The Effect of Wide Spread Adoption of Plug-in Hybrid Electric Vehicles on Emissions and Electric Generating Capacity

by

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I hereby declare that I am the sole author of this thesis. This is a true copy of the thesis, including any required final revisions, as accepted by my examiners.

I understand that my thesis may be made electronically available to the public.

ABSTRACT

Effects of the wide spread adoption of PHEVs on Ontario electric generating capacity from the year 2014 to 2030 is studied. Long-term forecasting models of load demands and the number of light-duty vehicles sold are developed by employing linear and non-linear regression techniques. Number of PHEVs is forecasted through consideration of three scenarios of penetration levels, such as mild, normal and aggressive ones. Four different scenarios of the charging pattern are also developed since not all people charge their PHEVs during the off-peak period. Extra required load demand for PHEVs charging purposes is calculated. The demands for the worst case, assumed highest transition of PHEVs penetration with the peak period charging pattern, is compared with generator availability at peak in Ontario. Results present that at the end of 2030 in which the total number of PHEVs is 890,362 vehicles, supply is less than the peak load demand. The additional electricity demand on the Ontario electricity grid from charging PHEVs is incorporated for electricity production planning purposes. Moreover, the impact of the socio-economic factors is analyzed. A penetration function is developed which consists of two parts, diffusion rate and the other representing the socio-economic factors. Three general scenarios are considered when deploying the penetration function. Each scenario presents the weight assigned to the diffusion rate and the socio-economic factors. Next, Aggressive, Average and Mild vehicles all-in costs, are studied the adoption rates for males and females separately. Overall, it is indicated that the EVs, HEVs and PHEVs adoptions will increase substantially in the future, comprising a fraction of approximately 30%-38% (depending on the considered scenario) of the total conventional vehicles sold by 2050. Furthermore, Zonal analysis is also accomplished. This study shows that with the increasing adoption of EVs and PHEVs, emissions decrease significantly through 2014 – 2050, specifically in three zones which are The Metropolitan Area of Toronto, Ottawa Ontario, and The Metropolitan Area of Hamilton. This is presented by assuming three different scenarios. The number of related EVs and PHEVs through each scenario is forecasted. To show the quantity of emissions produced in the zones considering the scenarios, initially the emissions factor for Greenhouse Gases (GHG) and Major Non-GHG pollutants are found. The results confirm that the total emissions per season will drop by roughly 40% to 50% of the quantity they would emit when no EVs or PHEVs are penetrated. Finally, the Ontario energy planning is optimized to minimize the value of the cost of the electricity over sixteen years (2014-2030). The mathematical objective function consists of the fuel costs, fixed

and variable operating and maintenance costs, the capital costs for a new power plant, and the retrofit costs of existing power plants (associated with fuel switching from coal to natural gas for coal-fired stations). The mathematical model of objective function and related constraints are applied in the GAMS software. Because of having mixed integer model, the programming code set to be solved through CPLEX solver. Five different case studies are performed with different penetration rate, type of new power plants, and CO_2 emission constraints. Among all the case studies, the one requiring the most new capacity, (~8,748 MW), is Case D, assuming the base case with 6% reduction in CO_2 in year 2018 and high PHEV penetration. The next highest one is Case B, assume the base case, doubled NG prices, medium PHEV and no CO_2 emissions reduction target with an increase of 34.78% in the total installed capacity in 2030. Furthermore, optimization results indicate that by not utilizing coal power stations the CO_2 emissions are the lowest; ~500 tonnes compared to ~900 tonnes when coal is permitted. To conclude, if the most likely scenario is followed (a) the Province cannot meet the expected demand and will need to build significant new capacity and (b) the Province will see significant reductions in CO_2 emissions.

