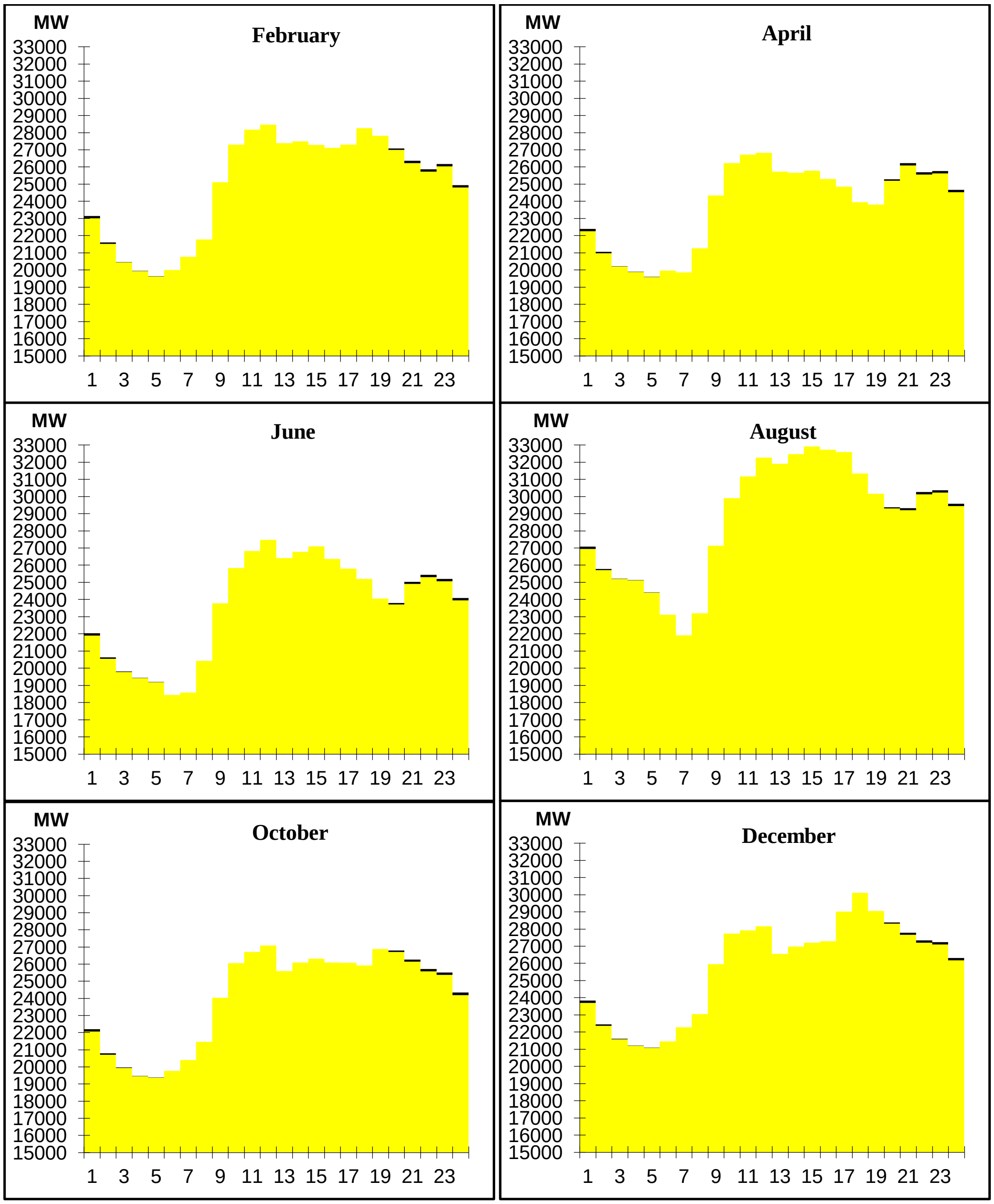

Figure 4.2: Daily Load Profile in 6 Days for Low Market and Delayed Charge Scenario

Table 4.12: Daily Results of Delayed Charging with Low Market Scenario

Month	Cost of Electricity Per Day (TL)	Daily CO2 Emissions (kg)	Daily Electricity (MWh)	Marginal CO2 (g/kWh)	Marginal Bid Costs (TL)	Primary Energy (GWh)
February	133,351	448,295	933	481	141,079	2,000
April	107,066	353,951	945	375	118,370	1,881
June	109,716	415,516	932	446	112,201	2,037
August	164,516	361,035	945	382	165,799	1,632
October	137,405	368,780	937	394	142,996	1,836
December	113,249	394,411	933	423	119,397	1,950
Average	**127,551**	**390,331**	**937**	**417**	**133,307**	**1,889**

In Table 4.13 energy mix for different months are seen. Delayed charging energy mix shows significant variance compared to uncontrolled charge scenarios. The main reason is the availability of cheaper fossil fuel powered power plants at off-peak times. On average natural gas powered plants supply 68% of marginal electricity for EV charging, peaking at 94% at June where hydro capacity is low. Share of hydroelectric sources drop to 21% on average. This result is aligned with the expected emission increase in delayed charge scenarios as the fossil fuels share increases compared to uncontrolled case. On average marginal CO_2 emission rate is 417 g/kWh with a maximum 481g/kWh in February. Coal plants are not getting a significant share which avoids electric vehicles to be more polluting than conventional cars.

Estimation of annual performance of EVs charged under delayed charging scenario is given in Table 4.14:

Table 4.13: Energy Mix of Marginal Demand for EVs in Low Scenario / Delayed Charge

Month	Percentage of Primary Energy Source in Marginal Generation									
	Large Hydro Dams	River Type Dams	Lake Type Dams	Natural Gas	Hard Coal	Lignite	Export Coal	Fuel Oil	Biogas	Diesel
February	11%	0%	0%	75%	13%	0%	0%	2%	0%	0%
April	22%	0%	0%	76%	0%	3%	0%	0%	0%	0%
June	1%	3%	0%	94%	0%	2%	0%	0%	0%	0%
August	52%	0%	0%	20%	2%	0%	27%	0%	0%	0%
October	25%	1%	0%	66%	0%	9%	0%	0%	0%	0%
December	11%	2%	0%	80%	0%	2%	2%	2%	0%	0%
Average	20%	1%	0%	68%	2%	3%	5%	1%	0%	0%

Table 4.14: Results of Step 2 for Low Market Penetration Scenario with Delayed Charge

Performance Measure	Result
Annual Primary Energy Consumption	889 GWh
Total Fuel Pathway CO_2 Emissions	190,088 Tons
Total Cost of Purchase to End User	179,229,570 TL
Total Energy Costs Before Taxes	79,399,939 TL

4.2.2.3. Comments on Step 1 and Step 2 Results

Literature related to EVs in Turkey has been missing a comparison that took different charge scenarios into account and which based calculation on real market data to determine marginal generators. At the end of Step 2, it is possible to compare the performance of the conventional fleet with the performance of EV's that are charged based on two most likely charge scenarios without any optimization effort.

Due to inefficiency of internal combustion engine powered vehicles, EV fleet surpasses conventional fleet's primary energy consumption even though losses in electricity supply chain such as losses in charger, transmission and distribution systems were taken into account. According to the low market scenario, a fleet consisting of 52,000 gasoline powered and 68,000 diesel powered vehicles would consume a total of 1,646 GWh of primary energy stored in crude oil in order to drive 14,000 kms annually. On the other hand EV fleet would consume 801 GWh if uncontrolled charge scenario happens and 889 GWh if delayed charging is encouraged by price tariffs. The main reason of the energy consumption's increase in delayed scenario is the increase in the percentage of fossil fuel powered plants' share in marginal energy mix from an average of 54% to 79% as seen in Figure 4.3 and Figure 4.4. As the efficiency of these plants are lower than hydroelectcity dams the overall energy consumption increases but even in this case it is possible to save 757 GWh annually by changing conventional vehicles with a fleet of BEVs and PHEVs.

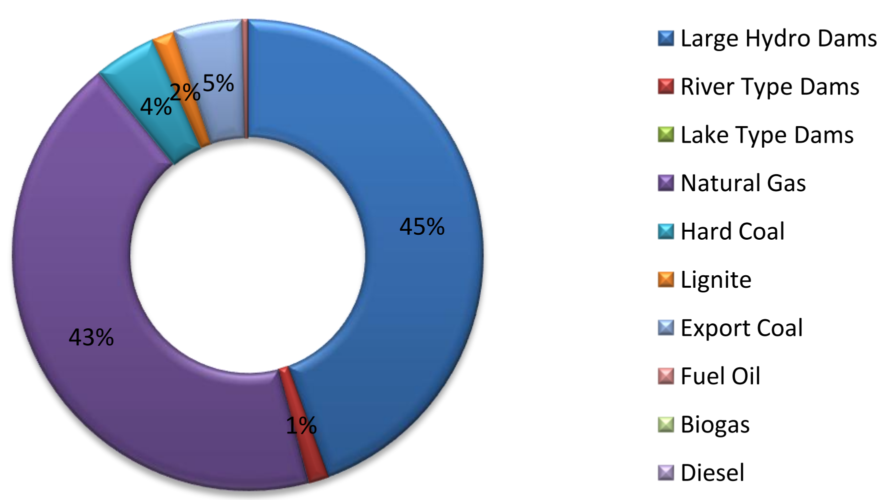

Figure 4.3: Energy Mix of Marginal Generators for Low Penetration/Uncontrolled Charge

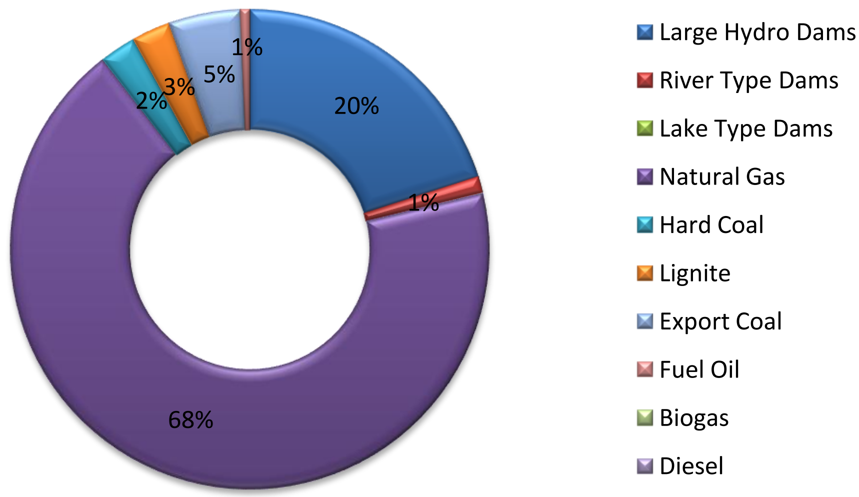

Figure 4.4: Energy Mix of Marginal Generators for Low Penetration/Delayed Charge

Second performance measure where EVs perform better than conventional fleet is CO_2 emissions. Inefficiency coupled with carbon intensity of conventional fuels lead to a very high CO_2 emission per kilometre for conventional vehicles. A conventional fleet of 130,000 vehicles driving emit 393,199 tons of CO_2 annually, which is equal to 207.2 g CO_2/km. On the other hand EVs emit 154,977 Tons when charged with uncontrolled scenario and 190,088 Tons when charged with delayed scenario in Turkey which is equal to 73.9 and 91.5 g CO_2/km emissions respectively. Similar to the primary energy consumption comparison uncontrolled scenario performs better in this performance measure as well due to higher share of clean sources of energy. Nevertheless, delayed scenario is shown to decrease the emissions as well, so the claim of performing worse than conventional vehicles when charged in late hours is not valid under the assumptions of this methodology. In Figure 4.5, life cycle emissions of three different scenarios are compared which clearly shows how clean EVs can be in Turkey even without any optimization effort.

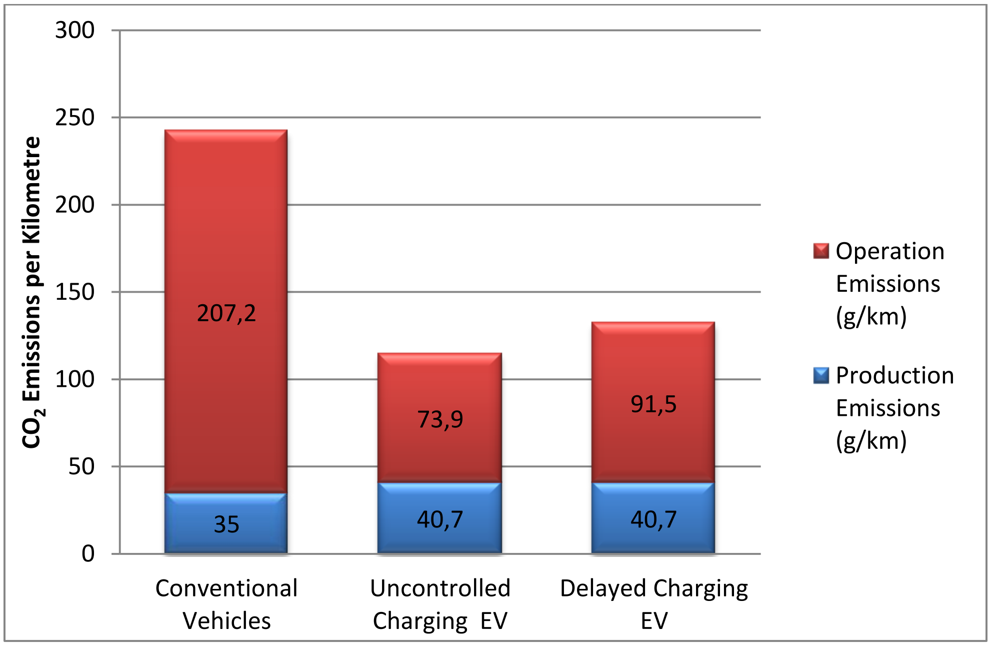

Figure 4.5: Comparison of Emissions per Kilometre for Step 1 and 2

The most significant advantage of the EVs compared to conventional vehicles is the cost measure. The approximate annual cost of energy purchase costs before taxes for conventional fleet of 130,000 vehicles is approximately 359 million TL whereas when taxes are added this figure increases to total of 538 million TL for end users at the gas station. By driving more efficient electric powered vehicles and utilizing the advantage of cheap energy cost of electricity compared to gasoline and diesel prices, end users can bring down the total costs to 179 million TL with delayed charge and 199 million TL with uncontrolled charge. In Figures 4.6 and 4.7 primary energy and CO_2 emission performances are compared together with the cost effect.

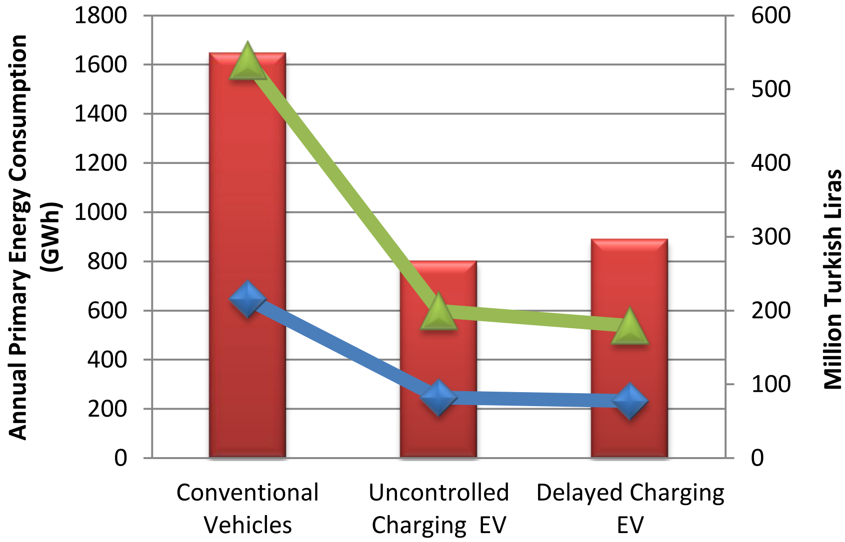

Figure 4.6: Comparison of Primary Energy Consumption and Costs for Step 1 and Step 2 for Low Market Penetration Scenario

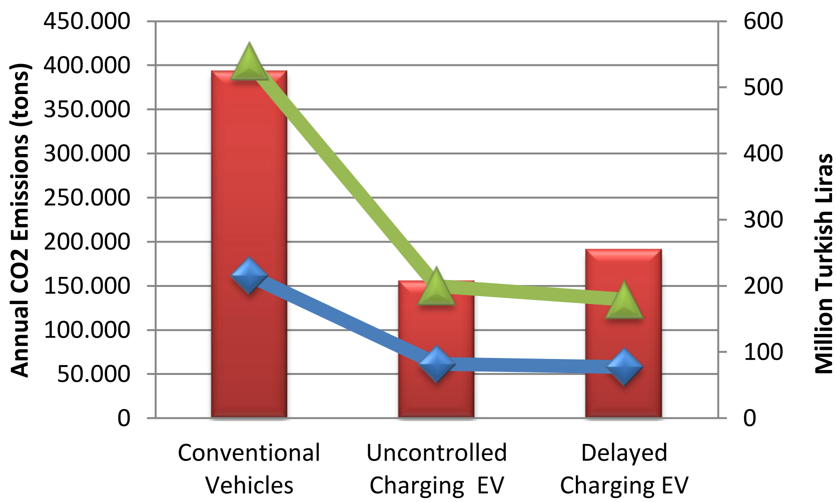

Figure 4.7: Comparison of Annual Emissions and Costs for Step 1 and Step 2 for Low Market Penetration Scenario

In summary, independent of the charging scenario, electric vehicles are shown to consume approximately half the primary energy of conventional vehicles, while emitting 39% (uncontrolled) to 48% (delayed) less CO_2 in the end-to-end view for a smaller purchase cost to the end user with the market structure as of 2012 in Turkey.

4.2.3. Step 3: Uncontrolled and Delayed Charge Results with Bi-Objective Optimization Results

Steps 2 did not include any different decision making method other than business as usual dispatching, which works with the merit order method, accepting the bid that is the cheapest. In Step 3, by applying bi-objective optimization, it is analyzed if a significant decrease in emissions might be achieved by introducing CO_2 emissions as an objective function to the model. The assumptions of the size of the fleet and charging scenarios and technical charging parameters are equal to those used in step 2 and the only change is the rule set of the dispatch problem.

The solutions picked up by the merit order method, which were the results analyzed in Step 2, are always the cheapest solutions but by accepting more expensive orders from cleaner sources it is possible to decrease the emissions further. For each month bi-objective optimization is run for two different charge scenarios and the solutions creating the efficient frontier are analyzed in detail. As the number of solution makes it impossible to compare each of them and as there is a necessity to compare performance of different months and compare the results with first two steps a rule to pick certain solutions was set. First of two comparison points is the solution where the share of coal generators drop to 0%. The reason is the speed of decrease in emissions by interchanging coal generators which emit 1000-1100 g CO_2/kWh with clean sources that were not accepted because of their bid price in merit order dispatch. This will be referred as solution A and related solution in graphs will be pointed A in the graphs.

Second solution that will be analyzed is the cleanest possible solution which is feasible at the time of charging. This is analyzed to see how the system would perform in a case were environmental objective function dominates the economic one. Related solution will be referred as solution B in the text and graphs will be marked with a B to show were the solution falls in the efficient frontier.

Model was run for 6 days in 6 different months similar to Step 2 and all solutions were analyzed. Efficient frontiers of 6 months for two different scenarios are shown in Figures 4.8 to 4.13 where solutions A and B are clearly marked.