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DEDICATION

To my beloved parents and grandparents

Simin and Masoud

Havva khattoon & Yousef, Razieh & Abbas Ali

True blessings from God, your words are always my strength and inspiration

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List of Abbreviations

AC	Alternating Current
CANDU	CANada Deuterium Uranium
CCS	Carbon capture and storage
CD	Charge-Depleting
CDM	Conservation and Demand Management
CDR	Charge-Depleting Range
CHP	Combined Heat and Power
CO	Carbon Monoxide
CO_2	Carbon Dioxide
COE	Cost of Electricity
CR	Charger Rate
CS	Charge-Sustaining
CVs	Conventional Vehicles
DC	Direct Current
DOE	Day of the Week
EDU	Number of newly graduated students
EIA	Energy Information Administration
EMP	Employment Rate
EVs	Electric Vehicles
GAMS	Generalized Algebraic Modelling System
GDP	Gross Domestic Product
GJ	Gigajoule
GHG	Greenhouse Gases
GSs	Generating Stations
GTA	Greater Toronto Area
HEVs	Hybrid Electric Vehicles
HRL	Hourly Load Demand
ICE	Internal Combustion Engine
IEO	International Energy Outlook
IESO	Independent Electricity System Operator
IGCC	Integrated Gasification Combined Cycle
INC	Income
IPSP	Integrated Power System Plan
Li-Ion	Lithium Ion
LRM	Linear Regression Models
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
MIP	Mixed Integer Programming
MILP	Mixed-integer linear programming
MINLP	Mixed-integer non-linear programming
MSE	Mean Square Error
Mt	Megatonnes
MW	Megawatts
MWh	Megawatt-hour
NiMH	Nickel Metal Hydride
NEB	National Energy Board

NG	Natural Gas
NGCC	Natural Gas Combined Cycle
NiMH	Nickel Metal Hydride
NLRM	Non-Linear Regression Models
NLRM	Non-Linear Regression Models
NO_x	Nitrogen Oxides
O&M	Operating and maintenance
OPA	Ontario Power Authority
OPG	Ontario Power Generation
PC	Pulverized Coal
PHEVs	Plug-in Hybrid Electric Vehicles
PCC	Post-Combustion Carbon Capture
POP	Population Size
RH	Relative Humidity
SO_2	Sulphur Dioxide
SOC	State of Charge
SPSS	Statistics Package for Social Science
T	Temperature
TWh	Terawatt hour

CHAPTER 1: INTRODUCTION

1.1 Motivation

The global demand for energy continues to increase in relation to the growth in population and the economy. The 2009 projections from the International Energy Outlook (IEO), indicate that the global energy consumption is expected to rise by 44% from 2006 to 2030 (EIA, 2010). Protection for the environment and availability of sufficient electricity should be considered in anticipation of soaring global demands for energy.

In Canada, a large part of the energy consumption is derived from the transportation sector, which accounts for approximately 31% of the current total national demand (Statistics Canada, 2009). Greenhouse gases (GHGs) trap the sunlight's energy, keeping the Earth sufficiently warm for life. However, excessive emissions of GHGs contribute to global warming by increasing Earth's average temperature.

New technologies applicable to vehicles have been developed successfully over past decades to improve their performance, reduce energy consumption, and lessen pollution released into the environment. Plug-in Hybrid Electric Vehicles (PHEVs) become fuel flexible vehicles because they use both gasoline and electricity for propulsion. One of the major challenges of using PHEVs is their environmental impact. Although PHEVs can reduce tailpipe emission, the emissions shift to the power plants where the electricity is produced. If the power plants use fossil fuels, emissions are still released. However, if electricity is produced from nuclear, solar, hydro, or wind power plants, emissions are near zero.

With the PHEV penetration into the automobile market, gasoline consumption will decrease in direct relation to the increasing numbers of PHEVs. However, electricity demand will correspondingly increase. The next challenge of PHEV penetration is to determine whether the electricity grid is capable of supplying the increased demand from charging PHEVs.

As mentioned, one challenge of PHEVs penetration is the increasing load demand. The question of whether the existing electricity production infrastructure can cope with the future load demand must be considered. What if Ontario experiences a large electricity deficit? If this proved to be true, then what are the solutions? One solution is to build new power plants. However, by building new power plants, more GHGs and other emissions could be released to the environment. Therefore, in anticipation of generating more electricity to meet rising load demands, both economic regulations and environmental aspects and targets must be considered. The main objective of the thesis is to discover what combinations of future supply technologies will meet the increased electricity consumption in Ontario as a result of PHEV penetration.

1.2 Objectives

The effect of a wide spread adoption of PHEVs on the electric generating capacity on Ontario is a challenging subject. **The main objective of this thesis is to develop a multi-period optimization model for electricity generation planning considering PHEV penetration.** The scope of the work includes following major sections.

1. Formulate the models for long-term forecasts, peak, base, and hourly load demands, and for light-duty vehicles sold in Ontario employing regression methods, as well as nonparametric regression methods by neural network.

2. Study the PHEV penetration and the impact on Ontario load demand

3. Develop a model considering the effect of socio-economic factors on PHEVs/EVs/HEVs adoption rates in Ontario.

4. Analysis the zonal emissions, from PHEVs/EVs penetration.

5. Develop a multi period MILP model to determine the optimal mix of electricity supply sources to satisfy load demand in the Ontario generating sector.

6. Develop different case studies to study the effect of various conditions on the optimization model including different adoption rate, emission restriction, and phasing out specific power stations

1.3 Contribution of the Research

The literature review reveals that no studies to date have been conducted regarding the optimization of energy planning considering the wide spread adoption of PHEVs.

The expected contributions of this study are

- Study the effect of PHEVs penetration on energy planning for long term (in literature, just developed for short period of time for example 24 hours)
- Employing more sophisticated data for predicting PHEVs penetration and load demands
- Developing model to use infrastructure of Ontario including all the current plans (in literature, multi period energy planning in Ontario has been done just using OPG data)
- Defining new and realistic charging scenarios on hourly bases. The results can contribute significantly to the establishment an Ontario government policy to encourage consumers to save energy.
- Developing different models considering the effect of socio-economic factors on PHEVs/EVs/HEVs adoption rates can significantly increase considering realistic penetration rate of PHEVs/EVs/HEVs in Ontario.

- Zonal vehicles emissions analysis would determine areas in Ontario that would make improvement from PHEVs/EVs penetration.

- Developing an optimization model to address optimal planning of the Ontario power generating sector in consideration of different PHEV penetration levels
- The optimization model can be used on a larger scale *i.e.*, for all Canadian provinces and territories, as well as for other parts around the world.

1.4 Thesis Outline

Chapter 2 consists of a concise review of the electricity supply technologies, PHEVs charging specifications, forecast methodology, optimisation methodologies, and relevant literature. Chapter 3 discusses the general methodologies for the research regarding forecasting, and energy planning. The forecasted results for the study, especially for forecasting, PHEVs penetration and charging scenarios, are presented in Chapter 4. The impact of the socio-economic factors is analyzed in Chapter 5. A penetration function is developed which consists of two parts, diffusion rate and the other representing the socio-economic factors. Three general scenarios are considered when deploying the penetration function. Each scenario presents the weight assigned to the diffusion rate and the socio-economic factors. Next, Aggressive, Average and Mild vehicles all-in costs, are studied the adoption rates for males and females separately. Chapter 6 studies the zonal penetration of EV and PHEV. This chapter indicates that with the increasing adoption of EVs and PHEVs, emissions decrease significantly through 2014 – 2050, specifically in three zones which are The Metropolitan Area of Toronto, Ottawa Ontario, and The Metropolitan Area of Hamilton. This is presented by assuming three different scenarios. The number of related EVs and PHEVs through each scenario is forecasted. To show the quantity of emissions produced in the zones considering the scenarios, initially the emissions factor for Greenhouse Gases (GHG) and Major Non-GHG pollutants are found. In Chapter 7, the Ontario energy planning is optimized to minimize the value of the cost of the electricity over sixteen years (2014-2030). The mathematical model of objective function and related constraints is applied in the GAMS software. Four different case studies are performed with different penetration rate, type of new power plants, and CO_2 emission constraints. Installed capacity, economic and emissions analysis of each case study are fully investigated.

CHAPTER 2: LITERATURE REVIEW

2.1 Introduction

This chapter provides an overview of the electricity supply technologies: thermal power, hydroelectric power, nuclear power, and wind power stations. It also presents the modes of operations, key benefits and challenges, battery charging time, and charger requirements for PHEVs. Then, different forecasting and regression models and the methodology are described, and optimization concepts of linear, nonlinear, and integer programming are studied. Finally, a review of other studies and papers on the energy planning optimization models and PHEV penetration are addressed.