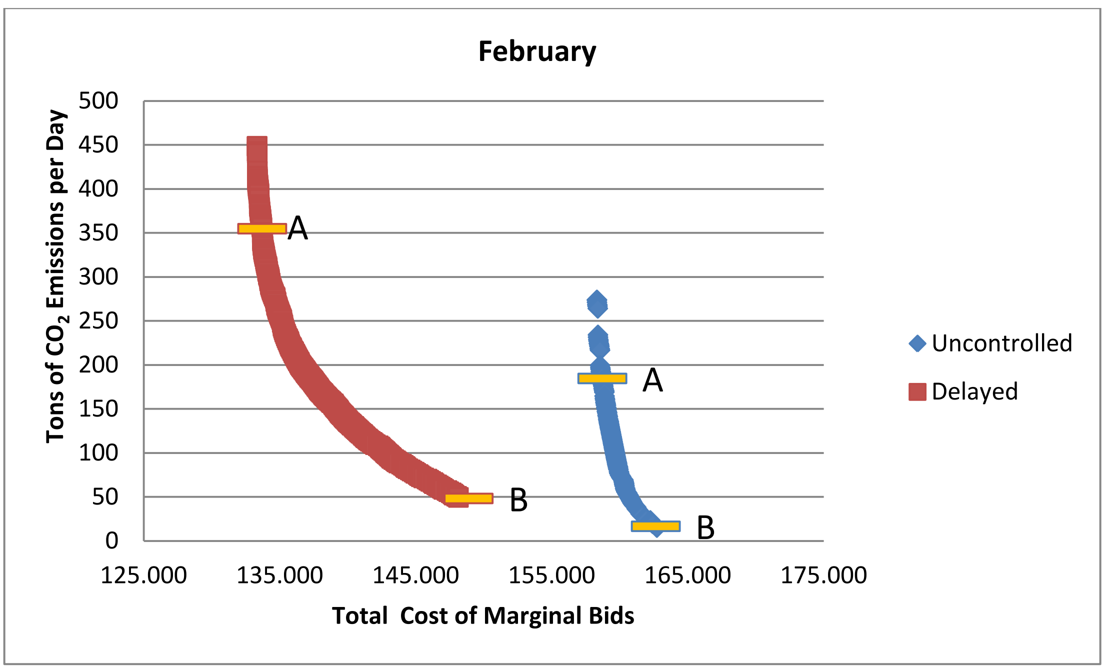

Figure 4.8: Efficient frontier on February 10 for Low Market Scenario

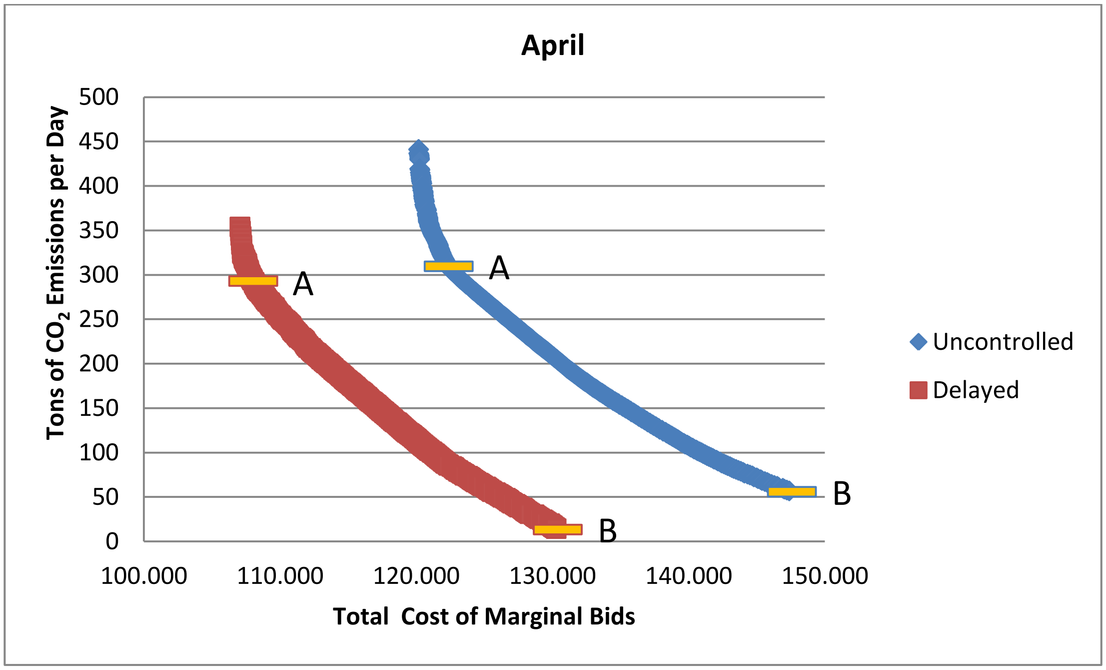

Figure 4.9: Efficient frontier on April 14 for Low Market Scenario

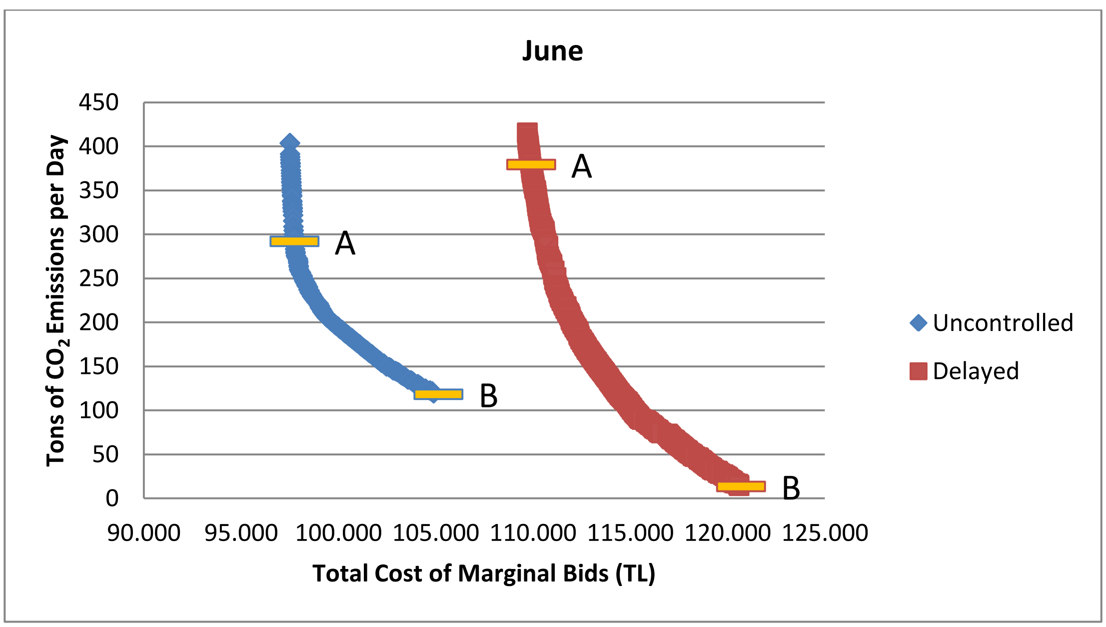

Figure 4.10: Efficient frontier on June 9 for Low Market Scenario

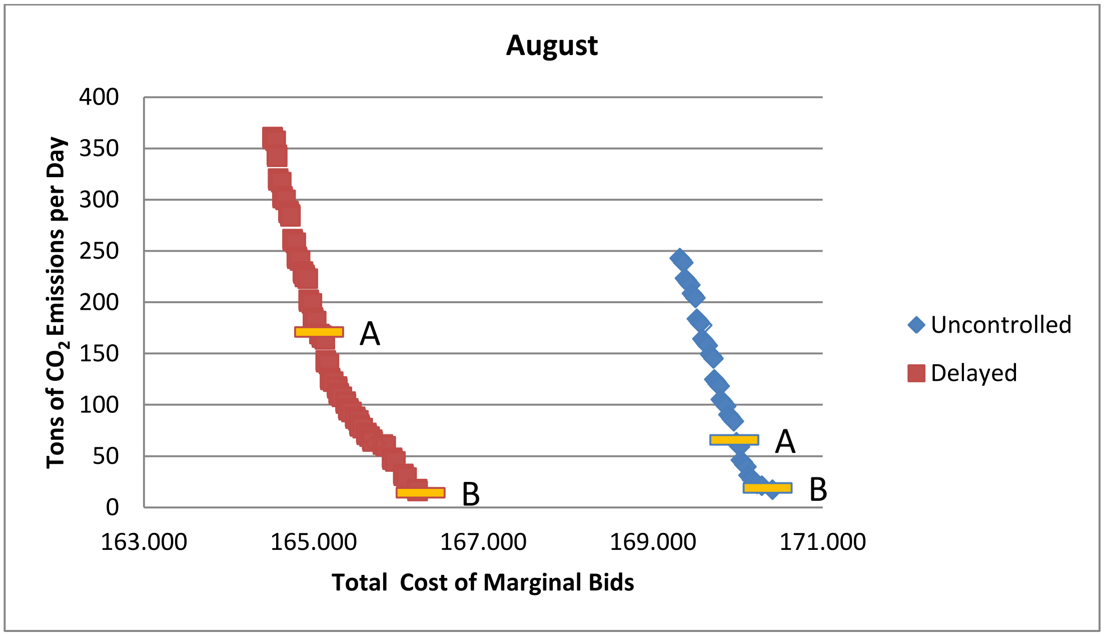

Figure 4.11: Efficient frontier on August 11 for Low Market Scenario

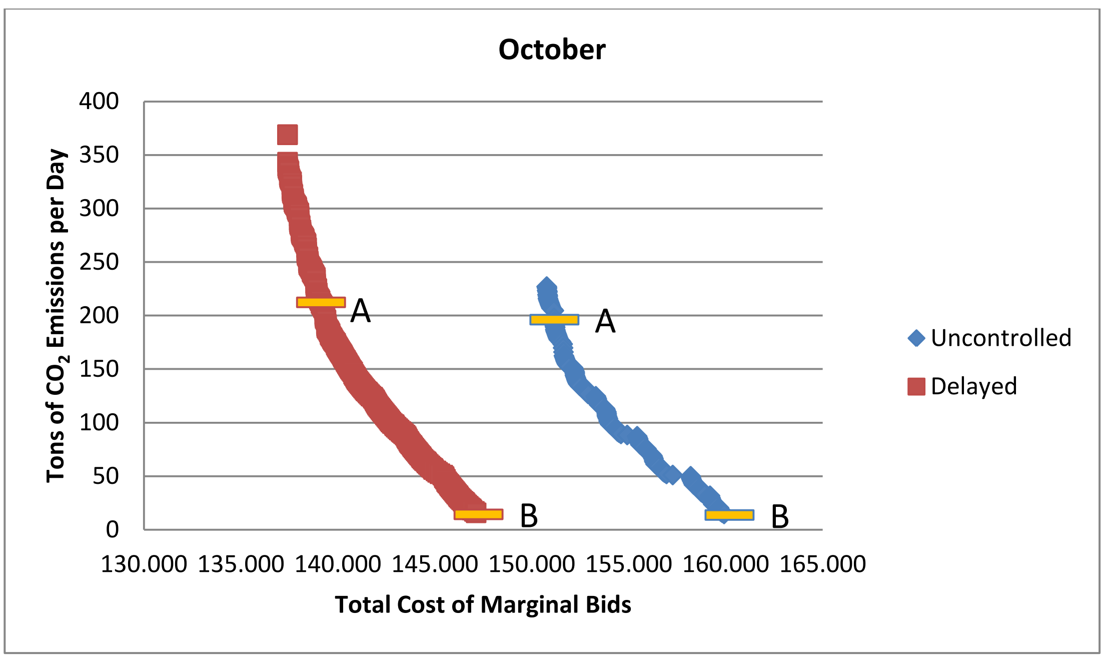

Figure 4.12: Efficient frontier on October 13 for Low Market Scenario

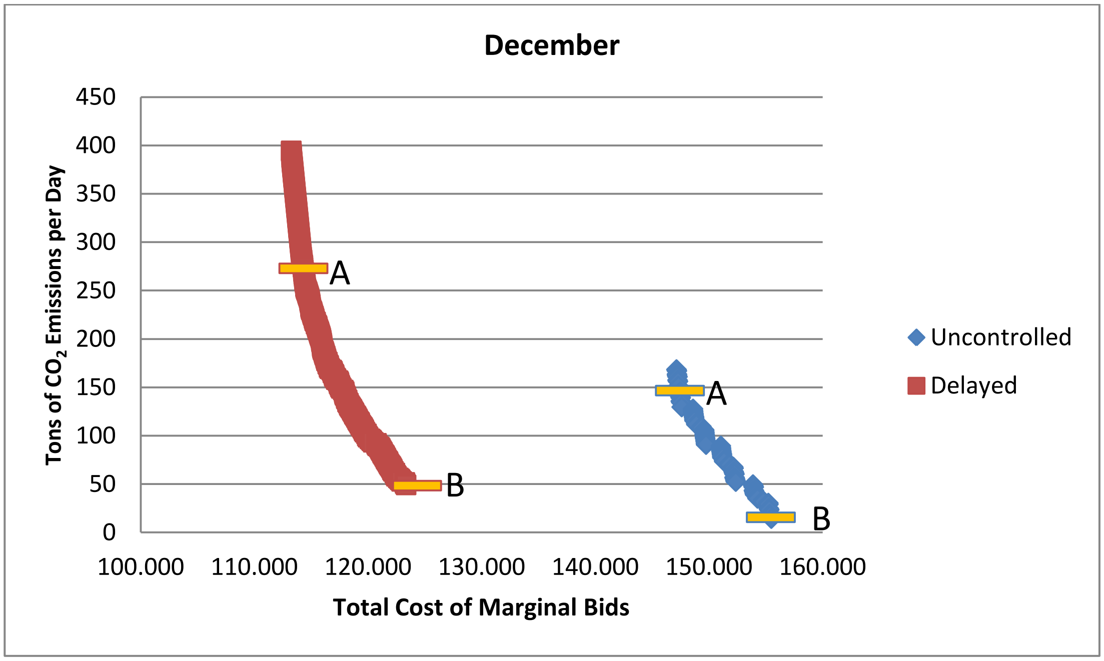

Figure 4.13: Efficient frontier on December 8 for Low Market Scenario

As it can be seen in efficient frontier figures, delayed scenario starts from a cheaper solution due to low cost of electricity in the night hours but it emits more CO_2 compared to uncontrolled scenario in 4 months (February, August, October and December) out of 6. From the start points, which correspond to Step 2 results, a sharp decrease to solution A is reached by interchanging coal powered generators with large hydro generator which emit less CO_2 for bids prices that are close to coal generators. Once coal's contribution to marginal energy mix drops to 0%, the speed of decrease slows down as further decreases are only reached by increasing the share of large hydro generators in expense of natural gas stations. This relation is clearly visible in example figures from February and October in Figures 4.14 and 4.15. Rest of the marginal mix change figures can be found in Appendix A.

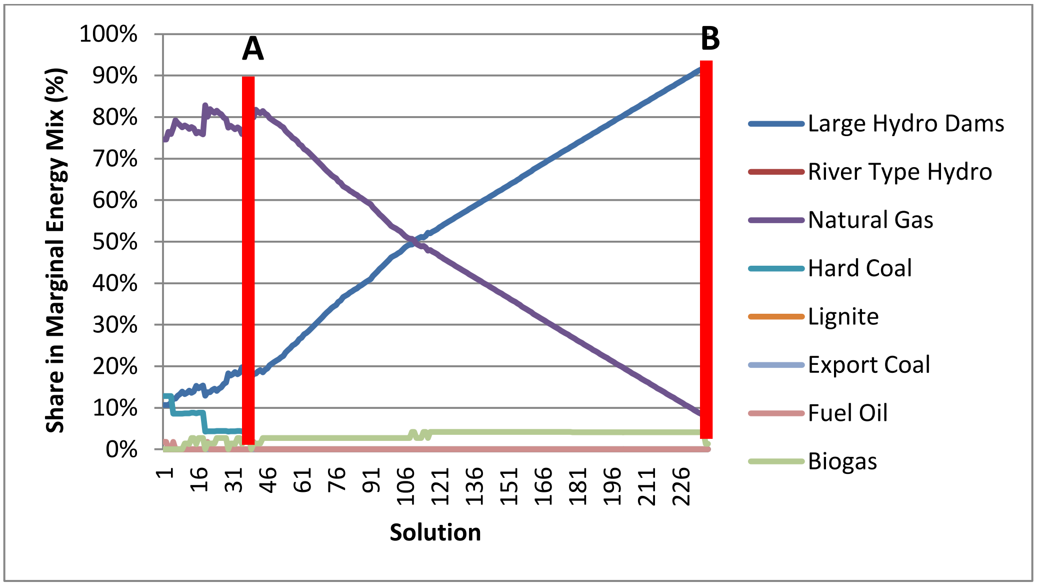

Figure 4.14: Change of marginal energy mix in Step 3 solutions for February delayed charging

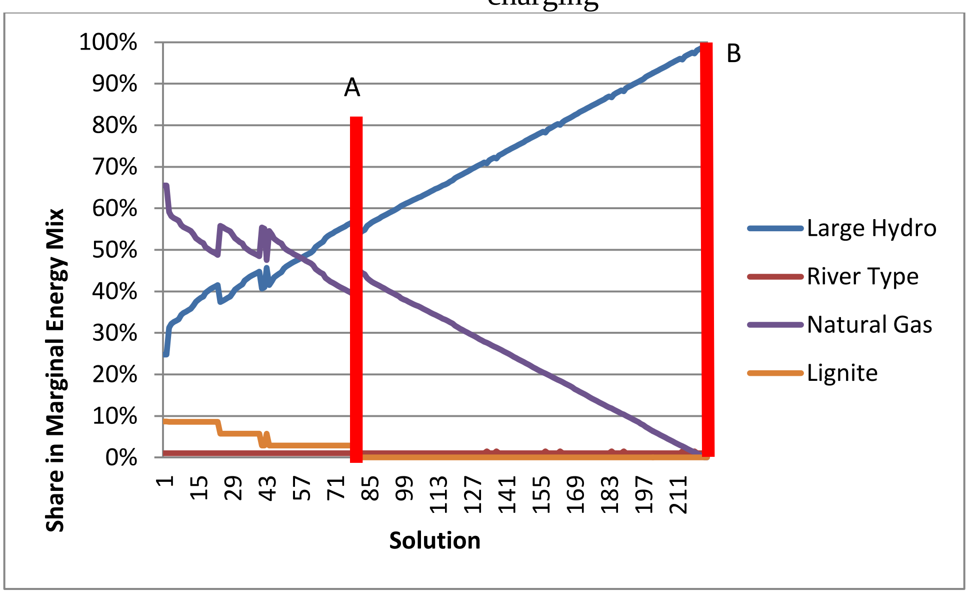

Figure 4.15: Change of marginal energy mix in Step 3 solutions for October delayed charging

Depending on the season of the year, the marginal energy mix shows variance which changes the performance of EVs. This variance is reflected into end to end CO_2 emissions of EVs as shown in Figure 4.16. The case where EVs perform worst in CO_2 emissions is February delayed charging where coal power generators have a share of 12% and natural gas has 74%. Even with this worst case scenario, EVs outperform conventional vehicles by emitting approximately half the $CO_{2.}$ Cleanest possible charging energy mix occurs in solution B of delayed charging cases where 100% of the marginal mix can be supplied by hydroelectricity generators. This case can only be achieved in the expense of an increase in the energy costs in the daily electricity market. Effects are visible in Figure 4.17 and 4.18 where every scenario's primary energy and daily total CO_2 emissions are compared against the cost performances. The purchase cost for end users stay stable whereas the purchase cost varies from 7,6 million liras to 5,8 million liras depending on the market conditions. Detailed numerical results are given in Appendix A.

A comparison with first two steps can be achieved by taking the average of solution A and B for every month and approximating annual performance of electric vehicles. CO_2 emissions per kilometre can be decreased down to 58 g CO_2/km in uncontrolled scenario and to 72 g CO_2/km in delayed scenario by interchanging coal bids with more clean sources at the time of charging. Similar to Step 2 results delayed charging is more polluting than uncontrolled charge scenario but both cases outperform conventional vehicles. The cleanest possible option to charge the electric vehicles under the assumptions of this methodology is to charge the vehicles with delayed scenario and then apply solution B which selects the cleanest possible energy mix lying on the efficient frontier. By doing so it is possible to reach an energy mix that only uses hydroelectricity and CO_2 emissions from operations can be taken down to 26 g CO_2/km compared to a lowest level of 29 g CO_2/km in solution B average of uncontrolled scenario. The reason for this is the increased number of hydroelectricity sources that are available in the bid pool at delayed hours where the conventional load is lower than peak hours of uncontrolled charging when hydro capacity is consumed by conventional load. Figure 4.19 visualizes the comparison of CO_2 per km.

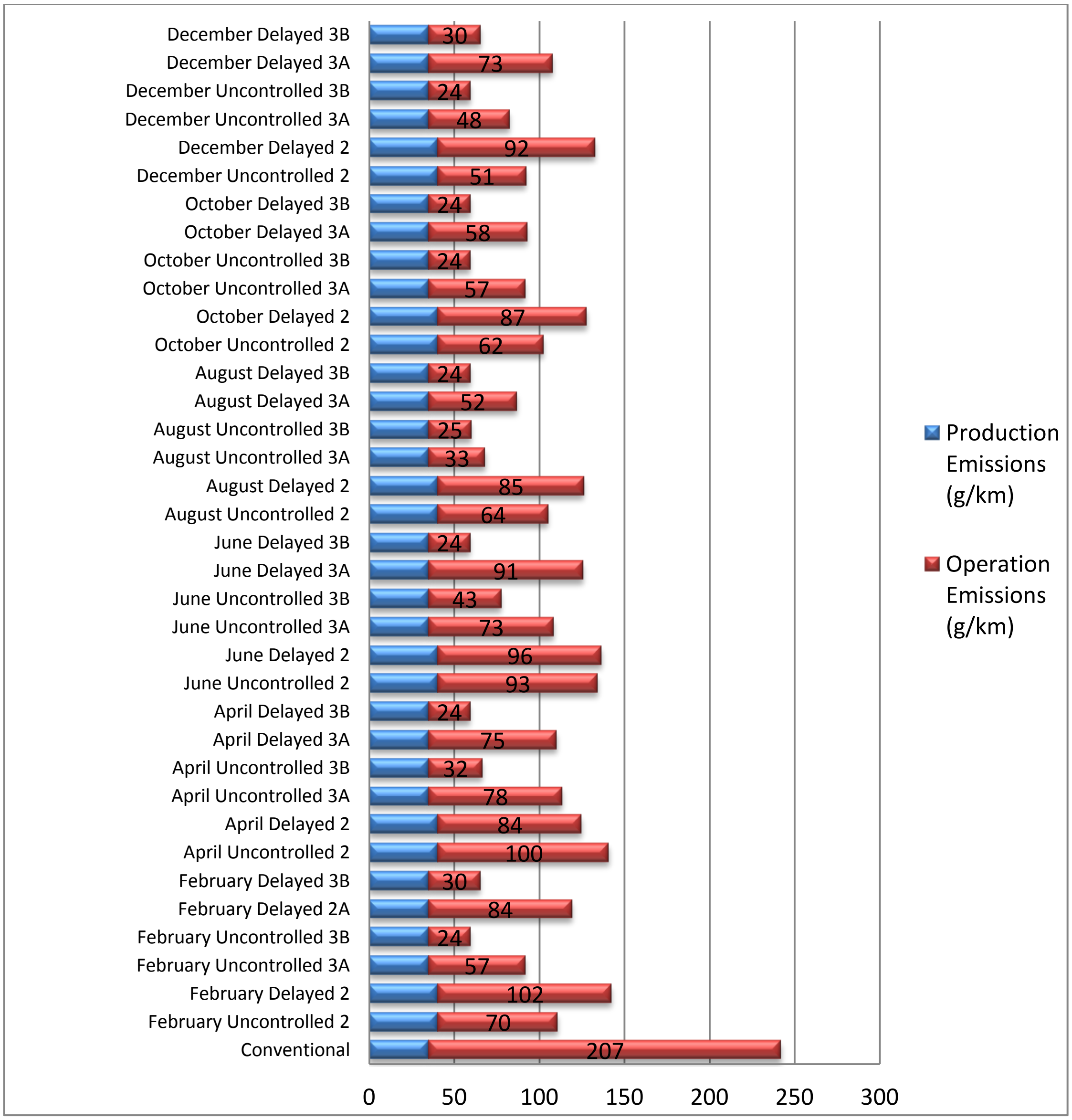

Figure 4.16: Comparison of End to end CO2 emissions for different charging scenarios/months

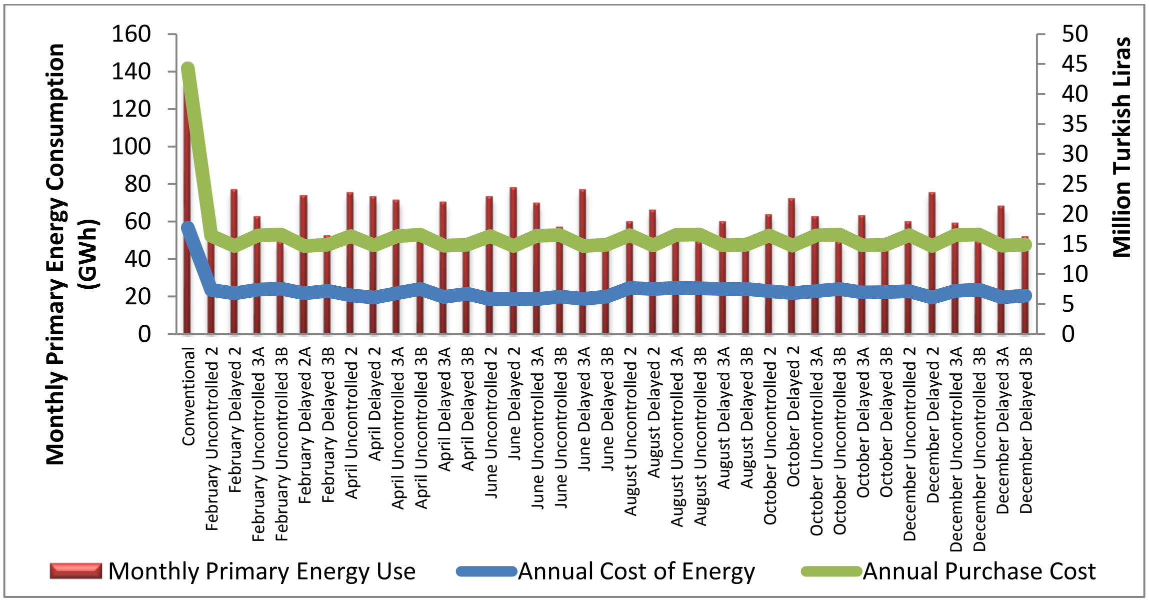

Figure 4.17: Primary energy consumption compared against cost measures for all scenarios

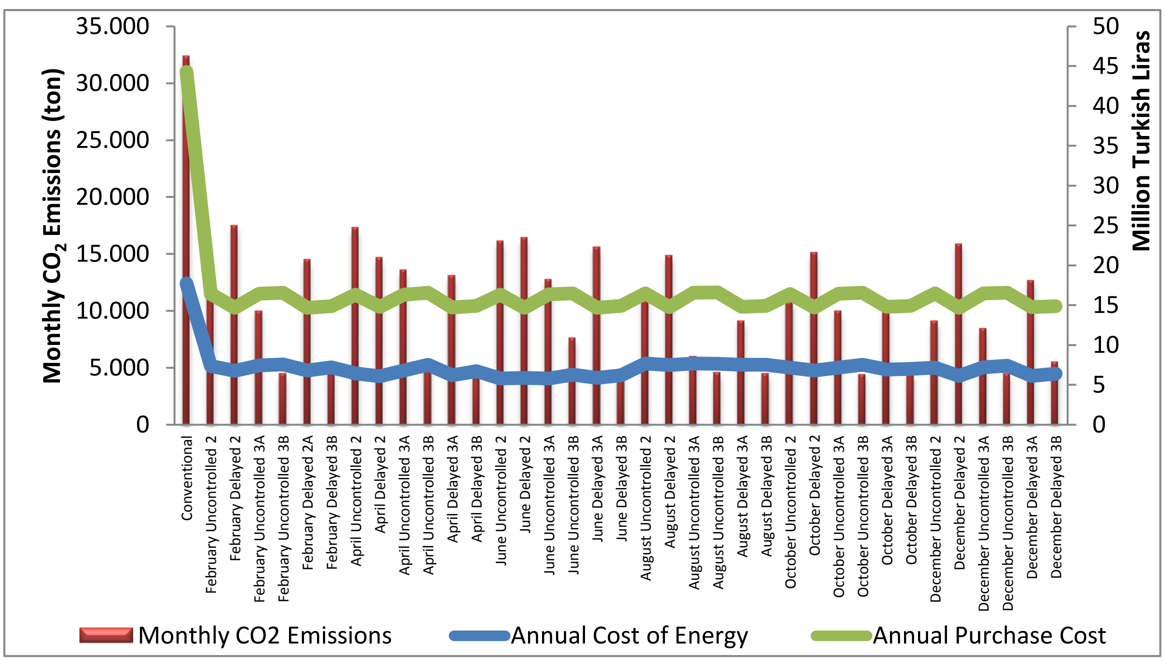

Figure 4.18: Monthly CO_2 emissions compared against cost measures for all scenarios

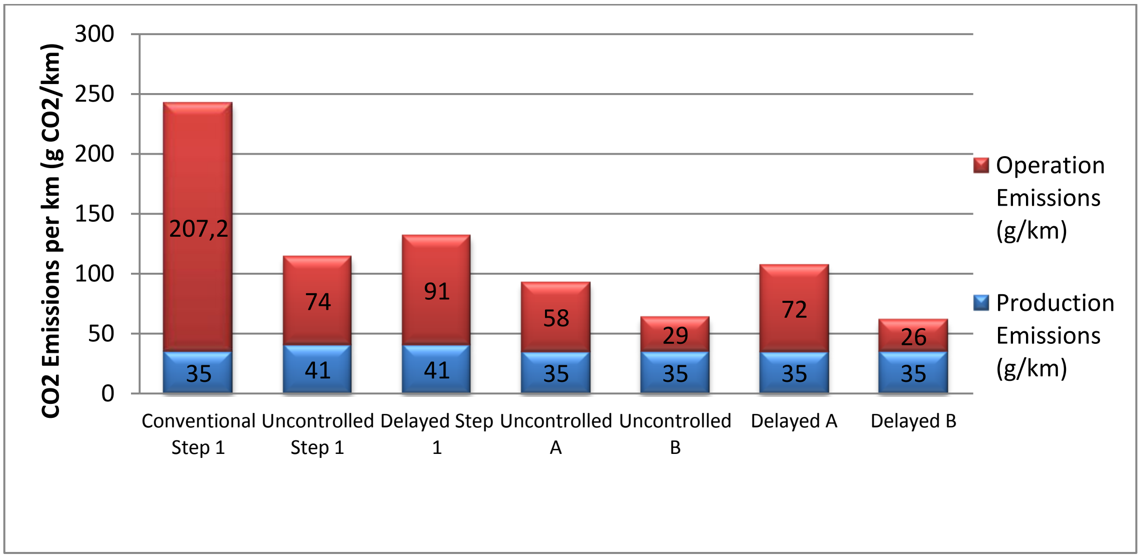

Figure 4.19: Comparison of Emissions per Kilometre for Step 1, 2 and 3

Performance measures for different steps of Uncontrolled and Delayed charging scenarios are compared in Tables 4.15 and 4.16.

Table 4.15: Comparison of annual performance of Step 3 results for Uncontrolled Scenario

	Step and Solution			
Performance Measure	**Conventional**	**Uncontrolled**	**Uncontrolled A**	**Uncontrolled B**
Annual Primary Energy Consumption	1,646 GWh	801 GWh	754 GWh	609 GWh
Total Fuel Pathway CO_2 Emissions	393,199 tons	154,977 Tons	121,004 Tons	61,912 Tons
Total Cost of Purchase to End User	538,728,320 TL	199,543,605 TL	199,543,605 TL	199,543,605 TL
Total Energy Costs Before Taxes	215,491,328 TL	84,320,189 TL	85,325,230 TL	88,981,671 TL

Application of bi-objective optimization to the marginal dispatch model, clarifies the possibilities to decrease emission further by increasing the cost. In controlled scenario, merit order dispatch used to decrease primary energy consumption by 52%, annual CO_2 emissions by 61% and purchase costs to end users by 63%. When the second objective function is introduced and all coal powered generators are taken out of marginal energy mix, it is possible to have an extra 33,973 tons decrease in annual CO_2 emissions in expense of a 1,005,041 TL. This is equal to a 29.5 TL/ ton CO_2 cost addition to decrease emissions. A further decrease can be achieved by accepting cleaner solutions in the efficiency set and in order to reach the cleanest possible solution. This option (solution B) would increase the costs by 3,656,441 TL compared to solution A, and decrease the emission by 59,092 tons. As it becomes less cost efficient to decrease emissions after removing coal generators from the system, costs to save one ton of CO_2 increase to 61.8 TL/ ton CO_2 from point A to B.

Table 4.16: Comparison of annual performance of Step 3 results for Delayed Scenario

	Step and Solution			
Performance Measure	**Conventional**	**Delayed**	**Delayed A**	**Delayed B**
Annual Primary Energy Consumption	1,646 GWh	889 GWh	822 GWh	598 GWh
Total Fuel Pathway CO_2 Emissions	393,199 tons	190,088 Tons	149,941 Yons	57,030 Tons
Total Cost of Purchase to End User	538,728,320 TL	179,229,570 TL	179,229,570 TL	179,229,570 TL
Total Energy Costs Before Taxes	215,491,328 TL	79,399,938 TL	80,002,773 TL	83,161,099 TL

The same relation applies to delayed scenario's results with different parameters. From Step 2 results of delayed charging it is possible to decrease the emissions by 40,147 tons by increasing the annual costs by 602,834 TL. This decrease is even sharper than the drops in uncontrolled case because cost to decrease one ton of CO_2 drops to 15 TL/ ton CO_2. If the emissions are required to be decreased further, the total costs can be increased by 3,158,326 TL to enable a 92,911 tons savings in annual CO_2 emissions. This is equal to a 33.9 TL/ton CO_2 decrease cost.

In summary, delayed charging starts with an emission disadvantage over uncontrolled charging for a cheaper cost but it enables to decrease emissions more effectively than uncontrolled charge as the clean sources become abundant. Comparison of annual performance measures for Step 3 with previous steps is in Figures 4.20 and 4.21.