Electricity consumption in Ontario is forecast to be approximately 1% by the Integrated Power System Plan (IPSP) (OEA, 2007) and 0.9% by the Independent Electricity System Operator (IESO) (IESO, 2005). Therefore, the energy load demand is predicted to grow from approximately 143.7 terawatt hour (TWh) in 2009 (CEA, 2009) and 145 TWh in 2010 to approximately 186 TWh in 2025 (OME, 2011b). The penetration of PHEVs into the automobile market is expected to increase in the coming years (Eppsteina *et al.*, 2011). This penetration will further increase the demand for electricity. To produce sufficient electricity to satisfy the future demand, supplementary supplies of power must be generated by power stations.

2.2 Overview of Supply Technologies in Ontario

Total generated electricity in Ontario was approximately 154 TWh in 2013 (IESO 2013). Fifty two percent of the electricity or 80.3 TWh was generated by OPG (OPG 2013). Thermal electricity, hydroelectric, and nuclear power plants account for 14%, 34%,and 52% of the OPG electricity generating capacity respectively (OPG 2013).

The installed capacity, measured in MW, is the amount the system is able to generate if it works to full capacity. Table 2.1 shows the total installed capacity of various power plants types in the Ontario in 2013. Approximately 60% of the total installed capacity is from nuclear and hydropower plants (IESO 2013). By considering capacity factors the actual amount of power generated can be calculated. Being able to manage shutdowns, unexpected peak demands, routine equipment maintenance of a power plant, the installed capacity should be always greater than actual generated power. As demonstrated in Figure 2.1, approximately 59.2% and 23.4% of power generated in Ontario was produced by nuclear and hydropower plants in 2013, respectively (IESO 2013).

Table 2.1 Total Installed Capacity for whole Ontario in 2003, 2010, 2013, and 2030 (OME 2011b) (IESO 2013)

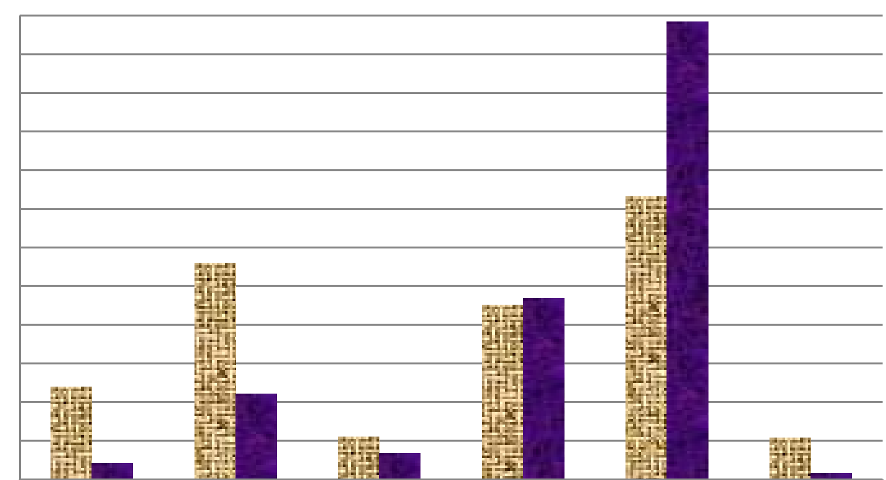
Installed Capacity (MW)	2003	2010	2013	2030 (projected)
Coal	7546	4484	572	0
Gas/Oil	4364	9424	9920	9200
Renewables-Wind, Solar, Bioenergy	155	1657	1948	10700
Renewables- Hydroelectric	7880	8127	8014	9000
Nuclear	10061	11446	12947	12000
Conservation	0	1837	1928	7100
Total	30006	36975	35329	48000

2.2.1 Thermal Power Stations

More than twenty existing thermal electricity GSs operated in Ontario by 2011 (Short, 2011). Five of them are owned by OPG: Atikokan, Nanticoke, Lambton, Thunder Bay, and Lennox GS. Atikokan and Thunder Bay GSs will be converted from coal to use biomass by the end of 2014. Nanticoke and Lambton GSs are fuelled by coal, and the fifth one, Lennox GS, is fuelled by oil and natural gas (OPG, 2013). The different types of thermal power stations are discussed in the following sections.

2.2.1.1 Natural Gas Power Stations

As it is obvious natural gas power stations are fuelled by natural gas. Steam turbines and gas turbines can be used to generate power for electricity production. A steam turbine is a type of turbine that produces thermal energy from steam and converts it to electricity through rotary motion using rotating turbine blades. A gas turbine uses gas expansion whereby the gas flow rotates the turbine by passing through a nozzle aimed over the turbine blades. Turbine drives electrical generator which generate electricity. The different types of natural gas power station technologies are discussed in the following sections.



	Coal	Gas/Oil	Renewables-Wind, Solar, Bioenergy	Renewables-Hydroelectric	Nuclear	Conservation
Installed Capacity 2013	0.12	0.28	0.055	0.226	0.366	0.054
Generation 2013	0.021	0.111	0.034	0.234	0.592	0.008

Figure 2.1 Installed and Generation Capacity for whole Ontario in 2013 (IESO, 2013).

Simple Cycle Gas Turbine

In a simple cycle gas turbine, air is compressed to higher pressure once it enters the compressor. In a combustion chamber, natural gas or other fuels are burned at high temperature and pressure with compressed air. The resulting high temperature combustion gas and air mixture are converted to work by expanding in the turbine and spinning an electrical generator to produce electricity.

Natural Gas Combined Cycle

A natural gas combined cycle (NGCC) power plant merges the steam turbine and gas turbine technologies to generate electricity. In a heat exchanger, steam is generated by using released heat from a gas turbine. Therefore, additional electricity is produced by a steam generator which works by the steam generated (or generated steam).

Combined Heat and Power/Cogeneration, CHP

Cogeneration systems produce both electricity and valuable heat at the same time. Similar to NGCC, electricity is generated from steam turbines. However, in cogeneration, steam is not used to produce electricity. In fact, thermal energy of steam is used for district heating, water desalination, etc. CHP overall efficiency (electricity + usable heat) is approximately 80 percent (OME 2011b).

2.2.1.2 Coal Power Stations

Two main groups of coal power plant technologies are:

Combustion (pulverized coal power stations)

Gasification (for instance, Integrated Gasification Combined Cycle (IGCC))

Pulverized Coal Power Stations

A boiler is fuelled by powdered coal which was ground for combustion. Heat is produced by burning these crushed coals. The heat then produces steam which rotates the turbines for electricity generation.

Integrated Gasification Combined Cycle, IGCC

Through IGCC plants, steam production from the gasification system and the combined cycle portion of this system are integrated together. Synthetic gas (syngas) is derived from gasified coal by partial combustion, in coal gasification. Then, the syngas is burned by combustion to turn gas turbine blades and generate electricity. Additional electricity is generated through smaller steam turbines, derived by produced steam from recovered waste heat of hot exhaust gases.

2.2.1.3 Thermal Power Resource in Ontario

After October 2010, coal-fired generation comprises approximately thirteen percent of Ontario’s electricity capacity and produced eight percent of the total power generated in Ontario (OME 2011b). In 2013, coal GSs generated 2.1% of the electricity generated in Ontario (IESO, 2013). Thermal electricity GSs have a combined capacity of 10,492 MW operating in Ontario. The generation capacity of the two coal power plants, Nanticoke and Lambton, is 572 MW (OPG, 2013).

The generated electricity in fossil fuel-fired thermal power plants converts only approximately 35% of the potential energy from coal into electricity. Heat is released into the environment as a form of the remaining energy. Carbon dioxide (CO_2), carbon monoxide (CO), sulphur dioxide (SO_2), nitrogen oxides (NO_x) and particulates are discharged from coal combustion into the atmosphere (IESO 2010).

Reducing the CO_2 by using CO_2 capture and sequestration is particularly expensive. For this reason and because of many other environmental issues (IESO 2010), two units at Lakeview (Mississauga) were phased out in April 2005. Four coal generation units at Lambton GS and Nanticoke GS were closed in October 2010. Two more units at Nanticoke GS were shut down by the end of 2011 (IESO 2010).The remaining coal power stations are scheduled to be closed by the end of 2014.