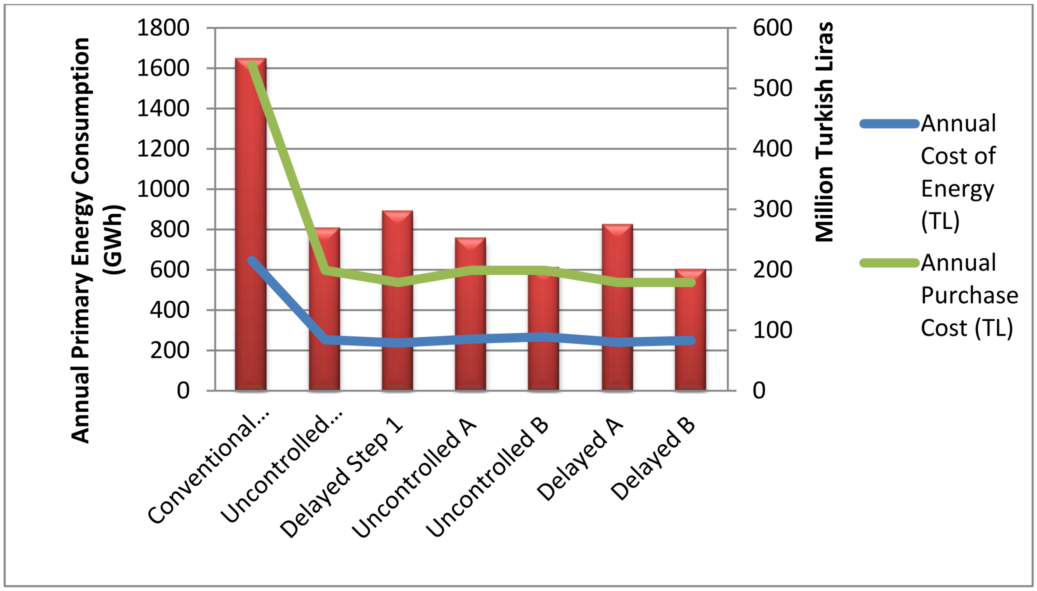

Figure 4.20: Annual primary energy consumption comparison of Steps 1-2-3

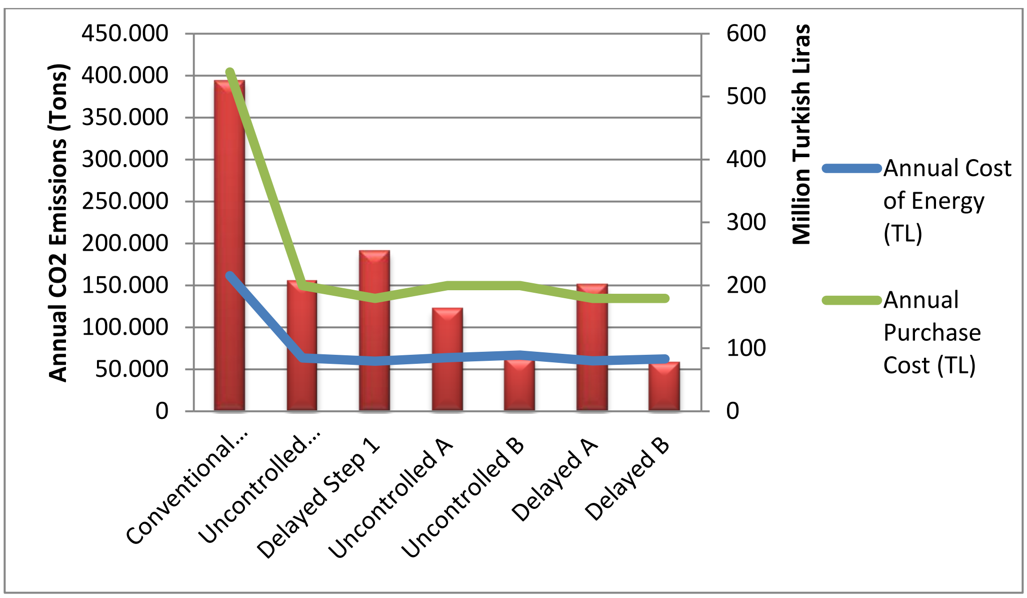

Figure 4.21: Annual CO_2 emissions comparison of Steps 1-2-3

4.2.4. Step 4: Hour Optimization Results

The fourth and last step of the methodology includes running the dispatch models with the charging hours defined as decision variables instead of predefined scenarios that limit the feasible set of solutions. Once the hours are defined as variables in the bi-objective model, solutions picked up show efficient frontier from the cheapest solution to the cleanest one. Only limitations on the charging hours are the rush hour constraints which limit the percentage of vehicles that can be charged in rush hours as the cars will most likely be on the roads. All other parameters are constant compared to previous steps.

Efficient frontiers are seen in Figures 4.22 to 4.27 where the comparison with Step 3 results is clearly visible. In majority of the months, Step 4 solutions start from the most polluting but the cheapest solution by moving the charging hours to hours where the conventional consumption is the lowest. By doing so, the dispatch model utilizes cheap energy sources such as coal to charge the EVs but the emissions climb to higher levels compared to previous steps.

In order to compare the results with previous steps, average of cheapest results (merit order) in 6 months and least polluting results in 6 months are taken. In the cheapest hours average contribution of fossil fuels climb up to 84% in the marginal energy mix (with a maximum of 99% in October) due to high share of fossil fuels in cheapest hours compared to 54% in uncontrolled scenario and 79% in delayed scenario. Therefore the CO_2 emissions in hour optimization model gives the maximum emission level compared to results of step 2 and 3. Nevertheless as it can be seen in Figure 4.28, EVs still emit less CO_2 compared to conventional vehicles.

Hours for cheapest charging are found to be hours from 03:00 am to 07:00 am. For the case of Turkey, this means if policies that encourage charging in early morning hours can be installed, any impact due to extra load of electric vehicles can be avoided, with a lower cost and emissions that still outperform conventional vehicles. If those emission levels are found to be high, than results of bi-objective optimization shows that it is possible to further decrease emission for an average CO_2 decrease cost of 64 TL/ton CO_2. There are some cases where a very efficient drop of emissions is possible. April efficient frontier is a very good example of this case (Figure 4.23). Although total emissions start from a higher point that uncontrolled and delayed scenarios, a very fast drop in emissions can be achieved by interchanging hard coal and natural gas bids with large hydro bids that are very close in bid prices. The cost to decrease one ton of CO_2 drops to 0.8 TL / ton of CO_2. This is a very efficient drop level which can be missed if only merit order dispatch is used. Therefore, these results highlight the necessity of tools that are able to track and determine those fast decreasing efficient frontiers and change the decision making procedure to benefit from the opportunity to decrease emissions in a cost effective way.

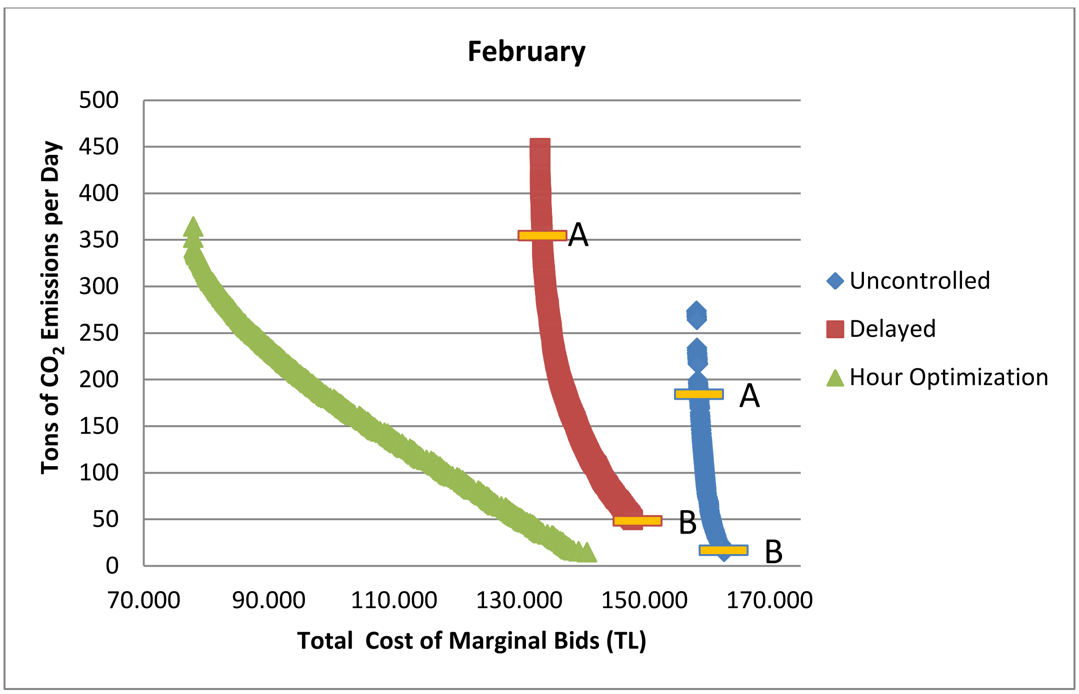

Figure 4.22: Efficient frontier on February 10 for Low Market Scenario Step 4

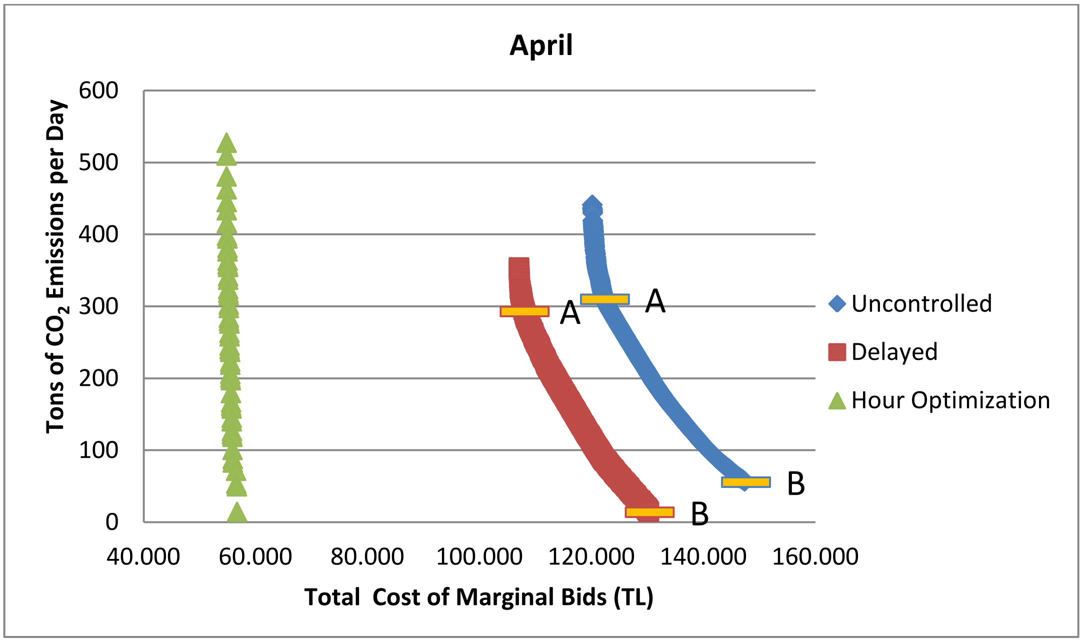

Figure 4.23: Efficient frontier on April 14 for Low Market Scenario Step 4

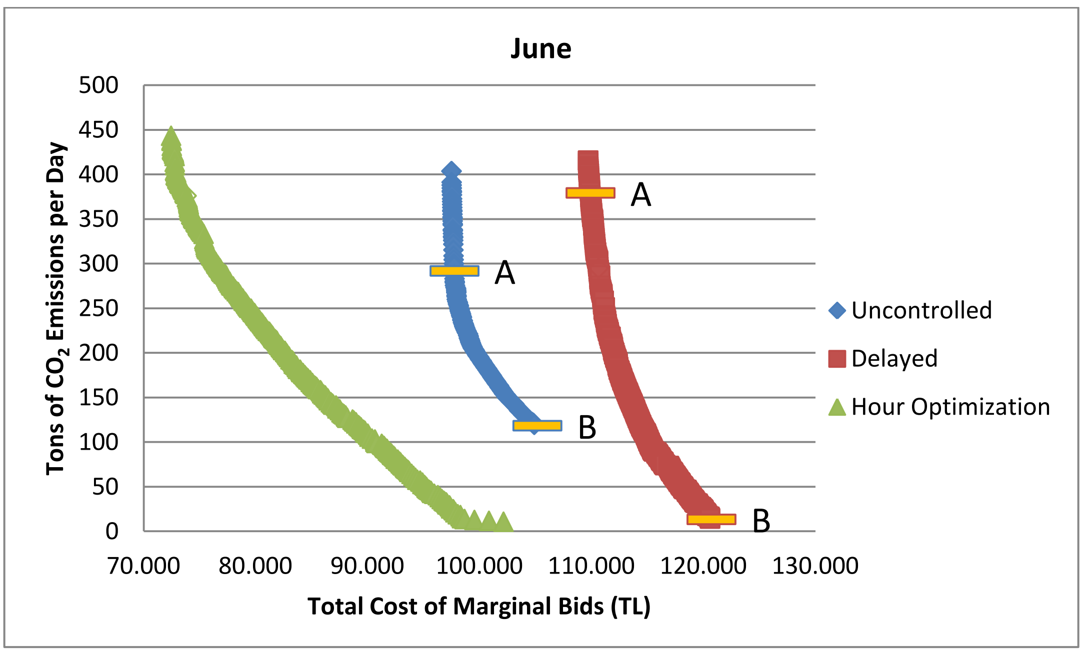

Figure 4.24: Efficient frontier on June 9 for Low Market Scenario Step 4

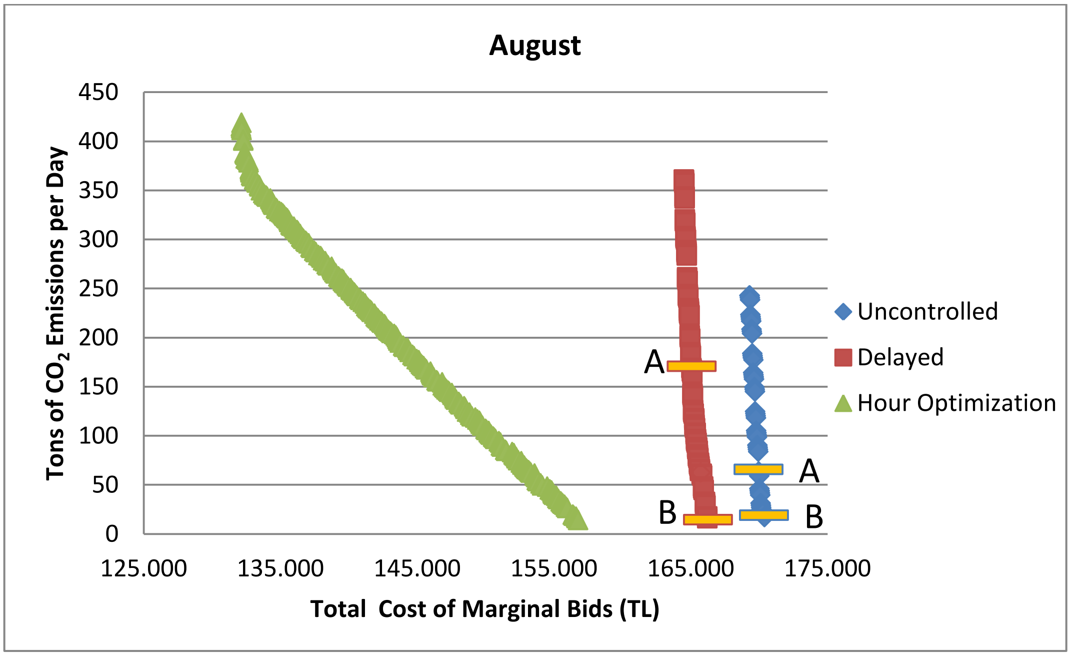

Figure 4.25: Efficient frontier on August 11 for Low Market Scenario Step 4

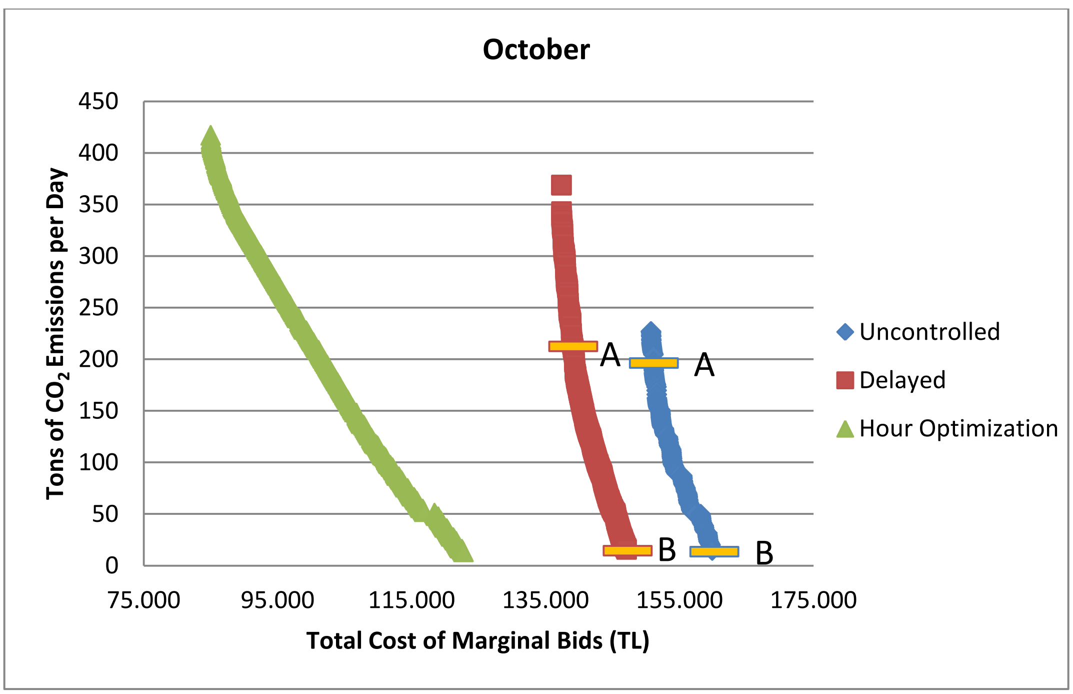

Figure 4.26: Efficient frontier on October 13 for Low Market Scenario Step 4

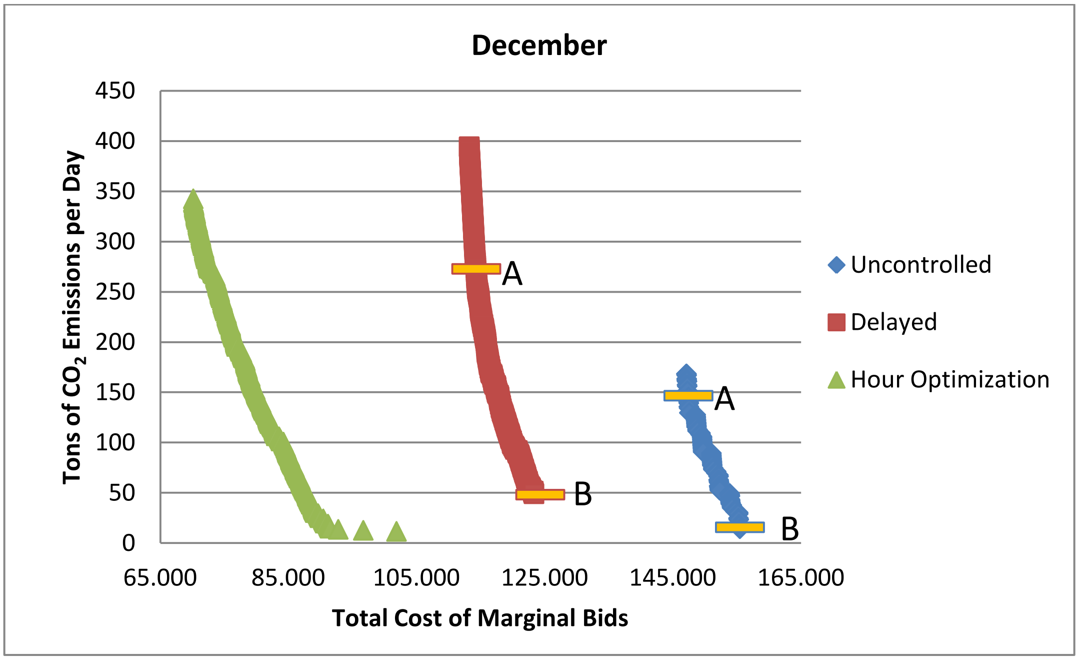

Figure 4.27: Efficient frontier on December 8 for Low Market Scenario Step 4

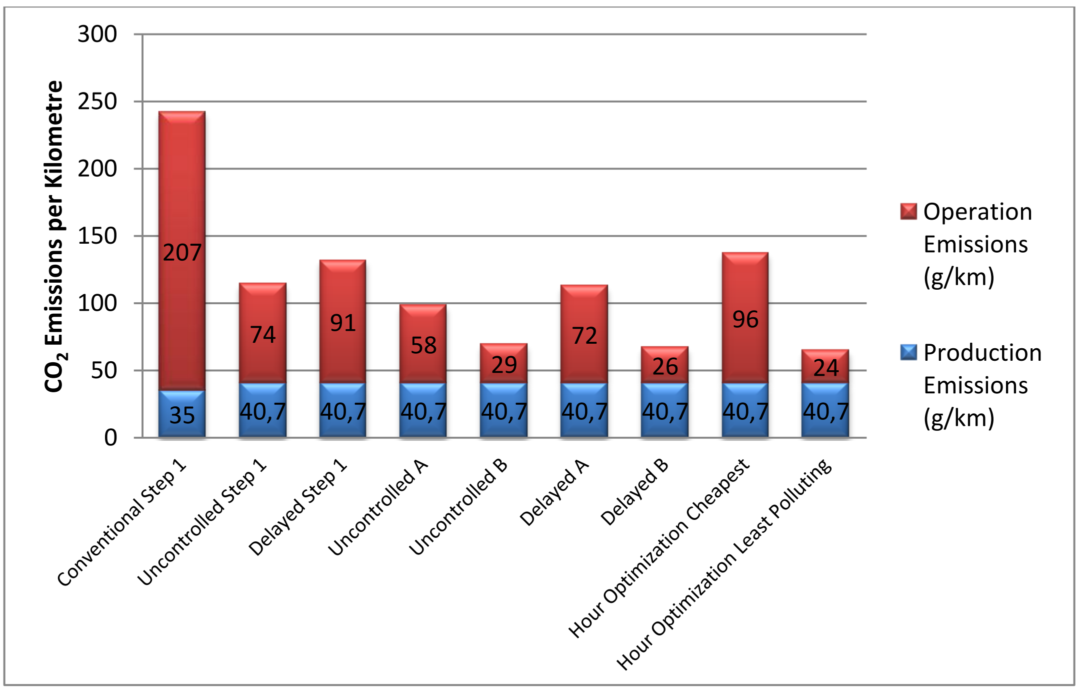

Figure 4.28: Comparison of Emissions per Kilometre for Step 1, 2, 3 and 4

Comparison of remaining performance measures are given in Figures 4.29 and 4.30. As described earlier, cheapest option starts with the maximum or primary energy consumption and CO_2 emissions compared to previous steps. But due to abundance of cheap and clean sources in night hours where the hour optimization model suggests, it is possible to decrease emissions and energy consumption to a level below all other scenarios investigated for the minimum cost of all scenarios. This clarifies that coupling EV introduction with a structured charging policy has the potential to save money in the supply chain and decrease emissions.

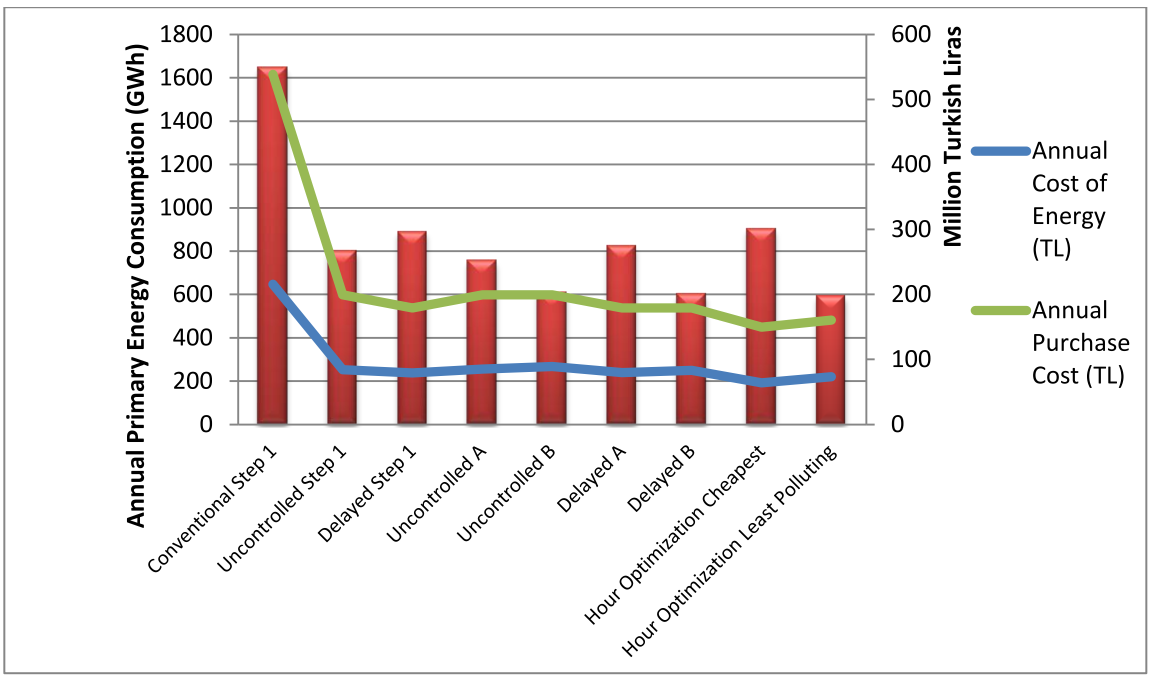

Figure 4.29: Annual primary energy consumption comparison of Steps 1-2-3-4

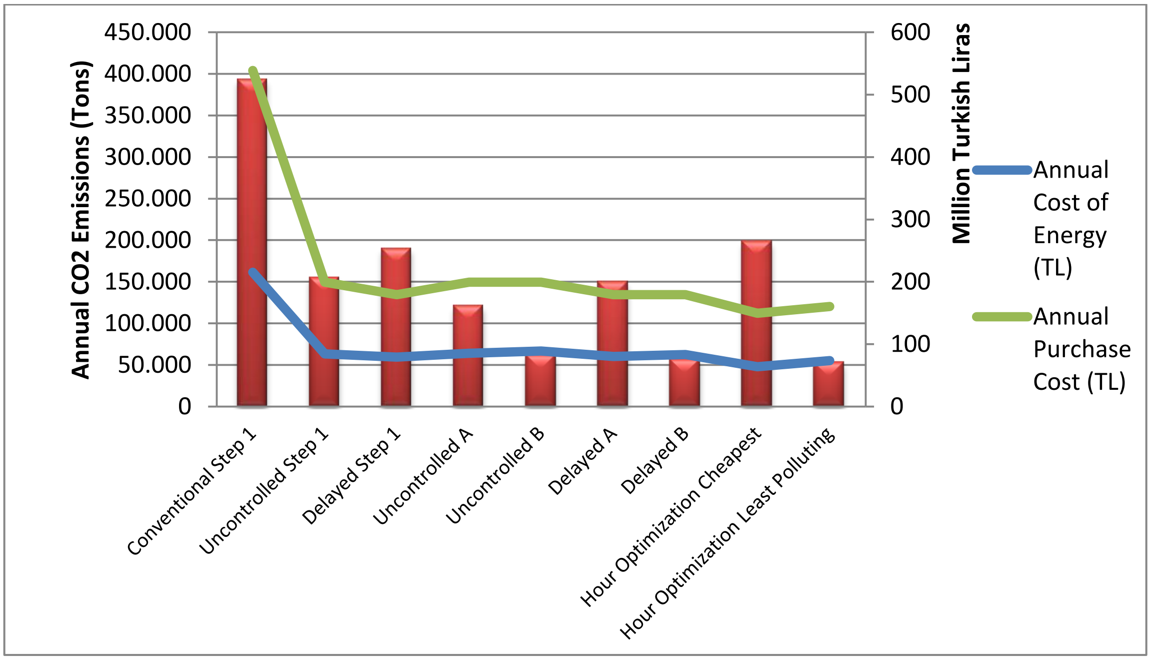

Figure 4.30: Annual CO2 emissions comparison of Steps 1-2-3-4

4.3. Results of Medium Market Penetration Scenario

Second scenario investigated for the case of Turkey is called Medium market penetration scenario and it assumes that BEVs and PHEVs will reach a market share of 5% and 11% respectively by 2020. This converts to replacing 112,000 gasoline powered and 168,000 diesel powered vehicles with 90,000 BEVs and 190,000 PHEVs, a total of 280,000 electric vehicles on the road. The reason to investigate results of this scenario is to see how the system reacts when the charging demand is increased.

In this section only summarized result comparison figures and comments for the same steps as low scenario will be given. Low scenario results section can be used as a reference where the reader needs to follow each step's details.

4.3.1. Step 1: Conventional Results

Performance measures are calculated as explained in Section 3.1. and the summary of results are given in Table 4.17.

Table 4.17: Results of Step 1 for Medium Market Penetration Scenario

Performance Measure	Result
Annual Primary Energy Consumption	3,544 GWh
Total Fuel Pathway CO_2 Emissions	846,890 tons
Total Cost of Purchase to End User	1,160,337,920 TL
Total Energy Costs Before Taxes	464,135,168 TL

4.3.2. Step 2: Uncontrolled and Delayed Charge Results in Business as Usual Market Operations Results

4.3.2.1. Uncontrolled Charge Results

In the uncontrolled charge scenario for low market penetration, it is assumed that 90,000 BEV and 190,000 PHEV will be charged without any type of regulation in an uncontrolled environment. 280,000 electric vehicles being charged from the grid according to uncontrolled scenarios increase the peak demand and total electricity consumption with the values seen in Table 4.18.

With this scenario on average electricity consumption in Turkey rises by 0.31%, whereas the average peak increases by 0.73% with a maximum increase of 1.77% in December at 18:00.

Table 4.18: Daily Results of Uncontrolled Charging with Medium Market Scenario

Month	Total Conventional Demand (MWh/day)	Charging Demand before Transmission Losses (MWh)	Increase percentage	Peak without Charging (MWh)	Peak with Uncontrolled Charging (MWh)	Increase in Peak
February	598,677	1,864	0.31%	28,472	28,803	1.16%
April	570,353	1,864	0.33%	26,823	26,830	0.03%
June	566,940	1,864	0.33%	27,487	27,494	0.02%
August	688,521	1,864	0.27%	32,926	32,926	0.00%
October	577,895	1,864	0.32%	27,083	27,460	1.39%
December	619,175	1,864	0.30%	30,114	30,648	1.77%
Average	**603,594**	1,864	**0.31%**	**28,818**	**29,027**	**0.73%**

Marginal energy mix sources for different months can be seen in Table 4.19. Hydro electricity and natural gas' share remained almost stable compared to low market scenario and they are equal at 46%. Coal's share is significant only in April and August, and this is also parallel with low market scenario. This energy mix enables a low marginal CO_2 emission rate of an average 277 g CO_2/kWh and a maximum 451 g CO_2/kWh in April where fossil fuels have a high share.

Table 4.19: Energy Mix of Marginal Demand for EVs in Medium Scenario / Uncontrolled Charge

Month	Percentage of Primary Energy Source in Marginal Generation								
	Large Hydro Dams	River Type Dams	Natural Gas	Hard Coal	Lignite	Export Coal	Fuel Oil	Biogas	Diesel
February	55%	0%	41%	4%	0%	0%	0%	0%	0%
April	10%	2%	78%	8%	0%	0%	2%	0%	0%
June	30%	2%	68%	0%	0%	0%	0%	0%	0%
August	76%	1%	5%	9%	0%	9%	1%	0%	0%
October	62%	1%	34%	0%	3%	0%	0%	0%	0%
December	45%	1%	51%	0%	1%	0%	2%	0%	0%
Average	**46%**	**1%**	**46%**	**3%**	**1%**	**1%**	**1%**	**0%**	**0%**

Performance measures calculated based on average of 6 months based on formulas given in Section 3.3.7 are given in Table 4.20.

Table 4.20: Results of Step 2 for Medium Market Penetration Scenario with Uncontrolled Charge

Performance Measure	**Result**
Annual Primary Energy Consumption	1,702 GWh
Total Fuel Pathway CO_2 Emissions	307,618 Tons
Total Cost of Purchase to End User	426,543,403 TL
Total Energy Costs Before Taxes	177,005,257 TL

4.3.2.2. Delayed Charge Results

In the delayed charge scenario for low market penetration, it is assumed that electric vehicles will be charged with a simple delayed approach starting at 22:00 when electricity costs without any type of regulation in an uncontrolled environment. Delayed charging scenario's affects on total consumption and the peak demand are seen in Table 4.21. Similar to low scenarios peak demand is not affected as the load is concentrated in off peak hours. Total consumption rises by 0.31%.

Marginal energy mix sources for different months can be seen in Table 4.22. Hydro electricity's share drops to 31% on average and natural gas' share increases to 63% when compared with uncontrolled case. This is similar result to low market case. This energy mix gives and average CO_2 emission rate of an average 345 g CO_2/kWh and a maximum 422 g CO_2/kWh in April.

Table 4.21: Affects of Medium / Delayed Demand on Conventional Load and Peak Demand

Month	Total Conventional Demand (MWh/day)	Charging Demand before Transmission Losses (MWh)	Increase percentage	Peak without Charging (MWh)	Peak with Uncontrolled Charging (MWh)	Increase in Peak
February	598,677	1864	0.31%	28,472	28,472	0.00%
April	570,353	1864	0.33%	26,823	26,823	0.00%
June	566,940	1864	0.33%	27,487	27,487	0.00%
August	688,521	1864	0.27%	32,926	32,926	0.00%
October	577,895	1864	0.32%	27,083	27,083	0.00%
December	619,175	1864	0.30%	30,114	30,114	0.00%
Average	**603,594**	1864	**0.31%**	**28,818**	**28,818**	**0.00%**

Table 4.22: Energy Mix of Marginal Demand for EVs in Medium Scenario / Delayed Charge

Month	Percentage of Primary Energy Sources in Marginal Generation									
	Large Hydro Dams	River Type Dams	Lake Type Dams	Natural Gas	Hard Coal	Lignite	Export Coal	Fuel Oil	Biogas	Diesel
February	15%	0%	0%	81%	4%	0%	0%	0%	1%	0%
April	17%	1%	0%	72%	4%	5%	0%	0%	0%	0%
June	20%	3%	0%	77%	0%	0%	0%	0%	0%	0%
August	54%	0%	0%	33%	1%	0%	12%	0%	0%	0%
October	49%	1%	0%	51%	0%	0%	0%	0%	0%	0%
December	27%	1%	0%	64%	0%	1%	6%	1%	0%	0%
Average	**30%**	**1%**	**0%**	**63%**	**1%**	**1%**	**3%**	**0%**	**0%**	**0%**

Performance measures calculated based on average of 6 months are given in Table 4.23.

Table 4.23: Results of Step 2 for Low Market Penetration Scenario with Delayed Charge

Performance Measure	Result
Annual Primary Energy Consumption	1,811 GWh
Total Fuel Pathway CO_2 Emissions	354,148 Tons
Total Cost of Purchase to End User	379,739,374 TL
Total Energy Costs Before Taxes	165,531,297 TL

4.3.2.3. Comments on Step 1 and Step 2 Results

Medium scenario results have very similar characteristics to low market scenario. With a higher rate of market penetration, EVs still do not lose advantage against conventional vehicles in all performance measures. In this scenario a conventional fleet of 280,000 vehicles would emit 846,890 tons of CO2, which is equal to 207 g CO2/km, whereas EVs would emit 307,618 tons with uncontrolled charging and 354,148 tons with delayed charging. Uncontrolled scenario performs better like low scenario, due to having a larger share of hydroelectricity sources in marginal mix and decreases emissions by 63% whereas delayed scenario can decrease emissions by 58%. Effects on costs to end users also have a similar trend to low scenario. EV chargers would pay 426,543,403 TL for uncontrolled charge and 379,739,374 TL for delayed charge whereas conventional fleet would need 1,160,337,920 TL for gasoline and diesel consumption. Comparisons of performance measures are given together with other steps' solutions in Figures 4.37 – 4.39.

These results show that without any optimization effort, medium market penetration of electric vehicles is a cheaper option that emits less CO2 and consumes less energy compared to conventional vehicles in both charging scenarios.

4.3.3. Bi-Objective Optimization Results

In this section, results of Step 3, which is the bi-objective optimization with charging scenarios and Step 4, which is bi-objective optimization with charging hours as decision variables are given. Efficient frontiers of 6 representative days can be seen in Figure 4.31 to 4.36. Like first two steps, results are very similar to low scenario results, only in a different magnitude due to fleet sizes. On average, uncontrolled scenario results begin with an expensive but less polluting solution compared to delayed scenario but application of bi-objective dispatch enables delayed scenario to end up with a cleaner result. Hour optimization forces the system to charge the vehicles in early morning hours but this leads to an increased CO2 emission compared to previous steps. Even in this case the maximum charging CO2 emission per kilometre (96.3 g CO2/km due to 92% fossil contribution in marginal mix) still outperforms emission performance of conventional vehicles which is 207 g CO2/km. Average of cheapest hour charging scenarios emit 88 g CO2/km. With hour optimization, it is possible to decrease emissions down to 25-30 g CO2 /km levels with comparable costs to other charging scenarios. From Figures 4.37 to 4.39, performance measure comparisons for all steps under medium market penetration case can be seen. Details of the results and summary tables can be found in Appendix A.

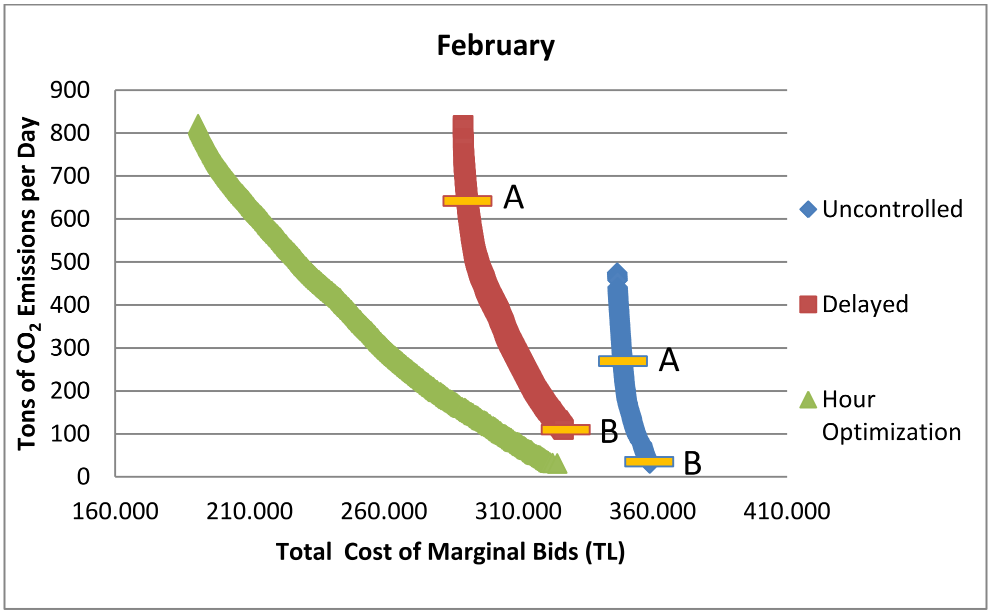

Figure 4.31: Efficient frontiers on February 10 for Medium Market Scenario

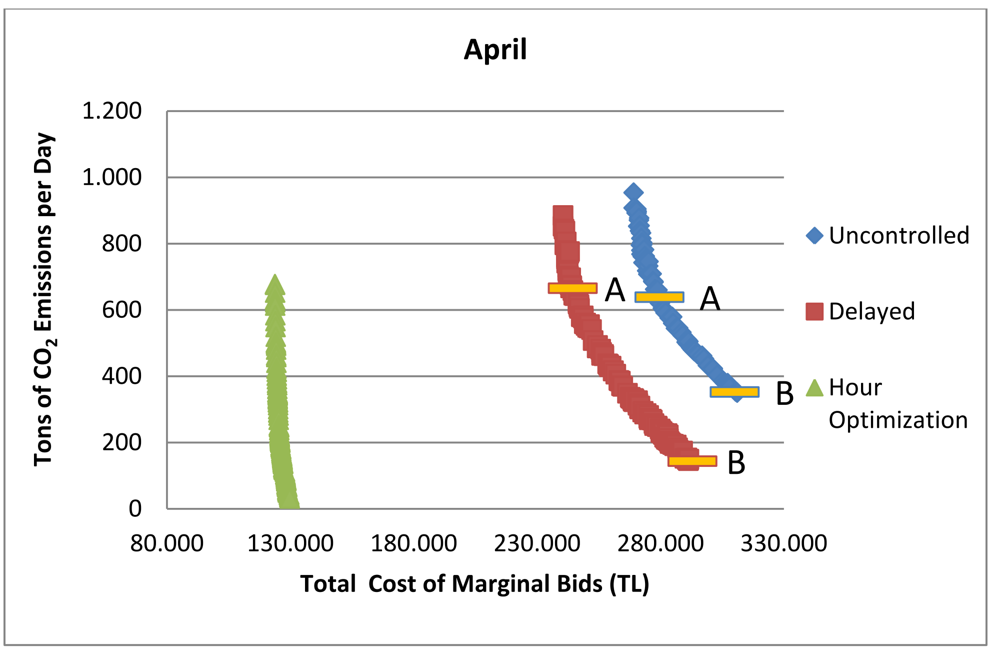

Figure 4.32: Efficient frontiers on April 14 for Medium Market Scenario

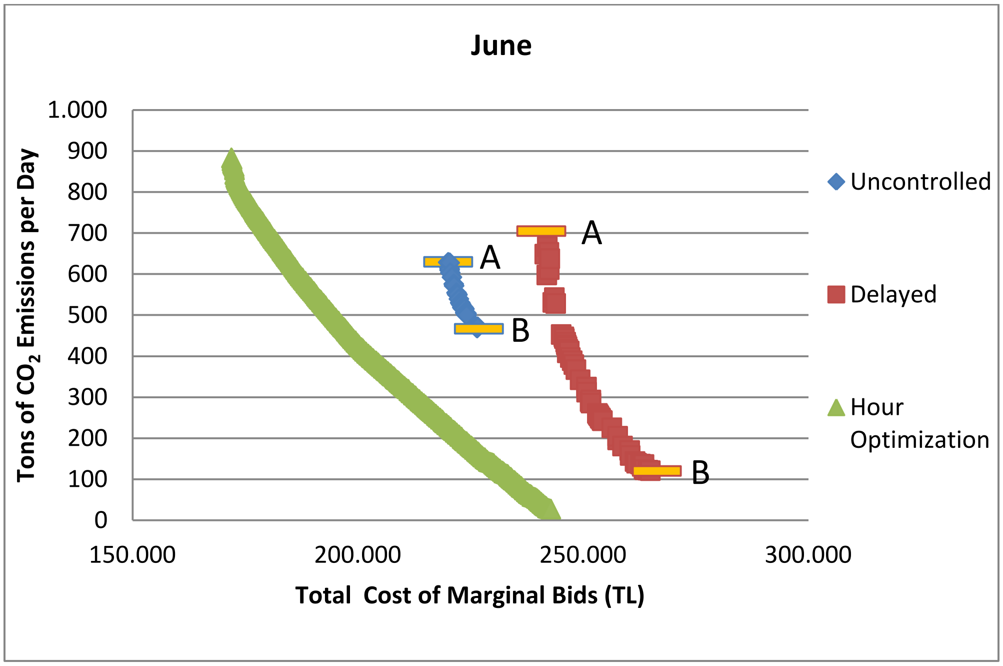

Figure 4.33: Efficient frontiers on June 9 for Medium Market Scenario

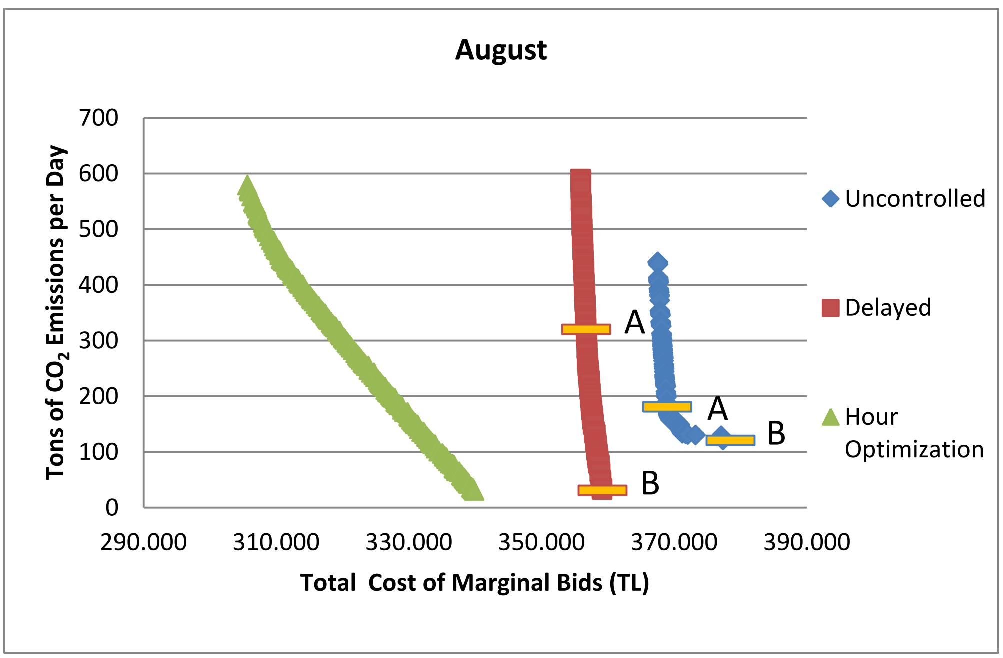

Figure 4.34: Efficient frontiers on August 11 for Medium Market Scenario

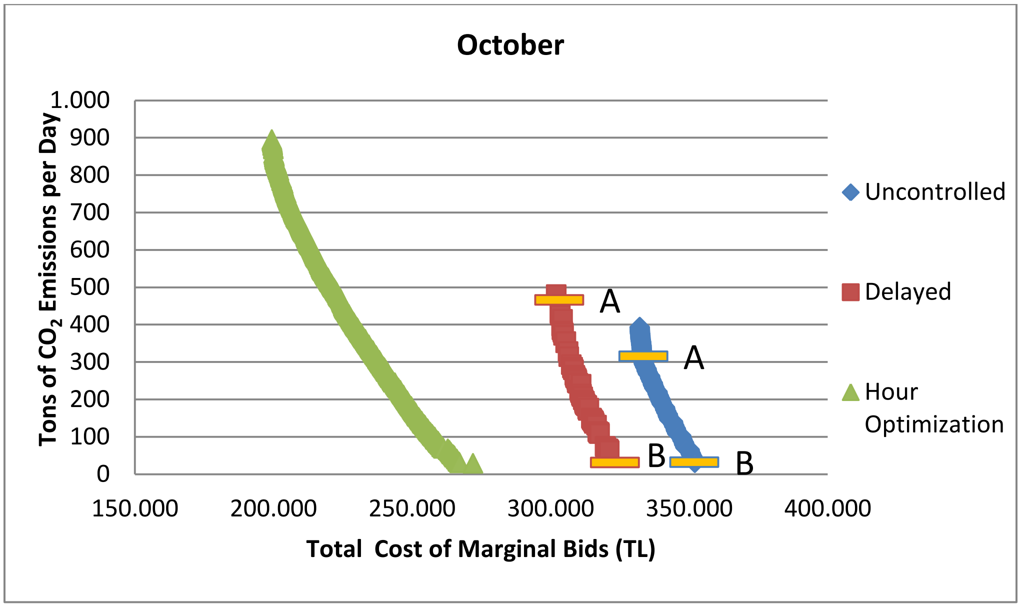

Figure 4.35: Efficient frontiers on October 13 for Medium Market Scenario

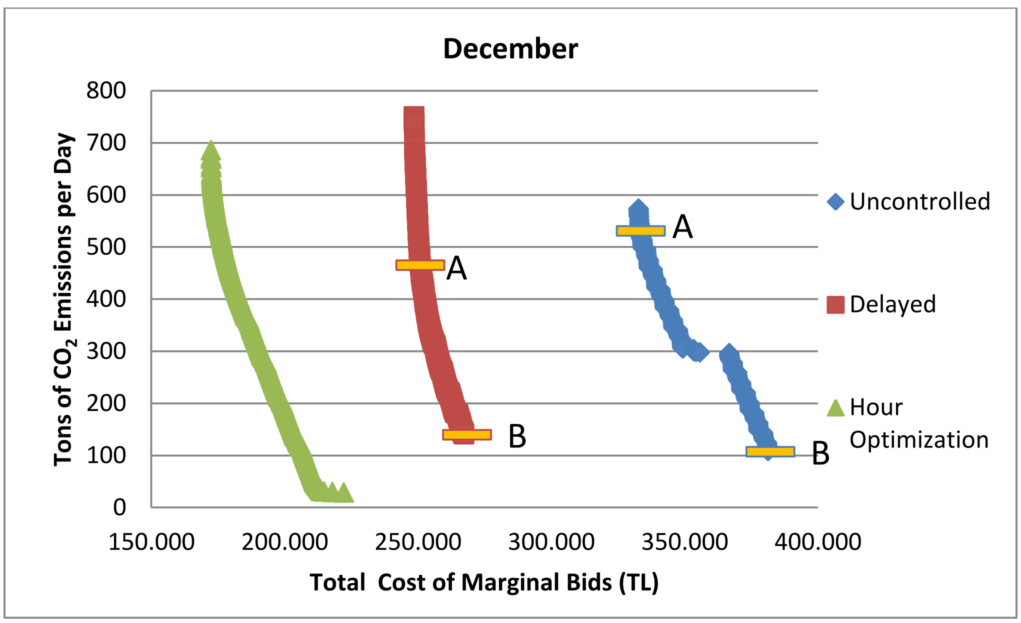

Figure 4.36: Efficient frontiers on December 8 for Medium Market Scenario

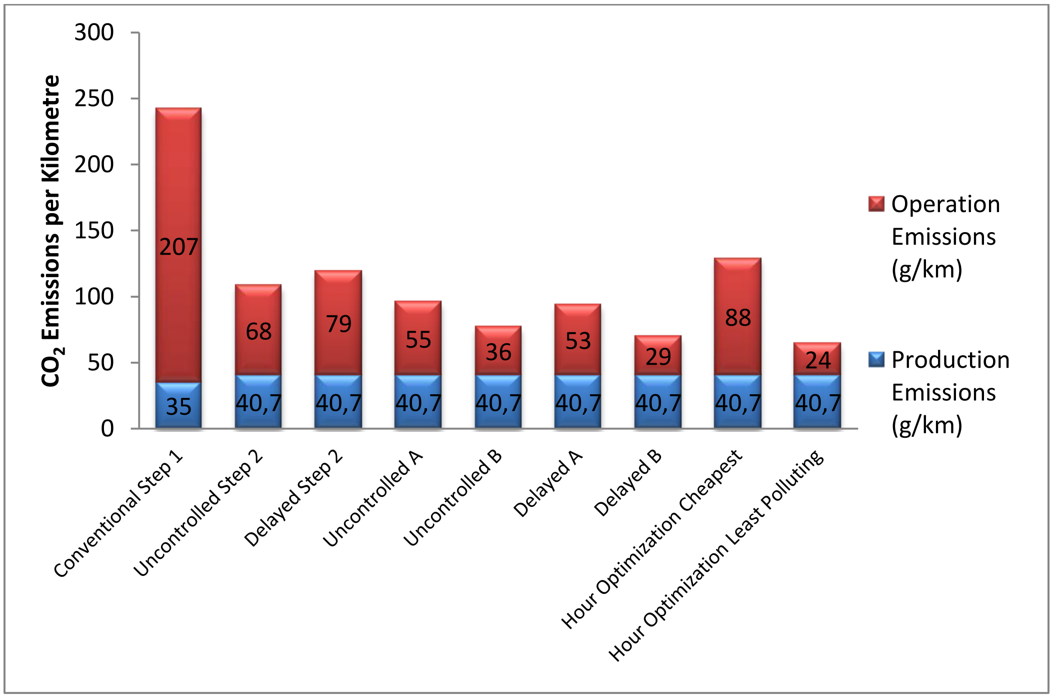

Figure 4.37: Comparison of Emissions per Kilometre for Step 1, 2, 3 and 4

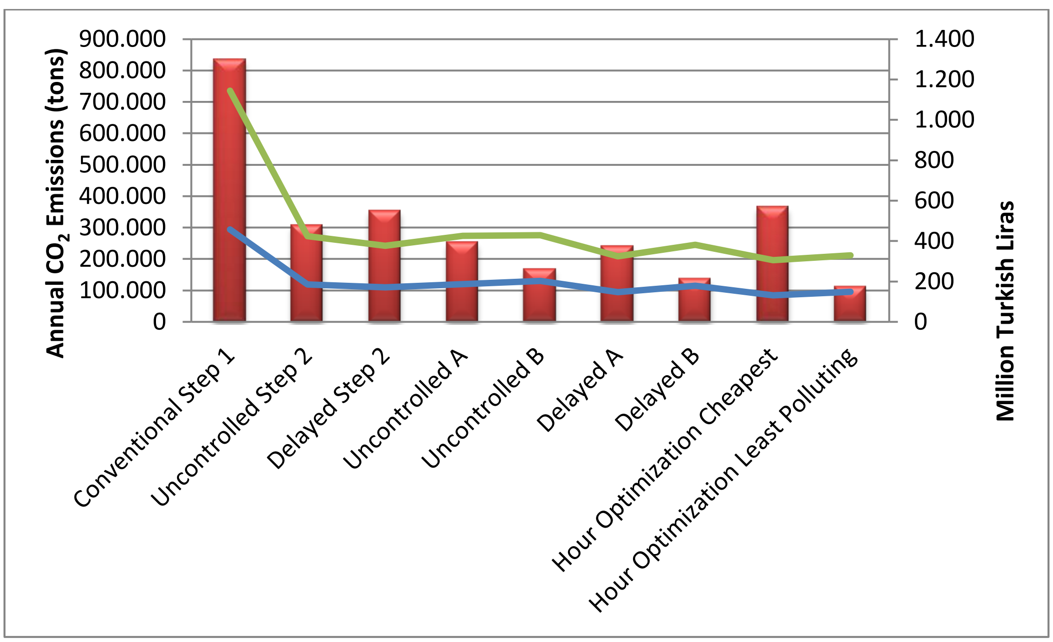

Figure 4.38: Annual CO_2 emissions comparison of Steps 1-2-3-4

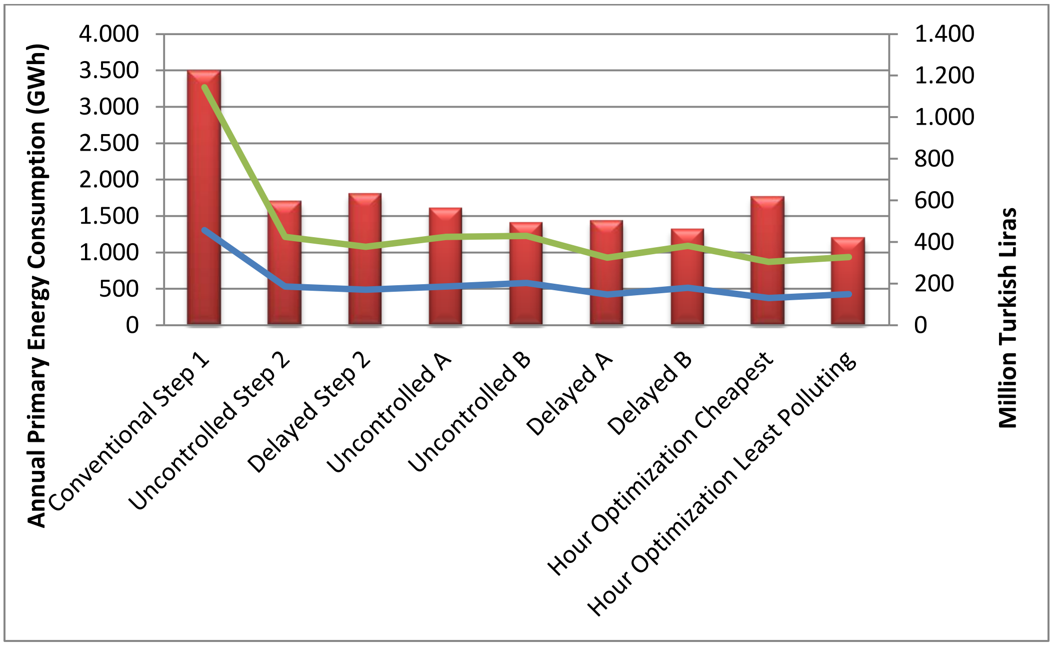

Figure 4.39: Annual primary energy consumption comparison of Steps 1-2-3-4

Similar to low market penetration case, EVs outperform conventional vehicles in all performance measures even in the worst cases for costs and emissions. Despite the fact that marginal demand increases by more than 2 times compared to low market penetration case, all seasons and charging scenarios can find a feasible solution. This shows that Turkish electricity market can cope with the short term demand expected to come from EVs even for medium penetration case. End costs are still less than 40% of the conventional case.