In addition, natural gas, biomass, and oil are additional fuelling options for some units. For example, OPG will consider natural gas as fuel at Nanticoke and Lambton GS in the near future (IESO 2010). Natural gas power plants produce a lower amount of CO_2 compared to other types of fossil fuels. Moreover, both small and large generators are required to have a reliable supply. Natural gas power plants are able to significantly improve the flexibility of the system to respond to the high demand during peak hours of electricity use. Since 2003, 5,574 MW of electricity generated by new natural gas power plant has been added to the supply network (IESO, 2013). At present, there is a capacity of 9,920 MW of electricity generation from natural gas/oil in Ontario (IESO, 2013).

A plan was developed in 2007, which included establishing new power plants in the next several years. The plan emphasizes the lower level of the contamination produced by the natural gas power plants, the operational flexibility, the cost of making new plants, and the speed of construction of the plants. In addition, in the GTA which is consuming a large amount of energy, natural gas is used in the power plants and the waste heat is used to provide space and water heating for other buildings in the same region (OME 2011b).

The third mentioned type of thermal power plants is CHP. In Ontario, CHP capacity is approximately 2,000 MW or 5.5 percent of installed generation capacity at present. In addition, there is a new capacity of 414 MW in Thorold, Oshawa, Kingsville, Sault Ste. Marie, Windsor, London, and Markham (IESO, 2013).

2.2.2 Hydroelectric Power Stations

Hydroelectric power GSs produce electricity by utilizing stored water behind a dam. Water is released on to turbine propellers which rotate the turbine shafts. Shafts are connected to the generator and thus produce electricity. In this procedure, as water is the only fuel that is used to generate electricity, hydropower is identified as a renewable resource by most governmental energy policies. However, there are still many discussions as to whether hydropower is a renewable and/or sustainable energy source in Canada (Freya and Linkeb, 2002).

2.2.2.1 Hydropower Resource in Ontario

Hydroelectric power stations provide approximately 23.4% of Ontario's electricity. The stations represent 22.6% of the installed capacity of the province's electricity-producing plants IESO, 2013). The Niagara plant group with its capacity of 2,278 MW is the largest hydropower GS in Ontario and is located on the Niagara River at DeCew Falls in St. Catharines (OPG 2011a). The total installed hydroelectric capacity in Ontario is 8,014 MW. The plan is to increase the installed capacity to 9,000 MW by 2018 (OME 2011b). Some of the completed and ongoing projects of building new hydro power stations in Ontario are noted in Table 2.2 (OME 2011b).

2.2.3 Nuclear Power Stations

Nuclear power plants generate and preserve energy from uranium atoms that have been divided into parts, i.e., the source of energy is the splitting of the uranium atoms. To generate electrical energy, the energy released from the nuclear reactions is used to heat water, produce steam, and move the generators (Sovacool 2008). A nuclear fuel cycle is grouped into two categories: "closed" and "once-through." During a once-through mode, the used fuel is disposed directly. Most of the conventional reactors work on a once-through basis. The main advantage of closed type reactor is that the used material can be recycled after separating the waste products from unused fissionable fuel.

Table 2.2 List of New Ontario Hydropower Generating Stations (OME 2011b)

Hydropower GS	Generating Capacity (MW)	Comments/Location
Niagara Tunnel Project	---	This project will increase the amount of water at the Sir Adam Beck GS.
The Lower Mattagami Project Expansion	440	The project is the largest one planned in the past 40 years.
Healey Fall Project	15.7	Campbellford, east of Peterborough
Lac Seul GS	12.5	Ear Falls
Trent Rapid Hydroelectric Station	8	Near Peterborough
Sandy Falls	5.5	Mattagami River, near Timmins

2.2.3.1 Nuclear Power Resource in Ontario

In Ontario, over half of the power used and thirty six percent of installed capacity (12,947 MW) are generated by nuclear power plants. Moreover, nuclear power generating plants are critical for providing reliable baseload power. Three CANada Deuterium Uranium (CANDU) nuclear plants with sixteen units operate in Ontario at the present time. The Pickering GS, Bruce Power Plant, and the Darlington GS have six, six, and four operating units, respectively (IESO, 2013).

Nuclear units, their gross capacity, as well as their estimated end-of-service dates are outlined in Table 2.3 (Winfield et al., 2004). The first commercial operation dates of most of the nuclear units are in the 1970s and 1980s. Therefore, the units which reach the end of their working lives will be retired or will need to be refurbished before 2020. Sixteen units will be taken out of service, two at a time, for refurbishment between 2010 and 2026. The refurbished units can operate for another thirty years (IESO 2009a). In addition, two units are planned to be added at the Darlington site in the 2020s (OME 2011b).