4.4. Results of High Market Penetration Scenario

Third and last scenario investigated for the case of Turkey is called High market penetration scenario and it assumes that BEVs and PHEVs will reach a market share of 5% and 11% respectively by 2020. This converts to replacing 250,000 gasoline powered and 375,000 diesel powered vehicles with 225,000 BEVs and 400,000 PHEVs, a total of

625,000 electric vehicles on the road. The reason to investigate results of this scenario is to see how the system reacts when the market penetration rates exceed expectations and reach very high numbers, putting the supply of electricity under threat.

Similar to medium scenario results, this section only gives summarized result comparison figures and comments for the same steps as low and medium scenarios. Low scenario results section can be used as a reference where the reader needs to follow each step's details.

4.4.1. Step 1: Conventional Results

Performance measures are calculated as explained in Section 3.1. and the summary of results are given in Table 4.24.

Table 4.24: Results of Step 1 for Medium Market Penetration Scenario

Performance Measure	Result
Annual Primary Energy Consumption	7,911 GWh
Total Fuel Pathway CO_2 Emissions	1,890,380 tons
Total Cost of Purchase to End User	2,590,040,000 TL
Total Energy Costs Before Taxes	1,012,656,000 TL

4.4.2. Step 2: Uncontrolled and Delayed Charge Results in Business as Usual Market Operations Results

4.4.2.1. Uncontrolled Charge Results

In the uncontrolled charge scenario for low market penetration, it is assumed that 225,000 BEV and 400,000 PHEV will be charged without any type of regulation in an uncontrolled environment. 625,000 electric vehicles being charged from the grid according to uncontrolled scenarios increases the peak demand and total electricity consumption with the values seen in Table 4.25.

With this scenario on average electricity consumption in Turkey rises by 0.69%, whereas the average peak increases by 2.04% with a maximum increase of 4.02% in October at 19:00.

Table 4.25: Daily Results of Uncontrolled Charging with High Market Scenario

Month	**Total Conventional Demand (MWh/day)**	**Charging Demand before Transmission Losses (MWh)**	**Increase percentage**	**Peak without Charging (MWh)**	**Peak with Uncontrolled Charging (MWh)**	**Increase in Peak**
February	598,677	4,180	0.70%	28,472	29,456	3.46%
April	570,353	4,180	0.73%	26,823	26,840	0.06%
June	566,940	4,180	0.74%	27,487	27,504	0.06%
August	688,521	4,180	0.61%	32,926	33,157	0.70%
October	577,895	4,180	0.72%	27,083	28,171	4.02%
December	619,175	4,180	0.68%	30,114	31,301	3.94%
Average	**603,594**	4,180	**0.69%**	**28,818**	**29,405**	**2.04%**

The most important finding in this scenario is the infeasible result reached in December. According to the data taken from TEİAŞ, the amount of available bids at 18:00 is 760 MW, whereas according to the uncontrolled charge scenario 1187 MW of new load is needed to supply the charging demand from EVs. Due to this shortage, the model ends up in an infeasible solution, where it is not possible to supply the new demand. In the next subsections it is shown that it is still feasible to charge the same amount of EVs by changing the charge hours but this is an important finding to show that uncontrolled charge might end up in a case where the network is not able to supply the new demand. In order to reach general results, February results have been used to approximate the annual results.

Marginal energy mix sources for different months can be seen in Table 4.26. Hydroelectricity's share in the marginal mix increases compared to low and medium market scenario due to the increased peak demand where peak load hydroelectric generators are abundant. Coal's share climbs to its maximum in the study in April where hydroelectricity supplies shift to base load as the prices fall due to high availability of Hydroelectricity generation capacity. This increases per kilometre emissions up to 139 g CO_2/km which is comparable with hybrid vehicles. However the average energy mix enables a low marginal CO_2 emission rate of an average 299 g CO_2/kWh and a maximum 704 g CO_2/kWh in April where fossil fuels have a high share.

Table 4.26: Energy Mix of Marginal Demand for EVs in High Scenario / Uncontrolled Charge

Month	Percentage of Primary Energy Source in Marginal Generation								
	Large Hydro Dams	River Type Dams	Natural Gas	Hard Coal	Lignite	Export Coal	Fuel Oil	Biogas	Diesel
February	68%	0%	29%	3%	0%	0%	0%	0%	0%
April	6%	1%	48%	3%	42%	0%	1%	0%	0%
June	10%	0%	84%	0%	0%	5%	1%	0%	0%
August	78%	1%	8%	6%	0%	5%	3%	0%	0%
October	74%	1%	23%	0%	2%	0%	0%	0%	0%
December	68%	0%	29%	3%	0%	0%	0%	0%	0%
Average	51%	1%	37%	3%	7%	2%	1%	0%	0%

Performance measures calculated based on average of 6 months based on formulas given in Section 3.3.7 are given in Table 4.27.

Table 4.27: Results of Step 2 for Low Market Penetration Scenario with Uncontrolled Charge

Performance Measure	Result
Annual Primary Energy Consumption	4,034 GWh
Total Fuel Pathway CO_2 Emissions	798,100 Tons
Total Cost of Purchase to End User	987,451,222 TL
Total Energy Costs Before Taxes	426,543,403 TL

4.4.2.2. Delayed Charge Results

Delayed charging scenario's affects on total consumption and the peak demand for high market scenario are seen in Table 4.28. Similar to low and medium scenarios peak demand is not affected as the load is concentrated in off peak hours. Total consumption rises by 0.69%

Table 4.28: Affects of High Scenario / Delayed Charge Demand on Conventional Load and Peak Demand

Month	**Total Conventional Demand (MWh/day)**	**Charging Demand before Transmission Losses (MWh)**	**Increase percentage**	**Peak without Charging (MWh)**	**Peak with Uncontrolled Charging (MWh)**	**Increase in Peak**
February	598,677	4,180	0.70%	28,472	28,472	0.00%
April	570,353	4,180	0.73%	26,823	26,823	0.00%
June	566,940	4,180	0.74%	27,487	27,487	0.00%
August	688,521	4,180	0.61%	32,926	32,926	0.00%
October	577,895	4,180	0.72%	27,083	27,083	0.00%
December	619,175	4,180	0.68%	30,114	30,114	0.00%
Average	**603,594**	4,180	**0.69%**	**28,818**	**28,818**	**0.00%**

Marginal energy mix sources for different months can be seen in Table 4.29. Hydro electricity's share drops to 45% on average and natural gas' share increases to 52% when compared with uncontrolled case. However, when these figures are compared with low and medium scenarios it is clearly visible that there is an increase in the share of hydroelectric sources. The reason is the following: as the demand increases and natural gas resources in the peak hours decrease, more peak hydro generator bids are accepted. This energy mix gives and average CO_2 emission rate of an average 278 g CO_2/kWh and a maximum 385 g CO_2/kWh in April.

Table 4.29: Energy Mix of Marginal Demand for EVs in High Scenario / Delayed Charge

Month	Percentage of Primary Energy Source in Marginal Generation								
	Large Hydro Dams	River Type Dams	Natural Gas	Hard Coal	Lignite	Export Coal	Fuel Oil	Biogas	Diesel
February	34%	0%	63%	3%	0%	0%	0%	1%	0%
April	27%	1%	62%	4%	6%	0%	0%	0%	0%
June	27%	1%	71%	0%	0%	0%	0%	0%	0%
August	71%	0%	23%	0%	0%	5%	0%	0%	0%
October	56%	0%	43%	0%	1%	0%	0%	0%	0%
December	48%	0%	47%	0%	0%	3%	0%	0%	0%
Average	44%	1%	52%	1%	1%	1%	0%	0%	0%

Performance measures calculated based on average of 6 months are given in table 4.30.

Table 4.30: Results of Step 2 for Low Market Penetration Scenario with Uncontrolled Charge

Performance Measure	Result
Annual Primary Energy Consumption	3,764 GWh
Total Fuel Pathway CO_2 Emissions	672,471 Tons
Total Cost of Purchase to End User	831,408,656 TL
Total Energy Costs Before Taxes	343,223,740 TL

4.4.2.3. Comments on Step 1 and Step 2 Results

High scenario results show similar characteristics to low and medium market scenario, however due to the increase in demand, hydroelectricity sources find more share in the marginal mix especially in uncontrolled charge hours. With this maximum rate of market penetration, EVs still perform better than conventional vehicles in all performance measures. In this scenario a conventional fleet of 625,000 vehicles would emit 1,890,380 tons of CO_2, which is equal to 207 g CO_2/km, whereas EVs would emit 798,100 tons with uncontrolled charging and 672,471 tons with delayed charging. Uncontrolled scenario, performs better like low and medium scenarios, due to higher share of renewable sources in marginal mix and decreases emissions by 57% whereas delayed scenario can decrease emissions by 64%. Effects on costs to end users also have a similar trend to low scenario. EV chargers would pay 987,451,222 TL for uncontrolled charge and 831,408,656 TL for delayed charge whereas conventional fleet would need 2,590,040,000 TL for gasoline and diesel consumption. This means that on average EV charges would pay 39% of what they pay for fuel in uncontrolled charge and 32% in delayed charge. Comparisons of performance measures are given together with other steps' solutions in Figures 4.46 – 4.48.

These results show that even in worst case of an extreme market introduction, electric vehicles are a cheaper option that emits less CO_2 and consumes less energy compared to conventional vehicles in both charging scenarios without any optimization effort. The only negative impact was the overload of December case where the system was not able to supply the charging demand. This could be overcome by charge hour regulations if such an aggressive penetration occurs.

4.4.3. Bi-Objective Optimization Results

In this section, results of Step 3, which is the bi-objective optimization with charging scenarios and Step 4, which is bi-objective optimization with charging hours as decision variables are given for high market penetration scenario. Efficient frontiers of 6 representative days can be seen in Figures 4.40 to 4.45. Efficient frontiers show a similar trend to low and medium scenario results; however, uncontrolled scenarios in the high market penetration scenario tend to have an increased emission due to necessity of coal generation support in heavily loaded hours of peak hour charging. In some extreme cases, coal contribution climbs up to 46% in April and fossil fuel contribution climbs up to 93% in June. This is due to increased consumption in summer days which couples with the lack of hydroelectricity sources. In February and October cases uncontrolled scenario shows the expected trend of being more expensive but less polluting than delayed case. On average uncontrolled scenarios enable a decrease from 59 g CO_2/km to 53 g CO_2/km by removing coal generators and further down to 41 g CO_2/km by changing natural gas sources with renewable. Delayed scenarios start from a higher average of 67 g CO_2/km but using bi-objective optimization enables a first decrease to 57 g CO_2/km by removing coal and a further decrease down to 38 g CO_2/km. This shows that by having a larger feasible set delayed case gives opportunity to decrease emissions more than uncontrolled case.

Hour optimization forces the system to charge the vehicles in early morning hours but this leads to an increased CO_2 emission compared to previous steps. Even in the worst case EVs emit 95 g CO_2/km which is less than half of average conventional vehicle emissions. Average of cheapest hour charging scenarios emits 80 g CO_2/km. With hour optimization, it is possible to decrease emissions down to 25-30 g CO_2 /km levels with comparable costs to other charging scenarios. This highlights the opportunity to utilize the clean sources in off-peak hours where they also have low cost.

In high scenario hour optimization case, bi-objective optimization tools enable very efficient decreases in emissions by interchanging coal generators with hydroelectricity sources which have bid prices that are very close to those of coal generators. For example cost of saving a ton of CO_2 is found to be as low as 19 TL/ton of CO_2 in December. In high market penetration, independent of the charging scenario, cost advantage of EVs to end users remains significant over conventional vehicles. Even in the most expensive case to end users which is the uncontrolled charging, driver would have paid 33% of the total amount of gasoline and diesel purchase price.

From Figures 4.46 to 4.48, performance measure comparisons for all steps under medium market penetration case can be seen. Details of monthly results for all steps and months can be found in Appendix A.

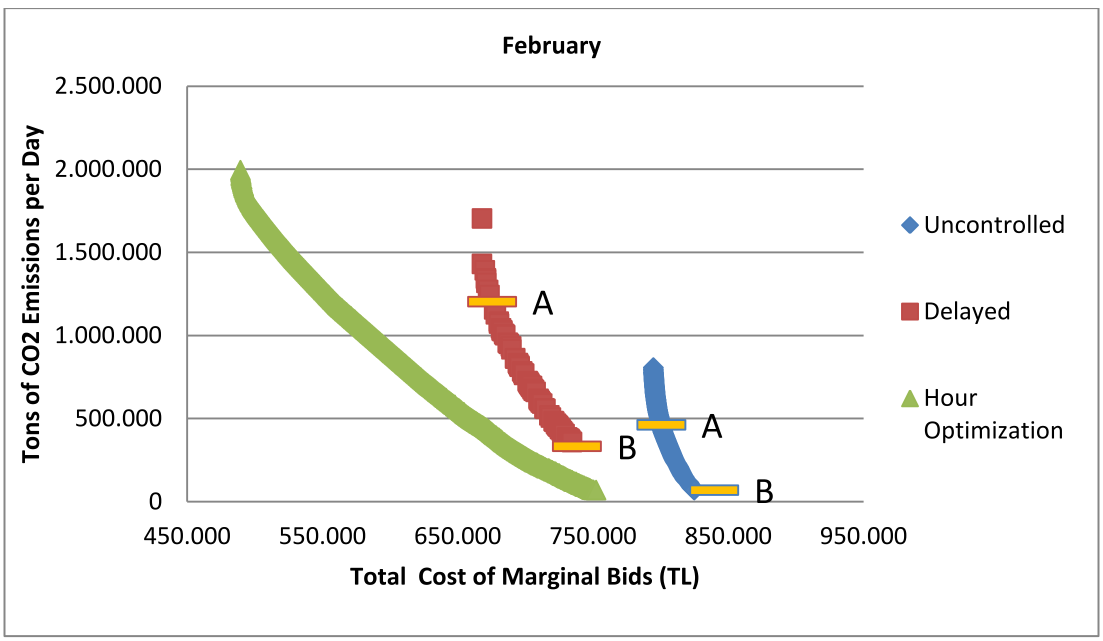

Figure 4.40: Efficient frontiers on February 10 for High Market Scenario

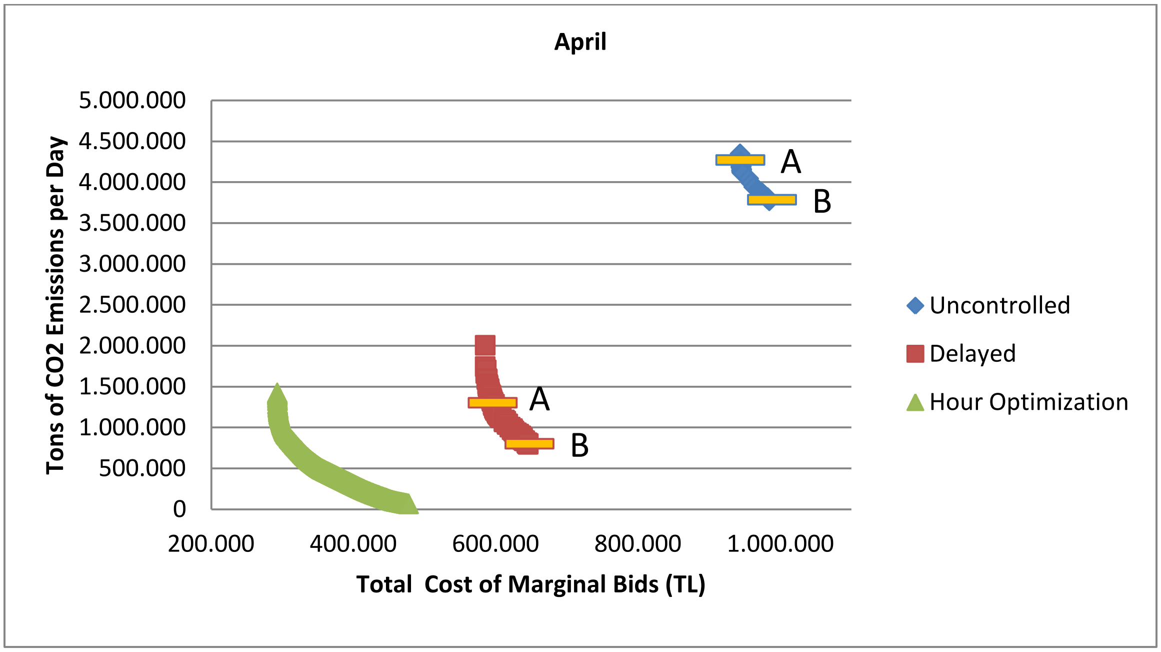

Figure 4.41: Efficient frontiers on April 14 for High Market Scenario

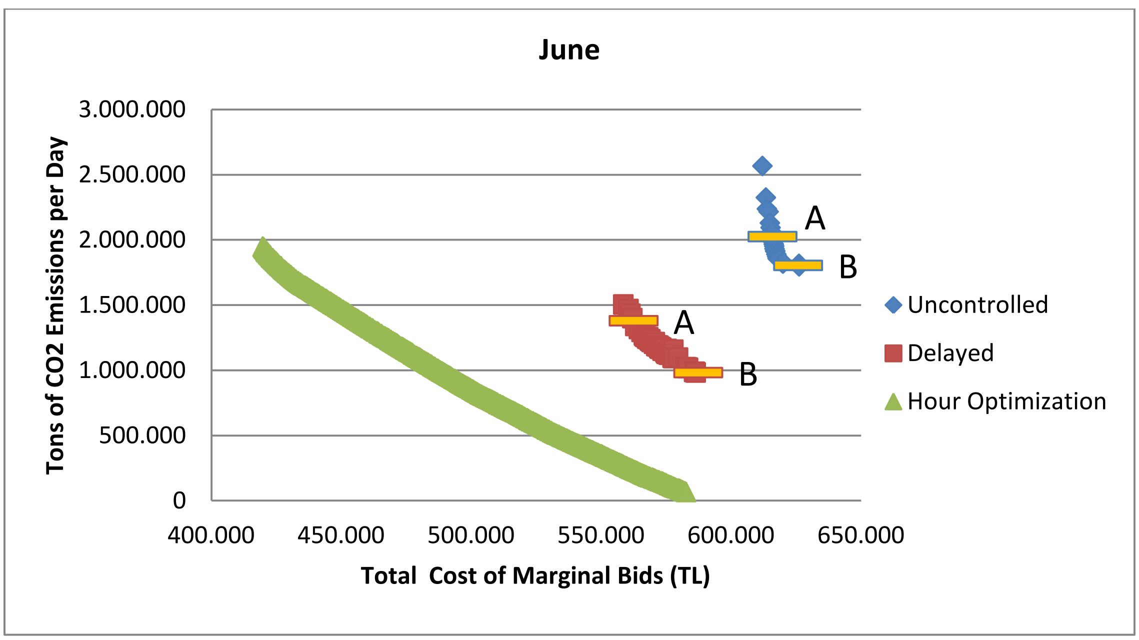

Figure 4.42: Efficient frontiers on June 9 for High Market Scenario

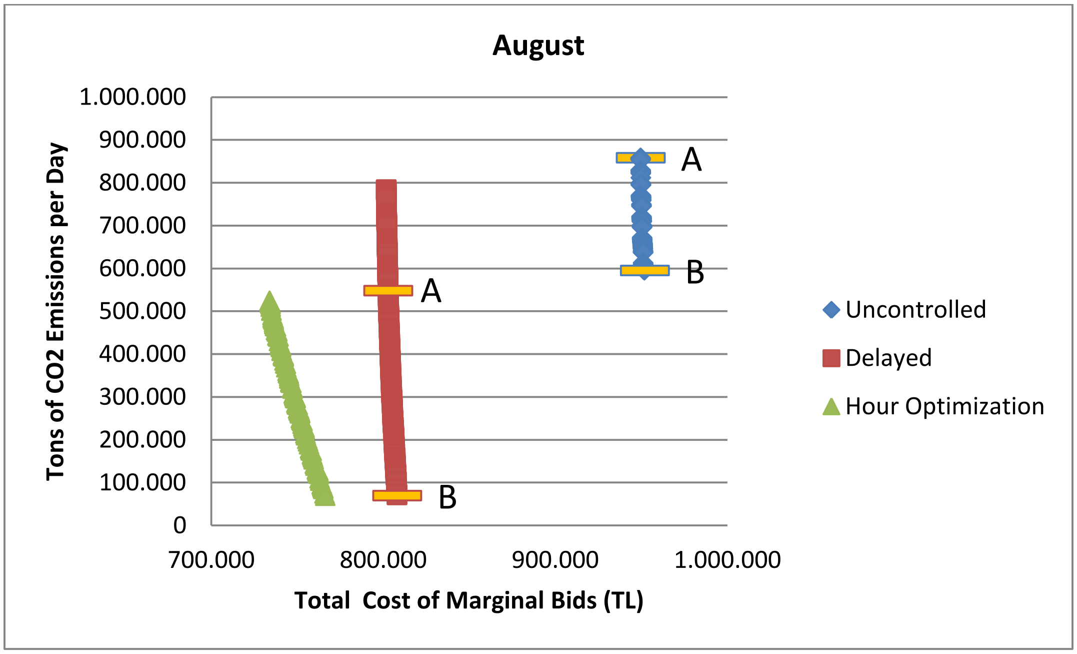

Figure 4.43: Efficient frontiers on August 11 for High Market Scenario

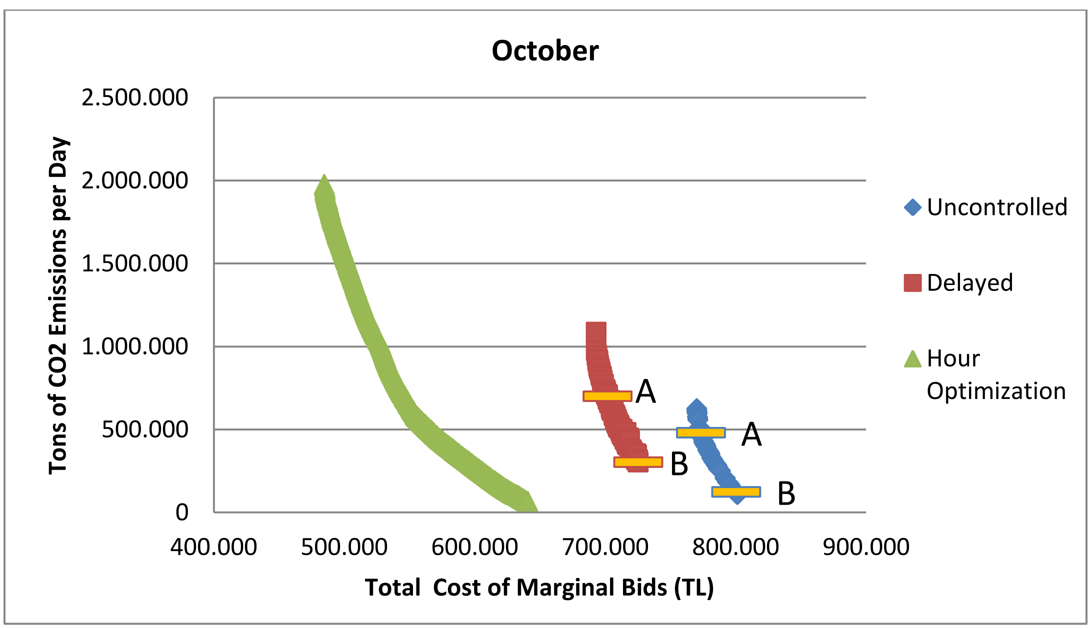

Figure 4.44: Efficient frontiers on October 13 for High Market Scenario

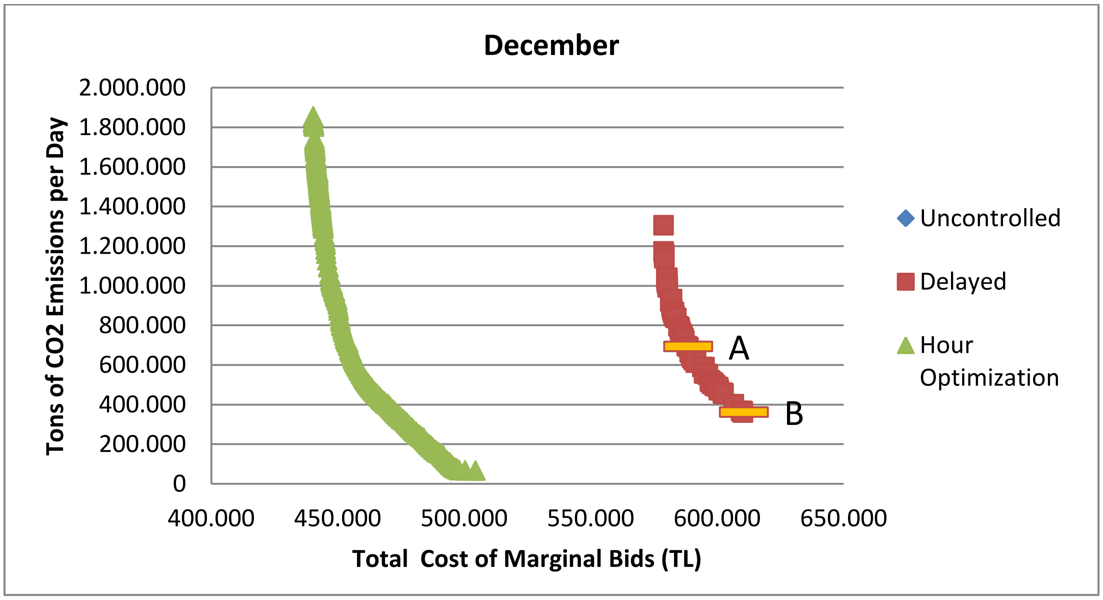

Figure 4.45: Efficient frontiers on December 8 for Medium Market Scenario

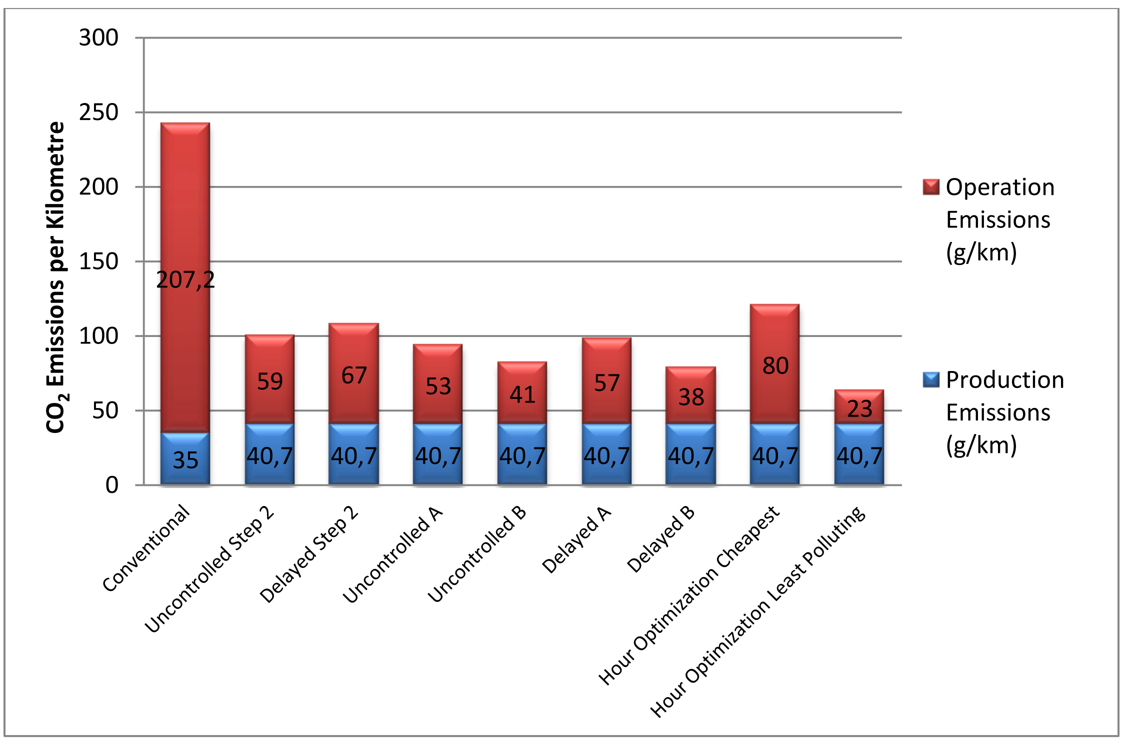

Figure 4.46: Comparison of Emissions per Kilometre for Step 1, 2, 3 and 4 for High Penetration

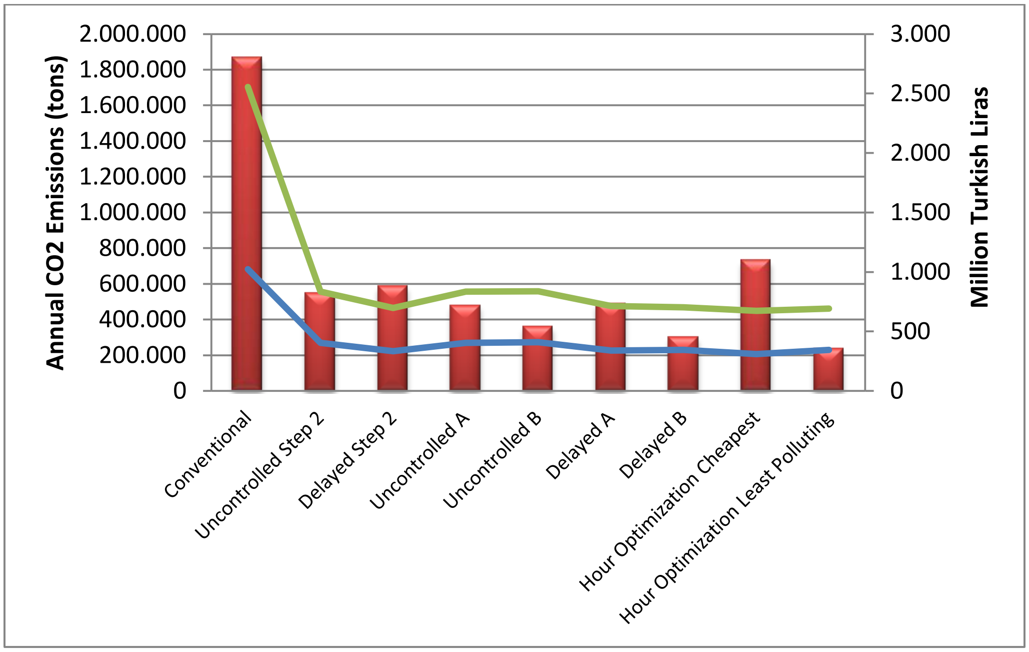

Figure 4.47: Annual CO_2 emissions comparison of Steps 1-2-3-4 for High Penetration

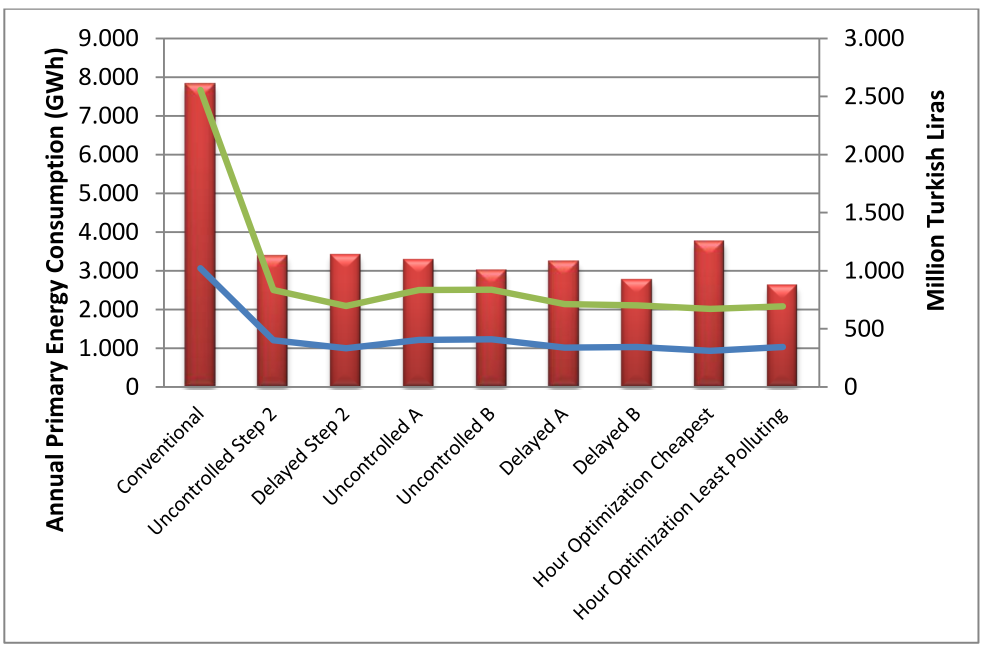

Figure 4.48: Primary Energy Comparison of Steps 1-2-3-4 for High Penetration

4.5. Comparison of Average Case with Marginal Energy Mix Results

One of the major contributions of this study is the emphasis put on marginal energy mix instead of assuming that EVs will be charged by the average mix. In order to prove that there is a significant variance between these two, one performance measure that is easier to compare for average mix is selected and results are compared.

According to annual energy figures by TEİAŞ monthly average CO_2 emissions per kWh has shown variance during the year according to availability of hydroelectric capacity and had an average of 492 g CO2/kWh emission in 2010. Monthly trend is presented in Figure 4.49 whereas average annual energy mix is given in Figure 4.50.

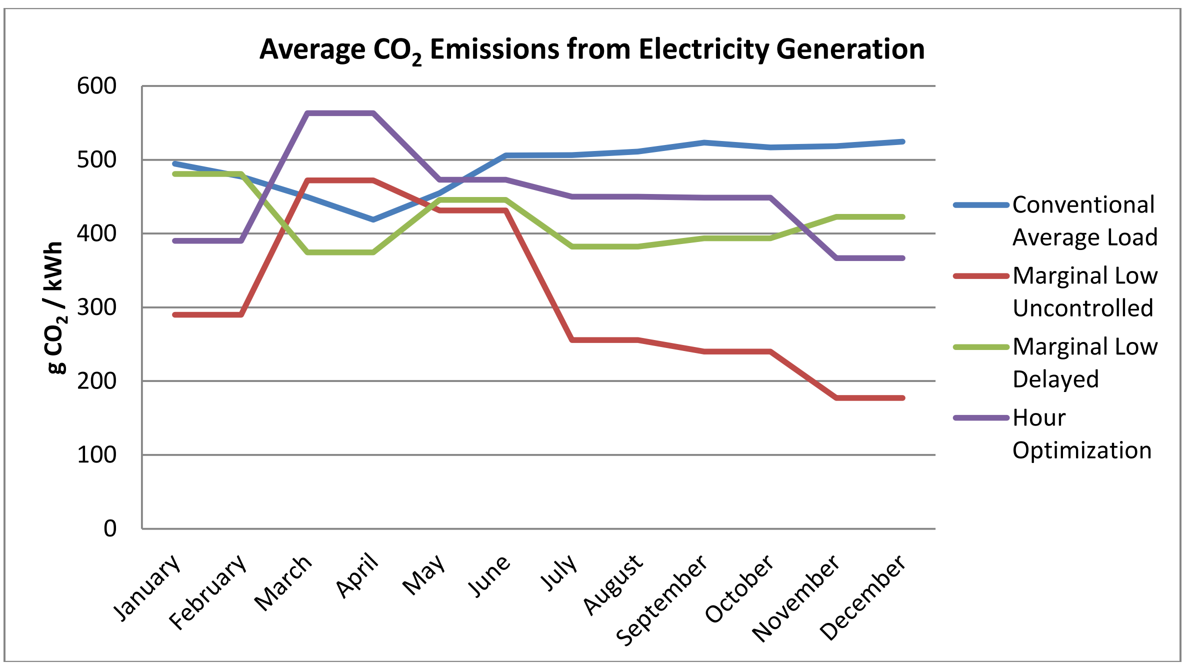

Figure 4.49: Monthly Average and Marginal CO_2 emissions in Turkey

When the marginal energy mix emissions are compared in the same graph with the average conventional mix, one of the most interesting results of this study becomes visible: In months where the average emissions are low, marginal mix emission are high. As explained in the scenario result analysis sections, this is strongly dependent on the hydro capacity availability and costs. In months where hydroelectricity in abundant (for example April) average emissions decrease by supplying a large share of demand by cheap renewable sources. However, this leaves the peak hours without any hydro option and any extra demand on the system can only be supplied by fossil fuel powered thermal generators. Therefore, emission rates increase. When hydro power is less abundant and expensive, hydro bids are only accepted when the bid prices go up. This means that peak demand is supplied with expensive renewable sources and emissions drop. This proves that the performance of the EVs is strongly dependent on the marginal mix which shows significant variance depending on the season. Also this graph shows how single objective driven decisions might end up in the worst environmental performance. Hour optimization proves to be more pollutant than uncontrolled and delayed cases and gives the worst emission rates in the study in April case, where the share of fossils climbs up to 73%.

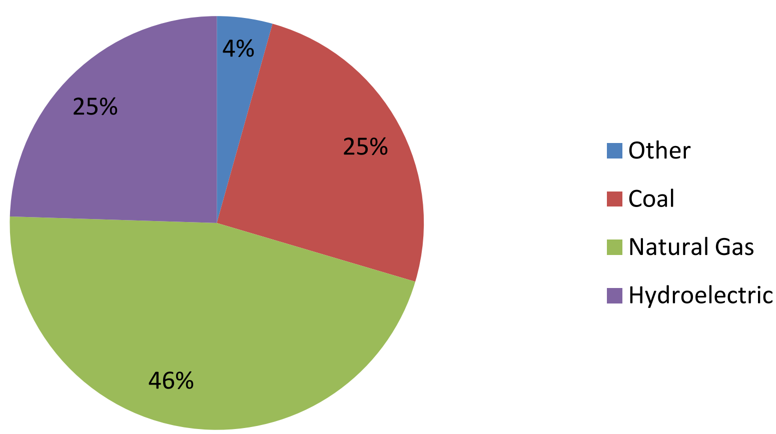

Figure 4.50: Average Energy Mix of Turkish Electricity Network in 2010

When a comparison with average mix is done, the magnitude of the variance is clearly visible. Due to high share of coal in base load, coal generators (hard coal, export coal and lignite are considered in this category) climb up to a contribution of 25% if average mix is used, whereas coal’s share has never exceeded 11% in average for any scenario considered in the study. If the policy decisions were to be based on this average EVs would be considered as emitting 105 g CO_2/km whereas in reality they emit around 80 g CO_2/km according to the average of all business as usual models. This means that 23% of environmental benefits of EVs are neglected when average mix is used to calculate the impacts. This variance shows the importance of using marginal energy mix in impact analysis studies.

Chapter 5

CONCLUSIONS

This thesis presented a high level methodology to analyze the impacts of EVs introduction to the passenger transportation market in short term, which can be used to estimate the performance of the technology in any region before the introduction takes place by using a mathematical model. Despite the fact that impacts of EV introduction was extensively analyzed in the literature the following gaps were found: (1) impact analyzes were based either on determined energy mix scenarios or average energy mix, (2) there was no effort to optimize charging hours, (3) single objective models were dominantly used to generate set of decisions and (4) none of the studies analyzed the impacts on Turkish electricity market. In order to address these gaps, a methodology which works on a mixed-integer bi-objective optimization model was created. This model focuses on determining the set of marginal generators under technical constraints. It enables decision makers to see full set of options that can be used as marginal generators by including a second objective function in the model. Additionally, it is possible to introduce charging hours as decision variables to the system thus analyses are not limited to charging scenarios only. By applying this model to Turkish electricity market and analyzing results, it can be concluded that an attempt to fill all four gaps defined above is made.

Conclusions can be separated into two groups: universal conclusions and Turkish market specific conclusions. First and most important universal conclusion of this study is that it demonstrates how application of bi-objective optimization tools provide decision makers a greater set of options and enables the system to get more environmental benefits from EVs. In regions where EVs are already performing cleaner that ICEVs this tools only enable to increase the advantage of EVs over ICEVs, whereas in regions where EVs operate with higher emissions compared to ICEVs due to carbon intense electricity generation, it proves to be an essential tool in the efforts to avoid this promising technology to end up in a worse result than the current technology. Without this approach, it would be impossible for decision makers to see the full set of options which include more expensive but cleaner energy mixes that could charge EVs and the system would get stuck in cost effective charge solutions in exchange for environmental benefits. In such cases, the efficient frontier gives the set of all feasible and efficient set of options for marginal generators and enables decision makers to choose among these based on their level of environmental consciousness and make EVs perform better than ICEVs with correct policies on electricity generation.

This study also proves that cost minimization objective can bring the system to solution where the emissions are maximized. Therefore, decision makers should take both economic and environmental aspects of the problem into account to avoid ending up in a case where the environmental benefits are minimized in expense of economic benefit. The specifications of the network should be analyzed in detail and both objectives should be considered before placing charging incentives that will encourage vehicle owners to charge at specific times of the day.

Hour optimization’s importance is also seen in the results of the application. By applying hour optimization and bi-objective solution at the same time, and encouraging drivers to charge at right hours of the day proposed by the model it is possible reach the same environmental performance with a less cost compared to pre determined scenarios.

By conducting the analysis on different seasons and days it is shown how the performance of the vehicles varies from time to time. This proves that there is no policy that can be the best solution for all months and all regions, therefore technologies to get real time information like Smart Grid is essential to get the best benefits from the EV technology. This will enable the system to gather enough data to run the methodology proposed in the study for as many days as possible and create different sets of decision, especially for charging hour policies for different time of the year. Increased share of renewable energy sources makes this even more important because only by using Smart Grid applications and accompanying optimization tools, it is possible to utilize the renewable energy sources at right times by charging the batteries with clean sources.

Another universal conclusion that can be reached is the variance of the marginal mix and its specifications from the average energy mix. Due to long term agreements and technical constraints some generators need to operate at constant levels of service throughout the year, hence they do not have any chance to react on demand increases. In short term, as it was assumed that the electricity network will not be able to add new generation capacity to the system in accordance with the EV charging demand, this increases the importance of tools that can determine the marginal generators. This methodology achieves this and the Turkish example has shown how significant the variance can be. If the decisions are based on average mix, wrong outcomes could be obtained and EV strategies might be misled. This result must encourage decision makers to focus their attention on using studies that calculate the marginal mix.

Turkish case results are also important to understand the performance of this emerging technology in Turkish market. EVs have outperformed ICEVs in every performance measure that was tracked in the study. First of all in all charge and market penetration scenarios dominant technologies that are determined by the model are either natural gas or hydro electric sources. This proves that coal generators are not taking part in the marginal generation in Turkey and EVs provide a great opportunity to decrease emissions. This result is further validated in CO_2 emission comparison. Even without applying any bi-objective optimization it is shown that EVs can decrease CO_2 emissions by

56% in delayed charging and 64% in uncontrolled charging. Primary consumption is decreased by more than 50% whereas costs to end users drop to 30% of what they would have paid to conventional vehicles. These figures charge slightly for different market penetration and charging scenarios but in all EVs outperform conventional vehicles.

The important finding about Turkey is that on average uncontrolled charge scenario has a better environmental performance compared to delayed charging. The reason is the share of peak demand hydro generators in peak hours. The methodology outputs a good representation of the efficient frontier so decision makers are able to choose among many options depending on their preferences of being more environmentally or economically oriented in charge policy decisions. Despite the fact that EVs already perform better than ICEVs without bi-objective optimization, this methodology shows that it is possible to save one ton of CO_2 for an 15 TL increase in costs for delayed scenario and 29.5 TL for uncontrolled scenario. This information will be valuable when the pressure on transportation sector increases to further decrease emissions. Charge hour optimization step has shown the optimal charging hours to be the off-peak hours between 02:00 and 06:00.

This is the first piece of work that has analyzed impacts of EVs in this level of detail in Turkey; therefore there are some future directions for improvement. As it was very difficult to obtain all data for such a large system and due to lack of real world data for EV technology which did not reach significant market share in any part of the world many simplifying assumptions were made to conduct this analysis. Once data is available these new findings should be included in the methodology by changing scenarios, technical assumptions or even by modifying the constraints and objectives of the model. One possible improvement in the model that is highlighted by the analysis of the results in Turkey is the necessity to constraint certain types of primary energy sources like hydroelectricity or other renewable which might have natural boundaries in generation capacity due to availability of resources like water supplies. As it is clearly visible in

Turkey results, the bi-objective model maximizes the use of hydroelectricity but it does not take limits on water supplies into account. Therefore a new set of constraints could be added to the model to improve the ability to model real world system. Such water availability data could be found from governmental agencies regulation water supplies.

Although it was not possible to apply the regional structure of the model due to market specifications in Turkey (all country is treated as a single region in the day-ahead market), differences in energy mix depending on the regional availability of supplies is an important feature of the proposed methodology. If the demand will be concentrated in one specific region, it is possible that only generators nearby will be used to supply the demand in order to minimize transmission losses or balance inter regional energy transfers. This would dramatically change the results as the energy mix will only include locally available sources. Thus, regional structure of the model should be applied with maximum level of technical details to model where possible to ensure providing correct results.

Local impacts of EV charging were not analyzed here but they can be included with a large set of local distribution constraints in the model if data can be reached. As the smart grid technology advances and applications and data structures become clearer this model can be modified to support necessary decision with right data according to the needs of Smart Grid. Another direction for improvement would be use of different charge technologies like fast charging stations.

As the technology matures more data will be available for EV market and related energy supply chains and the study can be improved by using this data in the above mentioned directions. However it is possible to utilize an important tool in operations research to have a better understanding of the results in the unclear environment. By conducting sensitivity analysis on parameters which are unclear (charging patterns, energy consumption of EVs, CO_2 emissions and efficiency of primary energy sources etc.), it is possible to obtain intervals for which the results are valid. This study has not conducted such a sensitivity analysis and this is a room for future improvement of the methodology to ensure that the results obtained by applying the model will be correct for the real world applications as well.

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Appendix A

SUPPORTIVE RESULTS

Table A.1: Detailed results for Low Market Scenario-1

Scenario: Low	Monthly CO2 Emissions (Kg)	Monthly Primary Energy Use (GWh)	Monthly Cost of Energy (TL)	Monthly Purchase Cost (TL)	Operation Emissions (g/km)	Total LCA Emissions (g/km)
Conventional	32,318	135	17,711,616	44,279,040	207	242
February Uncontrolled 2	12,195	65	7,447,693	16,631,434	70	111
February Delayed 2	17,436	77	6,849,819	14,892,572	102	142
April Uncontrolled 2	17,223	75	6,550,028	16,534,777	100	141
April Delayed 2	14,605	73	6,168,547	15,003,352	84	125
June Uncontrolled 2	16,099	73	5,898,709	16,554,329	93	134
June Delayed 2	16,452	78	5,983,473	14,890,297	96	137
August Uncontrolled 2	11,277	60	7,763,022	16,711,195	64	105
August Delayed 2	14,818	66	7,591,439	15,001,296	85	126
October Uncontrolled 2	10,793	64	7,247,786	16,647,939	62	102
October Delayed 2	15,050	72	6,907,324	14,930,270	87	128
December Uncontrolled 2	9,039	59	7,252,856	16,692,128	51	92
December Delayed 2	15,819	75	6,199,368	14,896,997	92	133
February Uncontrolled 3A	9,963	63	7,439,109	16,656,386	57	92
February Uncontrolled 3B	4,436	49	7,582,398	16,807,496	24	59
April Uncontrolled 3A	13,533	71	6,807,741	16,563,289	78	119
April Uncontrolled 3B	5,659	52	7,504,938	16,773,031	32	67
June Uncontrolled 3A	12,744	69	5,816,977	16,584,354	73	108
June Uncontrolled 3B	7,538	57	6,261,650	16,722,294	43	78
August Uncontrolled 3A	5,961	53	7,700,786	16,775,347	33	68
August Uncontrolled 3B	4,508	49	7,656,071	16,815,086	25	60
October Uncontrolled 3A	9,914	62	7,160,593	16,657,561	57	92
October Uncontrolled 3B	4,396	49	7,516,398	16,807,958	24	59
December Uncontrolled 3A	8,387	59	7,190,694	16,699,256	48	83
December Uncontrolled 3B	4,419	49	7,422,667	16,807,599	24	59

Table A.2: Detailed Results for Low Market Scenario- 2

Scenario	Monthly CO2 Emissions (Kg)	Monthly Primary Energy Use (GWh)	Monthly Cost of Energy (TL)	Monthly Purchase Cost (TL)	Operation Emissions (g/km)	Total LCA Emissions (g/km)
February Delayed 3A	14,495	74	6,785,232	14,910,484	84	119
February Delayed 3B	5,433	52	7,183,689	15,114,581	30	65
April Delayed 3A	13,016	70	6,211,902	14,940,613	75	110
April Delayed 3B	4,393	49	6,703,001	15,137,558	24	59
June Delayed 3A	15,600	77	5,891,423	14,900,774	91	126
June Delayed 3B	4,389	49	6,219,533	15,137,557	24	59
August Delayed 3A	9,115	60	7,516,940	15,036,087	52	87
August Delayed 3B	4,419	49	7,524,272	15,137,557	24	59
October Delayed 3A	10,121	63	6,925,274	15,006,960	58	93
October Delayed 3B	4,419	49	7,012,215	15,137,498	24	59
December Delayed 3A	12,623	68	6,123,901	14,966,073	73	108
December Delayed 3B	5,463	52	6,391,125	15,112,585	30	65
February 4 A	14,916	74	5,413,715	13,325,355	87	122
February 4 B	4,423	49	7,108,344	13,577,053	24	59
April 4 A	19,817	74	4,287,802	12,935,658	115	150
April 4 B	4,419	49	4,301,062	13,562,920	24	59
June 4 A	17,288	73	5,030,065	12,458,795	100	135
June 4 B	4,312	49	6,028,563	13,518,606	24	59
August 4 A	16,559	77	6,896,097	10,566,854	97	132
August 4 B	4,419	49	7,248,448	12,789,647	24	59
October 4 A	16,499	79	5,305,571	12,167,843	96	131
October 4 B	4,386	50	6,209,537	13,338,905	24	59
December 4 A	14,267	73	5,051,731	13,310,938	83	118
December 4 B	4,341	50	5,831,789	13,492,526	24	59

Table A.3: Detailed results for Medium Market Scenario-1

Scenario	Annual CO2 Emissions (Kg)	Annual Primary Energy Use (GWh)	Annual Cost of Energy (TL)	Annual Purchase Cost (TL)	Operation Emissions (g/km)	Total LCA Emissions (g/km)
Conventional	69,607	291	38,148,096	95,370,240	207	242
February Uncontrolled 2	22,665	135	16,099,521	35,172,258	60	101
February Delayed 2	32,954	161	14,498,628	31,366,953	89	130
April Uncontrolled 2	35,646	163	14,949,051	34,846,575	96	137
April Delayed 2	33,988	159	13,696,187	31,385,023	92	132
June Uncontrolled 2	27,313	149	12,617,501	34,986,287	73	114
June Delayed 2	29,555	155	12,954,387	31,411,067	79	120
August Uncontrolled 2	21,659	123	16,523,397	35,347,510	57	98
August Delayed 2	26,121	137	16,113,917	31,591,870	70	110
October Uncontrolled 2	20,211	129	15,777,020	35,209,394	53	94
October Delayed 2	22,829	138	14,846,654	31,565,344	61	101
December Uncontrolled 2	25,614	148	16,869,689	36,598,557	65	106
December Delayed 2	30,925	153	13,126,322	31,438,309	83	124
February Uncontrolled 3A	14,549	118	16,111,825	35,331,890	38	79
February Uncontrolled 3B	9,349	105	16,401,577	35,477,761	24	65
April Uncontrolled 3A	28,213	150	14,795,404	34,979,691	76	116
April Uncontrolled 3B	18,932	129	16,186,610	35,214,738	50	91
June Uncontrolled 3A	27,313	149	12,617,501	34,986,287	73	114
June Uncontrolled 3B	22,414	137	13,360,061	35,120,126	60	100
August Uncontrolled 3A	12,890	111	17,078,140	35,455,482	33	74
August Uncontrolled 3B	12,034	110	18,306,186	35,457,489	31	72
October Uncontrolled 3A	17,972	126	15,926,093	35,241,827	47	88
October Uncontrolled 3B	9,331	105	16,201,748	35,477,763	24	65
December Uncontrolled 3A	24,976	147	16,872,577	36,605,328	64	104
December Uncontrolled 3B	11,633	117	20,807,902	37,894,432	29	70
February Delayed 3A	27,799	151	14,498,337	31,451,392	75	115
February Delayed 3B	11,693	111	15,479,938	31,823,204	30	71
April Delayed 3A	28,373	152	13,791,801	31,438,139	76	117
April Delayed 3B	12,735	113	14,903,468	31,795,548	33	74
June Delayed 3A	22,008	136	13,542,576	31,583,839	58	99
June Delayed 3B	12,022	112	14,061,303	31,811,776	31	72