Table 2.3 Ontario's Nuclear Generating Stations Status, Capacity, Service Date (Winfield and others 2004, OPG 2013)

	Unit #	Status	Gross Capacity (MW)	First Commercial Operation	End of service date
Pickering Nuclear Plant					
Pickering A	1	Operational - Was returned to service in 2005	515	07/1971	n/a
	2	Out of service	515	12/1971	n/a
	3	Out of service	515	06/1972	n/a
	4	Operational -Was returned to service in 2005	515	06/1973	2016
Pickering B	5	Operational	516	05/1983	2020
	6	Operational	516	02/1984	2020
	7	Operational	516	01/1985	2020
	8	Operational	516	01/1986	2020
Bruce Nuclear Plant					
Bruce A	1	Operational -Was returned to service in 2011	750	09/1977	n/a
	2	Operational -Was returned to service in 2011	750	01/1977	n/a
	3	Out of service	750	01/1978	2012
	4	Operational	750	01/1979	2016
Bruce B	5	Out of service	785	03/1985	2011
	6	Out of service	820	09/1984	2011
	7	Out of service	785	04/1986	2011
	8	Out of service	785	05/1987	2012
Darlington Nuclear Plant					
Darlington	1	Operational	881	11/1992	2017
	2	Operational	881	10/1990	2015
	3	Operational	881	02/1993	2018
	4	Operational	881	02/1993	2018

2.2.4 Wind Power Plants

Wind powered plants produce electricity after turbine blades are rotated by wind. Theoretically, the generated electricity is a result of converted kinetic energy from wind's potential energy.

2.2.4.1 Wind Power Resource in Ontario

Melancthon EcoPower Centre (Amaranth I and Amaranth II) with a 199.5 MW capacity located near Shelburne is Canada's largest wind farm. In Ontario, more than 700 wind turbines operate currently. The number of wind turbines was ten in 2003 (OME 2011b). Tables 2.4 and 2.5 give amounts of power generated by wind turbines in Ontario in 2011 (IESO 2011).

Table 2.4 Current Ontario's Wind Power Generating Station's Capacity (IESO 2011)

Wind Farm	Capacity (MW)	Operational	Location
Amaranth I	67.5	Mar. 2006	Township of Melancthon
Kingsbridge I	39.6	Mar. 2006	Huron County
Port Burwell (Erie Shores)	99	May-06	Norfolk and Elgin Counties
Prince I	99	Sep. 2006	Sault Ste. Marie District
Prince II	90	Nov. 2006	Sault Ste. Marie District
Ripley South	76	Dec. 2007	Township of Huron-Kinloss
Port Alma (T1) (Kruger)	101.2	Oct. 2008	Port Alma
Amaranth II	132	Nov. 2008	Township of Melancthon
Underwood (Enbridge)	181.5	Feb. 2009	Bruce County
Wolfe Island	197.8	Jun. 2009	Township of Frontenac Islands
Port Alma II (T3) (Kruger)	101	Dec. 2010	Municipality of Chatham-Kent
Gosfield Wind Project	50	Jan. 2011	Town of Kingsville

Table 2.5 Ontario's Wind Power Generating Station's Capacity Recently added (IESO 2011)

Project	Capacity (MW)	In Service
Spence Wind Farm (Talbot)	98.9	2011-Q1
Dillon Wind Centre (Raleigh)	78	2011-Q1
Greenwich Wind Farm	98.9	2011-Q3
McLean's Mountain Wind Farm I	50	2011-Q3
McLean's Mountain Wind Farm III	10	2011-Q3
Comber East Wind Project	82.8	2011-Q3
Comber West Wind Project	82.8	2011-Q3
Pointe Aux Roche Wind	48.6	2011-Q3
Conestogo Wind Energy Centre I	69	2011-Q4
Summerhaven Wind Energy Centre	125	2012-Q1
Bow Lake Phase I	20	2012-Q2

2.3 Plug-in Hybrid Electric Vehicles, PHEVs

Plug-in hybrid electric vehicles (PHEVs) combine the combustion engine of conventional vehicles and the electric motor of electric vehicles. PHEVs have greater fuel efficiency because they consume less fuel than in conventional vehicles in which gasoline is the only energy source. PHEVs battery can be recharged by connecting into the electrical grid. This makes PHEVs "fuel flexible vehicles" because they can use both gasoline and electricity for propulsion (Figure 2.2). The challenge of PHEVs is their impact on the electricity grid. The amount of charge required by PHEVs increases correspondingly with the extent of PHEV penetration. The energy sector must anticipate and prepare for this extra demand and implement long-term planning for electricity production. The benefits and challenges of PHEVs are written in Table 2.6.