Table A.4: Detailed results for Medium Market Scenario-2

Scenario	Annual CO2 Emissions (Kg)	Annual Primary Energy Use (GWh)	Annual Cost of Energy (TL)	Annual Purchase Cost (TL)	Operation Emissions (g/km)	Total LCA Emissions (g/km)
August Delayed 3A	16,497	122	16,103,984	31,716,427	43	84
August Delayed 3B	9,349	105	16,130,794	31,874,027	24	65
October Delayed 3A	22,829	138	14,846,654	31,565,344	61	101
October Delayed 3B	9,346	105	15,225,013	31,874,029	24	65
December Delayed 3A	22,812	138	13,224,108	31,569,755	61	101
December Delayed 3B	12,605	113	13,973,210	31,798,831	33	73
February 4 A	33,039	164	11,953,994	27,128,097	89	124
February 4 B	9,349	105	15,460,860	29,459,840	24	59
April 4 A	28,749	140	9,232,884	27,916,148	77	117
April 4 B	9,349	105	9,577,555	26,971,357	24	65
June 4 A	34,929	160	11,074,851	26,779,694	94	135
June 4 B	9,242	105	13,450,343	30,534,713	24	64
August 4 A	20,988	96	9,703,137	17,356,656	96	137
August 4 B	8,849	67	10,055,488	19,579,449	24	65
October 4 A	35,276	169	12,132,540	25,565,974	96	136
October 4 B	9,286	108	13,502,880	28,274,272	24	64
December 4 A	28,989	154	11,506,620	27,727,688	78	119
December 4 B	9,335	108	12,314,488	29,490,198	24	65

Table A.5: Detailed results for High Market Scenario-1

Scenario	Annual CO2 Emissions (Kg)	Annual Primary Energy Use (GWh)	Annual Cost of Energy (TL)	Annual Purchase Cost (TL)	Operation Emissions (g/km)	Total LCA Emissions (g/km)
Conventional	155,374	650	85,152,000	212,880,000	207	242
February Uncontrolled 2	28,168	221	27,370,992	55,442,414	51	86
February Delayed 2	46,887	270	24,469,882	47,004,173	74	109
April Uncontrolled 2	132,145	429	36,010,030	71,139,542	139	174
April Delayed 2	56,395	280	22,747,114	46,923,181	86	121
June Uncontrolled 2	74,186	361	23,349,433	64,181,894	94	129
June Delayed 2	49,127	277	20,988,083	46,919,984	77	112
August Uncontrolled 2	43,469	279	47,999,209	80,846,825	49	84
August Delayed 2	41,240	274	35,567,197	69,253,864	49	84
October Uncontrolled 2	36,507	268	35,539,299	77,315,082	43	78
October Delayed 2	46,964	295	33,522,087	69,050,200	56	91
December Uncontrolled 2	Infeasible					
December Delayed 2	52,948	306	29,732,213	68,950,047	63	98
February Uncontrolled 3A	17,951	201	27,474,398	55,645,886	39	74
February Uncontrolled 3B	6,077	172	28,163,063	55,974,235	24	59
April Uncontrolled 3A	127,392	420	36,121,435	71,230,244	134	169
April Uncontrolled 3B	117,543	396	36,336,847	71,502,356	125	160
June Uncontrolled 3A	65,811	349	23,486,584	64,292,022	85	120
June Uncontrolled 3B	57,894	328	24,189,697	64,105,163	77	112
August Uncontrolled 3A	43,469	279	47,999,207	80,846,822	49	84
August Uncontrolled 3B	35,571	268	48,068,847	80,950,342	40	75
October Uncontrolled 3A	32,700	262	35,533,806	77,375,964	38	73
October Uncontrolled 3B	20,949	233	36,194,372	77,696,722	24	59
December Uncontrolled 3A	Infeasible					
December Uncontrolled 3B						
February Delayed 3A	40,088	257	24,597,873	47,108,620	66	101
February Delayed 3B	13,969	192	25,624,131	47,709,885	34	69
April Delayed 3A	46,207	267	23,433,247	47,018,966	73	108
April Delayed 3B	28,026	226	24,366,524	47,389,504	51	86
June Delayed 3A	45,992	271	21,374,801	46,996,965	73	108
June Delayed 3B	33,433	240	22,025,196	47,265,741	57	92

Table A.6: Detailed results for High Market Scenario-2

Scenario	Annual CO2 Emissions (Kg)	Annual Primary Energy Use (GWh)	Annual Cost of Energy (TL)	Annual Purchase Cost (TL)	Operation Emissions (g/km)	Total LCA Emissions (g/km)
August Delayed 3A	16,497	122	16,103,984	31,716,427	43	84
August Delayed 3B	9,349	105	16,130,794	31,874,027	24	65
October Delayed 3A	22,829	138	14,846,654	31,565,344	61	101
October Delayed 3B	9,346	105	15,225,013	31,874,029	24	65
December Delayed 3A	22,812	138	13,224,108	31,569,755	61	101
December Delayed 3B	12,605	113	13,973,210	31,798,831	33	73
February 4 A	33,039	164	11,953,994	27,128,097	89	124
February 4 B	9,349	105	15,460,860	29,459,840	24	59
April 4 A	28,749	140	9,232,884	27,916,148	77	117
April 4 B	9,349	105	9,577,555	26,971,357	24	65
June 4 A	34,929	160	11,074,851	26,779,694	94	135
June 4 B	9,242	105	13,450,343	30,534,713	24	64
August 4 A	20,988	96	9,703,137	17,356,656	96	137
August 4 B	8,849	67	10,055,488	19,579,449	24	65
October 4 A	35,276	169	12,132,540	25,565,974	96	136
October 4 B	9,286	108	13,502,880	28,274,272	24	64
December 4 A	28,989	154	11,506,620	27,727,688	78	119
December 4 B	9,335	108	12,314,488	29,490,198	24	65

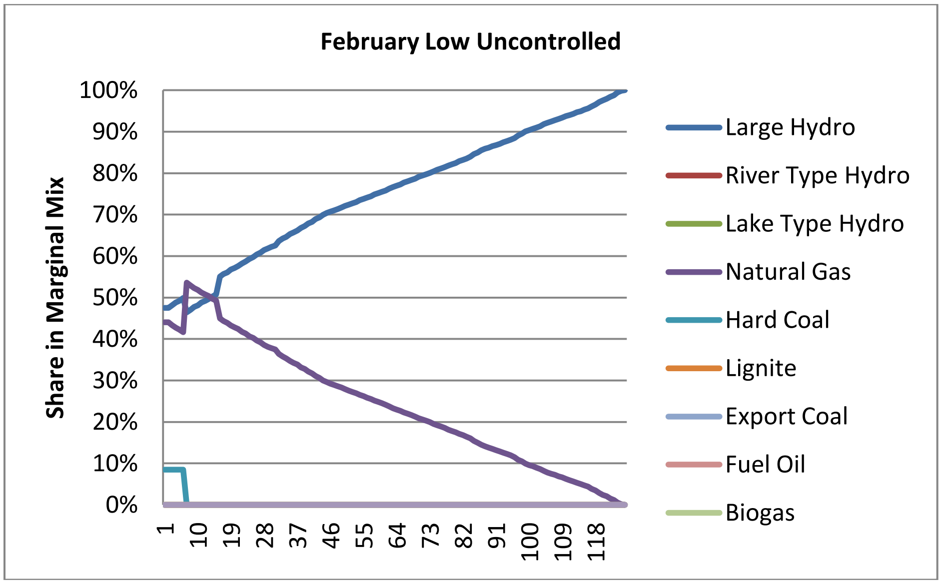

Figure A.1: Change in Marginal Mix for February Low Uncontrolled

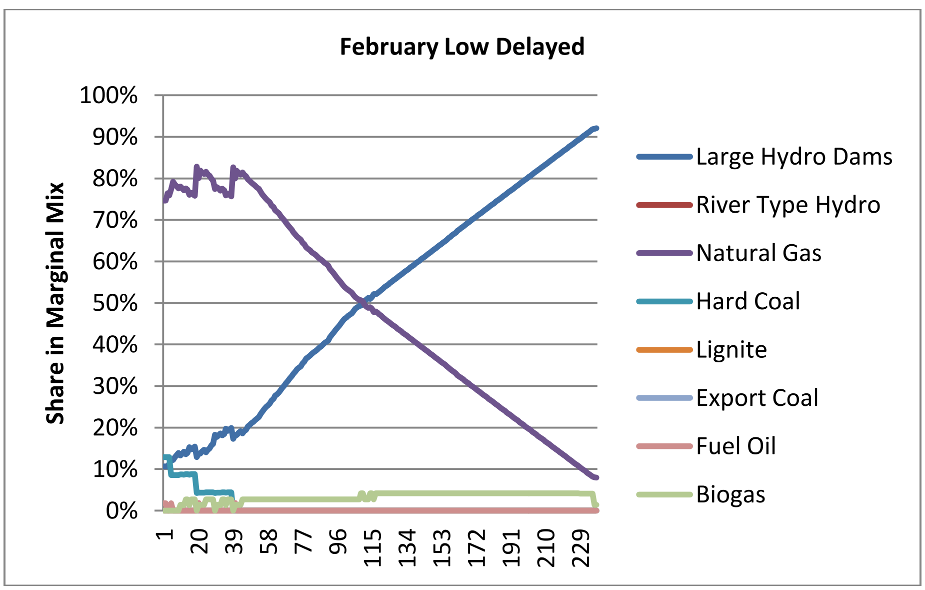

Figure A.2: Change in Marginal Mix for February Low Delayed

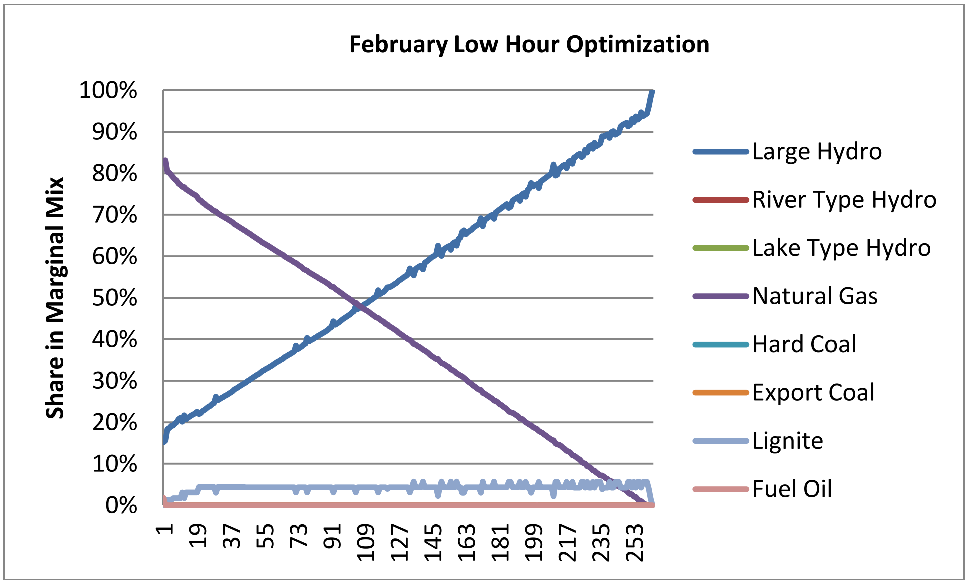

Figure A.3: Change in Marginal Mix for February Low Hour Optimization

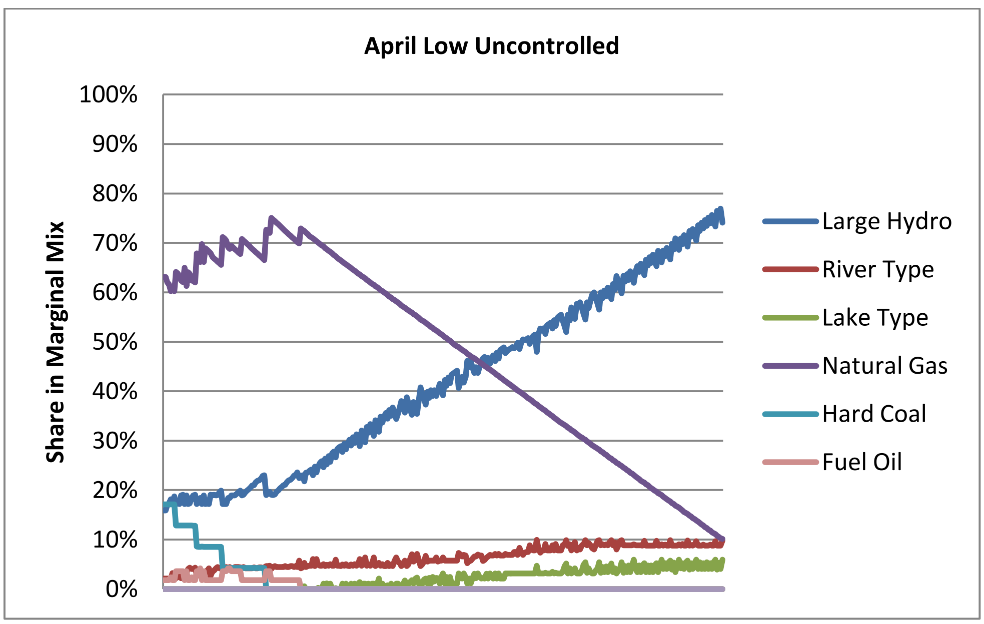

Figure A.4: Change in Marginal Mix for April Low Uncontrolled

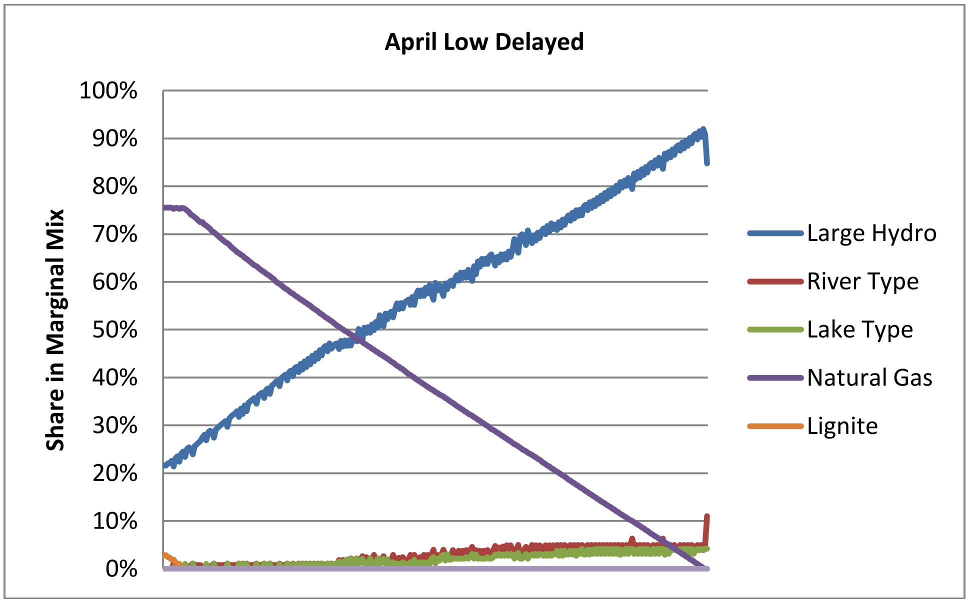

Figure A.5: Change in Marginal Mix for April Low Delayed

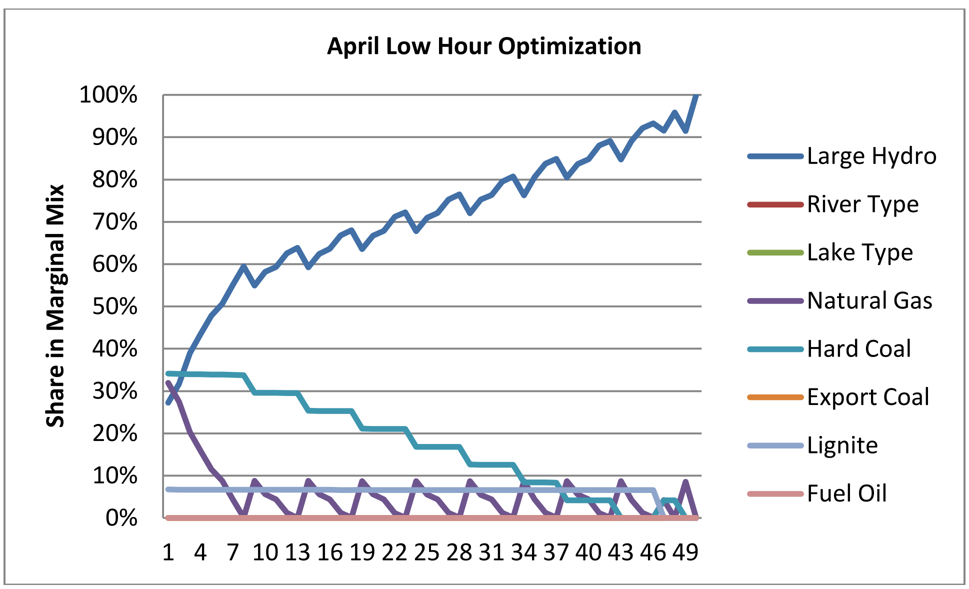

Figure A.6: Change in Marginal Mix for April Low Hour Optimization

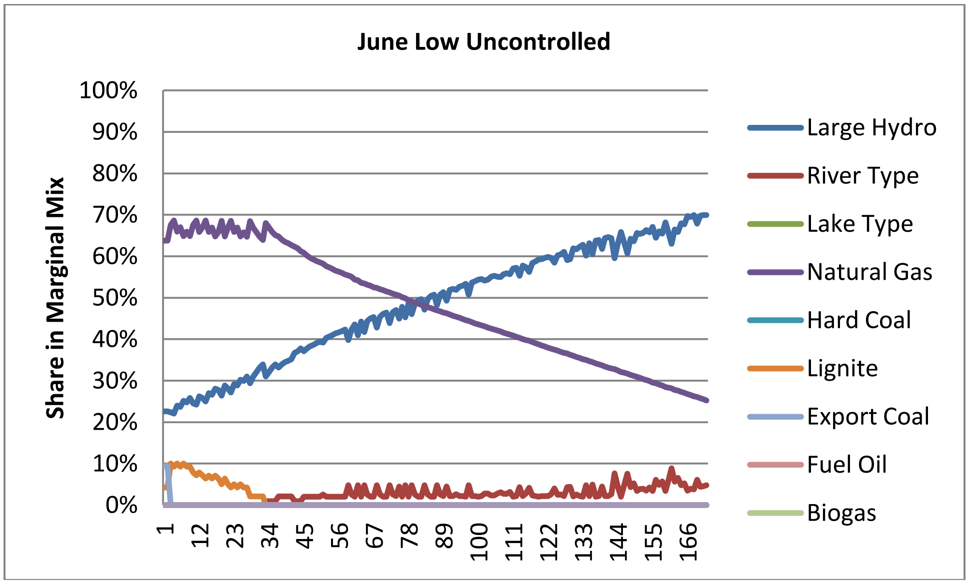

Figure A.7: Change in Marginal Mix for June Low Uncontrolled

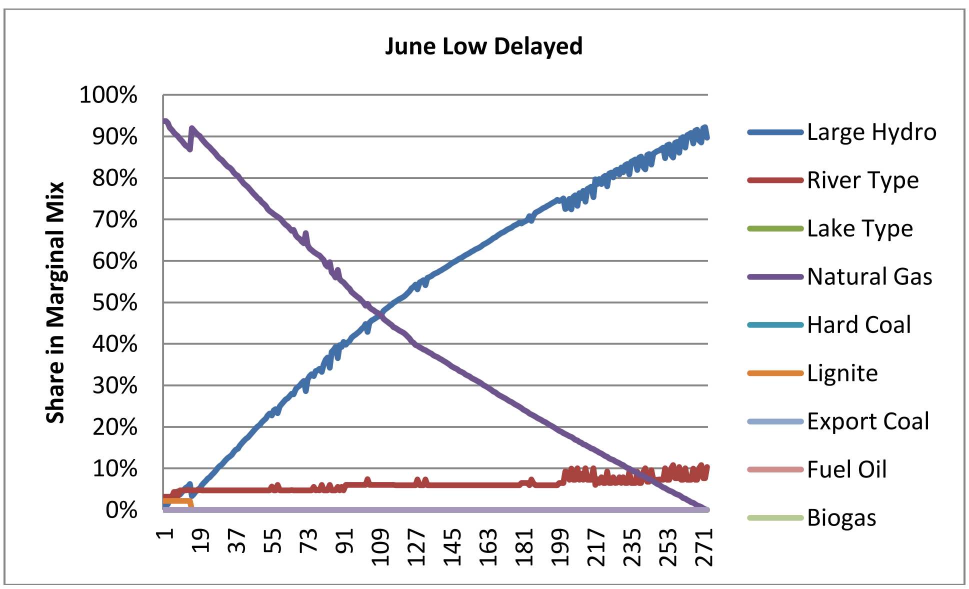

Figure A.8: Change in Marginal Mix for June Low Delayed

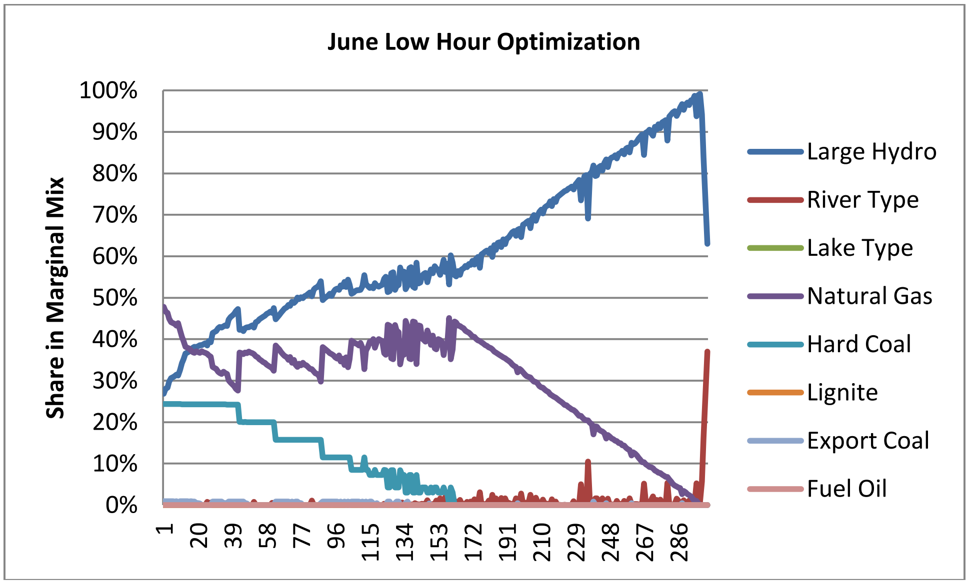

Figure A.9: Change in Marginal Mix for June Low Hour Optimization

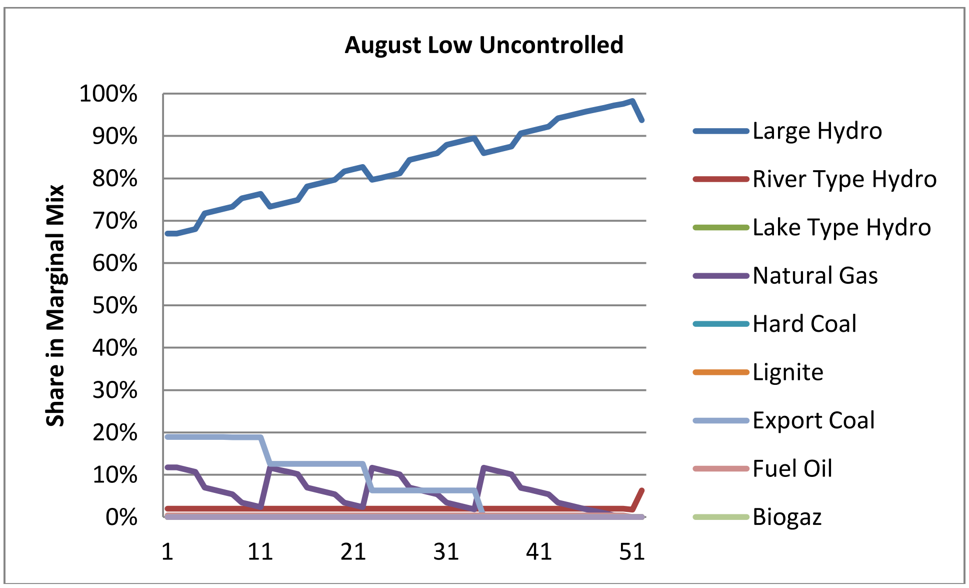

Figure A.10: Change in Marginal Mix for August Low Uncontrolled

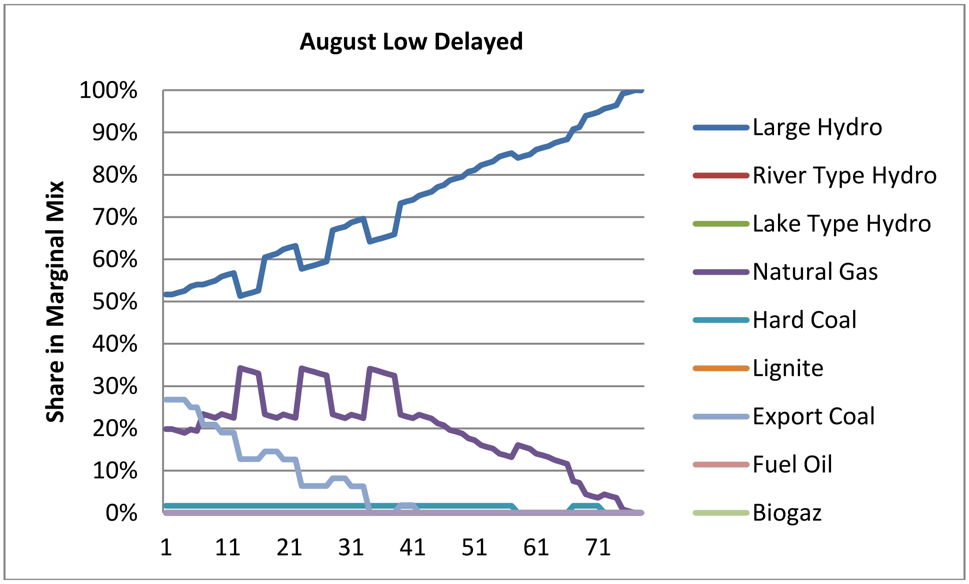

Figure A.11: Change in Marginal Mix for August Low Delayed

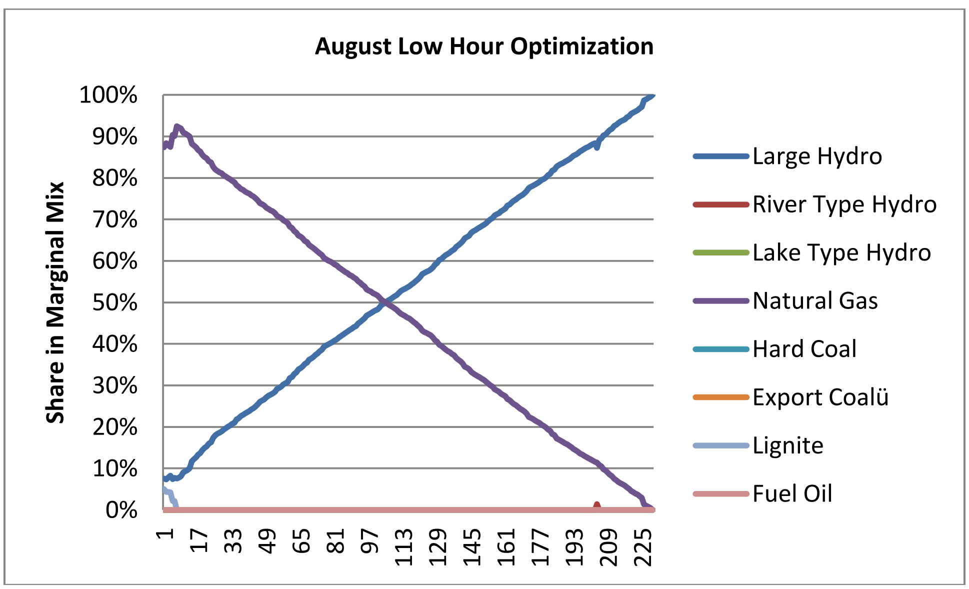

Figure A.12: Change in Marginal Mix for August Low Hour Optimization

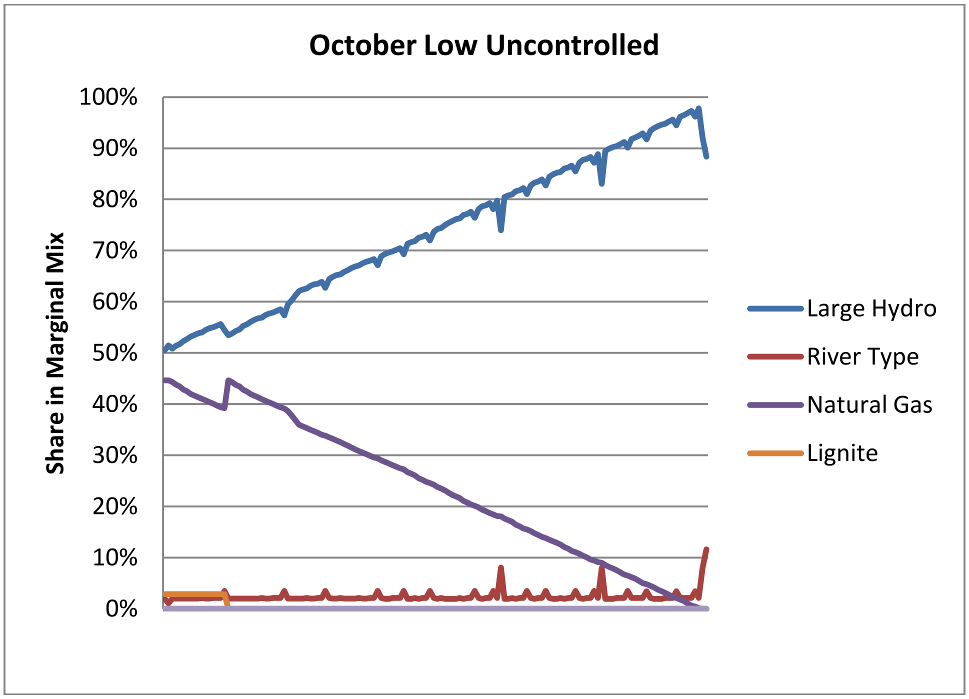

Figure A.13: Change in Marginal Mix for October Low Uncontrolled

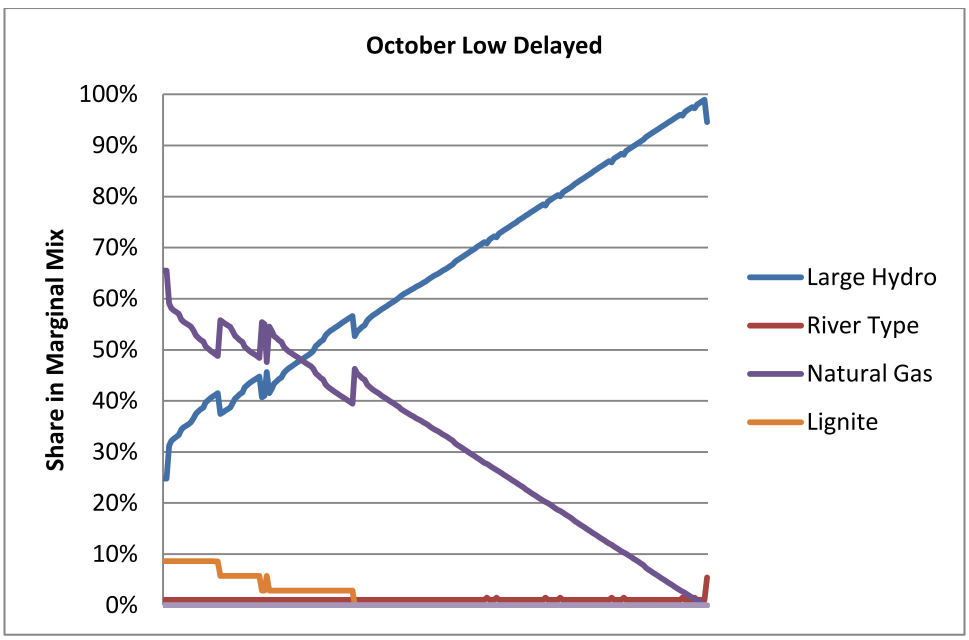

Figure A.14: Change in Marginal Mix for October Low Delayed

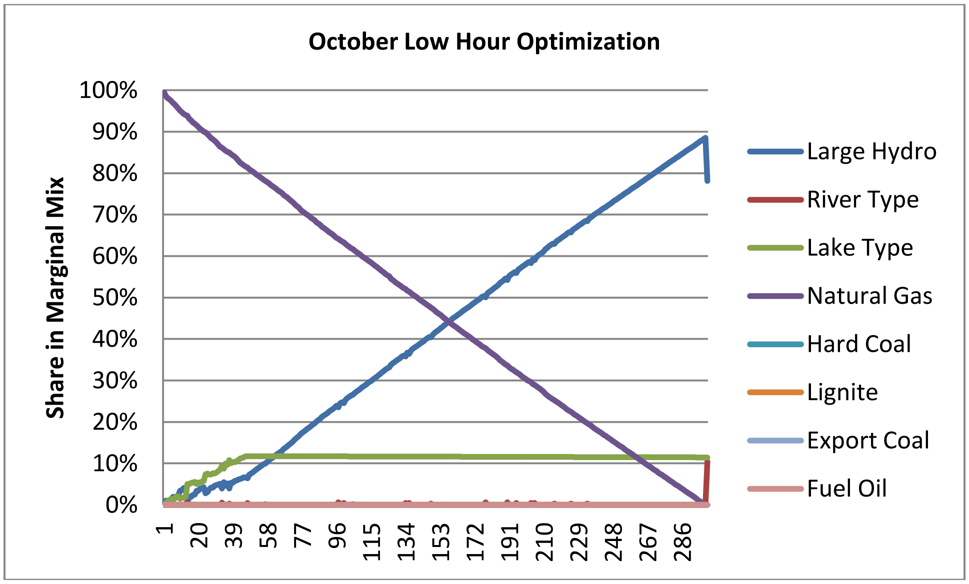

Figure A.15: Change in Marginal Mix for October Low Hour Optimization

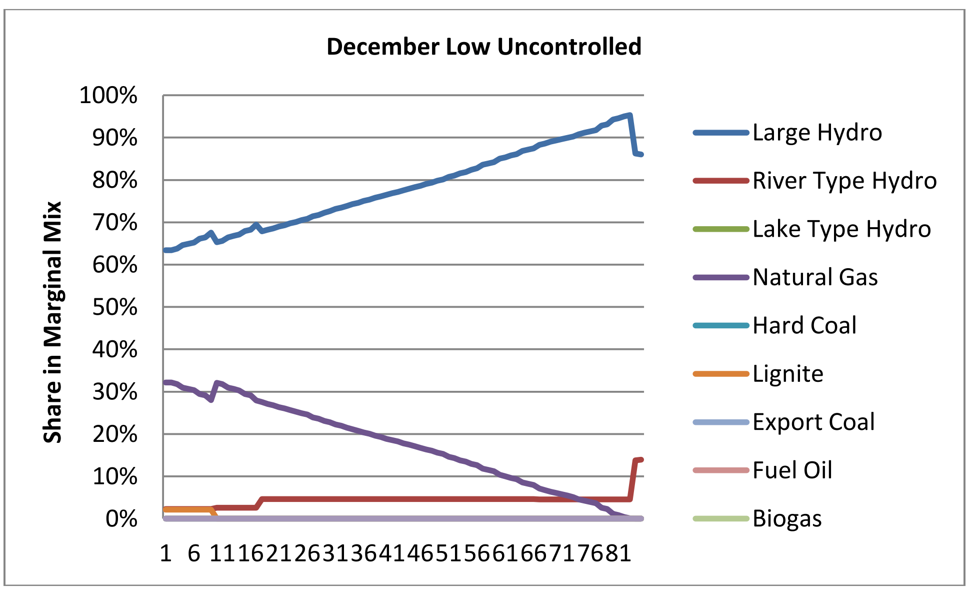

Figure A.16: Change in Marginal Mix for December Low Uncontrolled

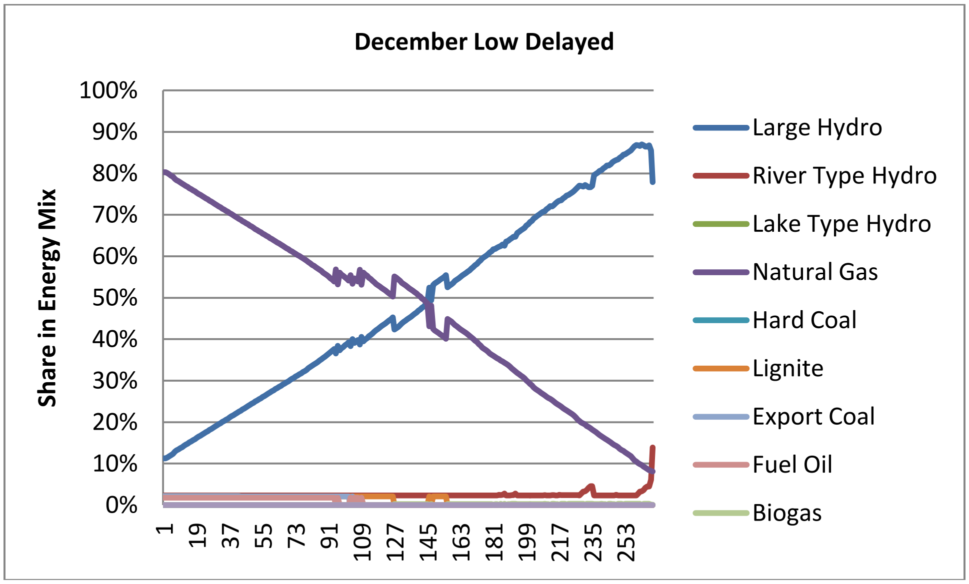

Figure A.17: Change in Marginal Mix for December Low Delayed

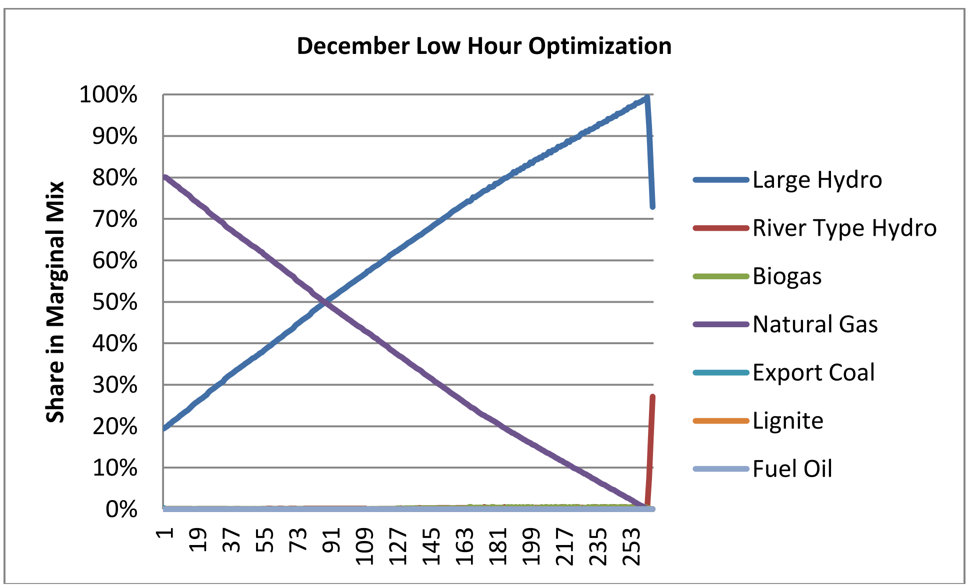

Figure A.18: Change in Marginal Mix for December Low Hour Optimization

Appendix B

COMPUTER MODEL

```
#include "Epsilon.h"

#include <fstream>
#include <iostream>
#include <string.h>
#include <numeric>
#include <math.h>

using namespace std;

Epsilon::Epsilon(void)
{
	counter=0;
	number = 0;
	int i;

	try
	{

		//Cplex object
		cplex= IloCplex(env);

		//cplex parameters
		cplex.setParam(IloCplex::NodeLim, 1000000000);	//MIP node limit
		cplex.setParam(IloCplex::TreLim, 1000000000);	//tree memory limit
		cplex.setParam(IloCplex::EpGap, 0.0);		//relative MIP gap tolerance
		cplex.setParam(IloCplex::ItLim, 1000000000);	//absolute MIP gap
iteration limit
		cplex.setParam(IloCplex::MIPDisplay, 2);	//Dislay option
		cplex.setParam(IloCplex::Threads, 8);			//number of threads
		cplex.setParam(IloCplex::ParallelMode, -1);
```

```
//Expressions
obj1=IloExpr(env);
obj2=IloExpr(env);

//set of constraints
cons=IloConstraintArray(env);


//lower and upper bound
zint=new double[2];
zend=new double[2];

//initial model solutions
zint[0]=numeric_limits<double>::infinity();
zint[1]=numeric_limits<double>::infinity();

//number of rows
m= 115;

//number of hours
n=24;

//
s1=4;
s2=2;

//Decision Variables
x=NumVarMatrix(env, m);
y=NumVarMatrix(env,m);
for(i = 0; i < m; i++)
{
        x[i] = IloNumVarArray(env, n, 0, IloInfinity, IloNumVar::Float);
        y[i] = IloNumVarArray(env, n, 0, 1, IloNumVar::Bool);
}

w=IloNumVarArray(env, n, 0, IloInfinity, ILOFLOAT);
```

```
c=new double[m];

p=new double* [m];
u=new double* [m];
for (i=0; i<m; i++)
{
        p[i]=new double[n];
        u[i]=new double[n];

}

EV=new double[n];
PEV=new double[n];
bbeta = new double[m];


delta = new double[s1];
delta[0]=3.5/1000;
delta[1]=2.2/1000;
delta[2]=1.0/1000;
delta[3]=0.5/1000;


alpha = new double[s2];
alpha[0]=3.7/1000;
alpha[1]=2.7/1000;


EV[0]=0;
EV[1]=0;
EV[2]=0;
EV[3]=0;
EV[4]=0;
EV[5]=0;
EV[6]=0;
EV[7]=0;
EV[8]=2000;
EV[9]=2000;
EV[10]=0;
```

```
EV[11]=0;
EV[12]=0;
EV[13]=0;
EV[14]=0;
EV[15]=0;
EV[16]=10000;
EV[17]=14000;
EV[18]=12000;
EV[19]=0;
EV[20]=0;
EV[21]=0;
EV[22]=0;
EV[23]=0;

PEV[0]=0;
PEV[1]=0;
PEV[2]=0;
PEV[3]=0;
PEV[4]=0;
PEV[5]=0;
PEV[6]=0;
PEV[7]=0;
PEV[8]=4500;
PEV[9]=4500;
PEV[10]=0;
PEV[11]=0;
PEV[12]=0;
PEV[13]=0;
PEV[14]=0;
PEV[15]=0;
PEV[16]=22500;
PEV[17]=31500;
PEV[18]=27000;
PEV[19]=0;
PEV[20]=0;
PEV[21]=0;
PEV[22]=0;
PEV[23]=0;
```

```
            //beta
            beta=new double[2];
        }
        catch (IloException& ex)
        {
            cerr << "Error: " << ex << endl;
        }
        catch (...)
        {
            cerr << "Error" << endl;
        }

}

Epsilon::~Epsilon(void)
{
        //cout<<"destruct"<<endl;
        cplex.end();
        env.end();
        delete[] zint;
        delete[] zend;
}

void Epsilon::getParameters(char* fileName)
{

        //outfile name
        name=fileName;

        int i,j,k;
        char str[256];

        ifstream inFile1("Cit.txt");
        for (i=0; i<m; i++)
        {
            inFile1 >> str;
            c[i] = atof(str);
        }
```

```
inFile1.close();


ifstream inFile2("Pit.txt");
for (i=0; i<m; i++)
{
        for (j=0; j<n; j++)
        {
                inFile2 >> str;
                p[i][j] = atof(str);

                if (p[i][j] == -1)
                {
                        p[i][j] = 1000;
                }
        }
}
inFile2.close();


ifstream inFile3("Uit.txt");
for (i=0; i<m; i++)
{
        for (j=0; j<n; j++)
        {
                inFile3 >> str;
                u[i][j] = atof(str);
        }
}
inFile3.close();

ifstream inFile4("Betai.txt");
for (i=0; i<m; i++)
{
        inFile4 >> str;
        bbeta[i] = atof(str);
}
inFile4.close();
```

```
//objective function-1
for (j=0; j<n; j++)
{
        obj1 += w[j];
}

//objective function-2
for (i=0; i<m; i++)
{
        for (j=0; j<n; j++)
        {
                obj2 += c[i] * x[i][j];
        }
}
//cout<<obj1<<endl;
//cout<<obj2<<endl;

/*
//set-1
for (j=0; j<n; j++)
{
        IloExpr constraint(env);
        for (
        for (j=0; j<cols; j++)
        {
                inFile>>val;

                val=val-1;
                constraint += x[val];
        }

        cons.add(constraint >= 1);
        constraint.end();

        number = number +1;
}
*/
```

```
//Set-1
for (i=0; i<m; i++)
{
	for (j=0; j<n; j++)
	{
		cons.add(w[j] >= p[i][j]*y[i][j]);
		number = number +1;
	}
}


//set-3
for (i=0; i<m; i++)
{
	for (j=0; j<n; j++)
	{
		cons.add(x[i][j] <= u[i][j]*y[i][j]);
		number = number +1;
	}
}

//set-2


double expr2, expr3;
for (j=0; j<n; j++)
{

	IloExpr expr1(env);

	expr2 = 0;
	expr3 = 0;

	for (i=0; i<m; i++)
	{
		expr1 += bbeta[i] * x[i][j];
	}

	if (j==0)
```

```
		{
			expr2 = delta[0] * EV[0] + delta[1] * EV[23] + delta[2] * EV[22] + 
delta[3] * EV[21];
			expr3 = alpha[0] * PEV[0] + alpha[1] * PEV[23];
		}
		else if (j==1)
		{
			expr2 = delta[0] * EV[1] + delta[1] * EV[0] + delta[2] * EV[23] + 
delta[3] * EV[22];
			expr3 = alpha[0] * PEV[1] + alpha[1] * PEV[0];
		}
		else if (j==2)
		{
			expr2 = delta[0] * EV[2] + delta[1] * EV[1] + delta[2] * EV[0] + 
delta[3] * EV[23];
			expr3 = alpha[0] * PEV[2] + alpha[1] * PEV[1];
		}
		else
		{
			for (k=0; k<s1; k++)
			{
				expr2 += delta[k] * EV[j-k];
			}

			for (k=0; k<s2; k++)
			{
				expr3 += alpha[k] * PEV[j-k];
			}
		}

		cons.add(expr1 >= expr2 + expr3);

		number = number +1;


		expr1.end();

	}
	cout<<number<<endl;
```

```
}

void Epsilon::initialModel(double* beta, double* obj)
{

	int i, j;

	IloExpr objFunc(env);
	IloModel epsilonM(env);

	//Weighted objective function
	objFunc = beta[0] * obj1 + beta[1] * obj2;
	epsilonM.add(IloMinimize(env, objFunc));

	//bound for the objective function
	epsilonM.add(obj1 <= zint[0]);

	//constraints
	for (j=0; j<number; j++)
	{
		epsilonM.add(cons[j]);
	}

	//extract the model
	cplex.extract(epsilonM);

	if (cplex.solve())
	{
		obj[0] = cplex.getValue(obj1);
		obj[1] = cplex.getValue(obj2);

		for (i=0; i<m; i++)
		{
			for (j=0; j<n; j++)
			{
				cout<<cplex.getValue(y[i][j])<<"\t";
			}
			cout<<endl;
```

```
                }
        }
        else
        {
                obj[0]=-numeric_limits<double>::infinity();
                obj[1]=-numeric_limits<double>::infinity();
        }

        epsilonM.end();

}


void Epsilon::epsilonModel(double *z, double* obj)
{

        int j;

        IloExpr objFunc(env);
        IloModel epsilonM(env);

        //Weighted objective function
        objFunc = (z[1]-zend[1]) * obj1 + obj2;

        epsilonM.add(IloMinimize(env, objFunc));

        epsilonM.add(obj2 <= z[1]-0.001);

        //Capacity constraint
        for (j=0; j<number; j++)
        {
                epsilonM.add(cons[j]);
        }

        //extract the model
        cplex.extract(epsilonM);

        IloNumArray vals(env);
        if (cplex.solve())      //solve the model
```

```
    {
        obj[0] = cplex.getValue(obj1);
        obj[1] = cplex.getValue(obj2);
    }
    else
    {
        obj[0]=-numeric_limits<double>::infinity();
        obj[1]=-numeric_limits<double>::infinity();
    }

    epsilonM.end();


}

void Epsilon::mainLoop(void)
{

    int i;
    Eff effTemp;

    double* obj=new double[2];
    double* z=new double[2];

    //Step 0.1: Solve problem for the first objective function
    beta[0]=1;
    beta[1]=0;


    initialModel(beta, z);
    counter=counter+1;
    cout<<z[0]<<"\t"<< z[1]<<endl;


    //Optimize second objective function
    beta[0]=0;
    beta[1]=1;

    //optimal for f2(x,y) -- zend
```

```
initialModel(beta, zend);
counter=counter+1;
cout<<zend[0]<<"\t"<< zend[1]<<endl;


//Obtain first efficient solution
//optimal for f1(x,y)
zint[0]=z[0];
zint[1]=z[1];

initialModel(beta, z);
counter=counter+1;
cout<<"zzz "<<z[0]<<"\t"<< z[1]<<endl;


effTemp.e1=z[0];
effTemp.e2=z[1];

eff.push_back(effTemp);
cout<<"ttt\t"<<z[0]<<"\t"<< zend[1]<<endl;

/*
while ( z[1] > zend[1])
{
        epsilonModel(z, obj);
        counter++;

        effTemp.e1=obj[0];
        effTemp.e2=obj[1];

        eff.push_back(effTemp);

        z[0]=obj[0];
        z[1]=obj[1];

}


char outName[50];
```

```
    strcpy(outName, "EffSet_");
    strcat(outName, name.c_str());

    ofstream outFile(outName);

    for (i=0; i<(int)eff.size(); i++)
    {
        outFile<<i+1<<"\t"<<eff[i].e1<<"\t"<<eff[i].e2<<endl;
    }

    cout<<eff.size()<<endl;
    cout<<"counter\t"<<counter<<endl;

    outFile.close();

*/

}
```

Appendix C

RESULT STATISTICS

Table C.1: Result statistics 1

Step	Name of Scenario	Market Scenario	Number of Solutions	Real Time	User Time
Step 3	February Uncontrolled	Low	124	70.1	75.3
Step 3	February Delayed	Low	237	148.4	173.7
Step 3	April Uncontrolled	Low	321	226.4	245.8
Step 3	April Delayed	Low	281	202.5	213.4
Step 3	June Uncontrolled	Low	174	124.5	352.1
Step 3	June Delayed	Low	272	131.1	143.0
Step 3	August Uncontrolled	Low	50	20.0	21.3
Step 3	August Delayed	Low	76	34.6	36.5
Step 3	October Uncontrolled	Low	144	81.7	86.5
Step 3	October Delayed	Low	221	161.8	168.4
Step 3	December Uncontrolled	Low	83	35.4	37.8
Step 3	December Delayed	Low	266	178.9	201.4
Step 4	February Hour	Low	266	128.4	142.3
Step 4	April Hour	Low	52	25.7	27.6
Step 4	June Hour	Low	302	129.6	140.2
Step 4	August Hour	Low	241	120.4	127.4
Step 4	October Hour	Low	300	180.1	190.9
Step 4	December Hour	Low	265	148.8	162.7
Step 3	February Uncontrolled	Medium	248	120.0	130.3
Step 3	February Delayed	Medium	491	323.3	424.0
Step 3	April Uncontrolled	Medium	78	24.7	25.5
Step 3	April Delayed	Medium	142	60.1	61.8

Table C.2: Result Statistics 2

Step	Name of Scenario	Market Scenario	Number of Solutions	Real Time	User Time
Step 3	June Uncontrolled	Medium	34	8.0	8.1
Step 3	June Delayed	Medium	51	11.5	11.6
Step 3	August Uncontrolled	Medium	126	61.5	65.6
Step 3	August Delayed	Medium	180	89.8	95.9
Step 3	October Uncontrolled	Medium	249	144.3	153.4
Step 3	October Delayed	Medium	76	29.9	29.9
Step 3	December Uncontrolled	Medium	289	137.8	147.8
Step 3	December Delayed	Medium	424	251.1	272.3
Step 4	February Hour	Medium	532	240.5	265.8
Step 4	April Hour	Medium	111	56.4	58.7
Step 4	June Hour	Medium	578	228.3	278.0
Step 4	August Hour	Medium	274	119.7	125.4
Step 4	October Hour	Medium	487	274.2	284.5
Step 4	December Hour	Medium	574	350.4	382.9
Step 3	February Uncontrolled	High	467	228.9	248.4
Step 3	February Delayed	High	88	25.2	25.6
Step 3	April Uncontrolled	High	37	11.6	11.6
Step 3	April Delayed	High	199	67.6	68.9
Step 3	June Uncontrolled	High	37	9.1	9.0
Step 3	June Delayed	High	107	25.4	26.8
Step 3	August Uncontrolled	High	97	48.8	51.2
Step 3	August Delayed	High	257	119.7	126.3
Step 3	October Uncontrolled	High	120	43.4	43.9
Step 3	October Delayed	High	265	98.7	98.9
Step 3	December Uncontrolled	High	Infeasbile		
Step 3	December Delayed	High	95	26.0	26.1
Step 4	February Hour	High	747	273.4	287.6
Step 4	April Hour	High	686	373.3	401.7
Step 4	June Hour	High	1051	330.9	339.2
Step 4	August Hour	High	222	81.8	82.3
Step 4	October Hour	High	740	386.7	393.6
Step 4	December Hour	High	534	218.9	228.8