In this thesis, it is assumed that PHEVs are commercially produced starting January, 2014. Besides, only new light-duty vehicles are considered as potentially new PHEVs since they have more potential to be PHEVs. Batteries capacity is another issue, especially for charging patterns. Deeper battery charging and discharging cycles than conventional hybrids are required for PHEVs. Since battery life is influenced by the number of full cycles; PHEVs battery life may be smaller than in traditional HEVs which do not deplete their batteries as much as PHEVs. In addition, design issues and trade-offs against battery life, capacity, heat dissipation, weight, costs, and safety are batteries limitations. In this thesis 80% safety factor and 82% of charger efficiency are assumed. To calculate the demand from charging, identification of types of PHEVs that will penetrate the transportation sector is essential. Based on the average commuting distance in Ontario, 12.9 km, PHEV-20 is assumed to be the main PHEV that will penetrate the light-duty vehicles sector. Another assumption is that no PHEVs are retired during the period under study, 2014–2030.

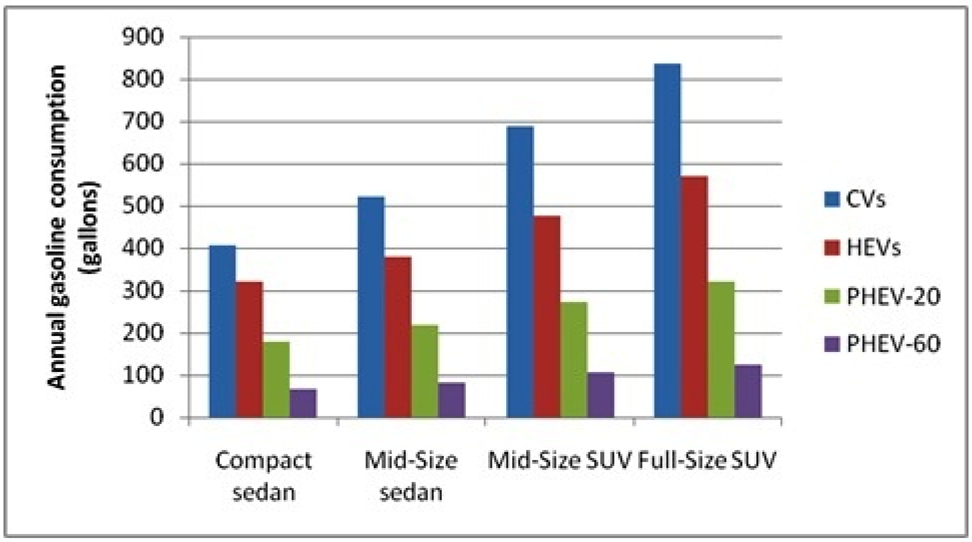


Figure 2.2 Fuel Consumption of CVs, HEVs, PHEVs (EPRI 2001; EPRI 2002)**.**

Table 2.6 PHEVs Benefits and Challenges

Benefits	Challenges
Flexibility of fuel GHGs emissions reduction Gasoline consumption reduction Improved fuel economy	Battery cost Shifted emissions to power plants Load demand increase

2.4 Regression Models

Electricity demand forecasts are essential to the efficient operation of electric utilities, governmental energy agencies, engineering and construction firms, and policymakers. Naturally, forecasts must accurately anticipate the future behaviour of users before decisions are made.

Generally, forecasts are generated for points in time that may be a number of hours, days, weeks, months, quarters and/or years in the future. This length of time is known as the time horizon or time frame. The length of the time horizon is usually categorized by the three forecast types presented in Table 2.7 (Al-Alawi and Islam, 1996). Different forecast horizons are associated with different uses or purposes, different types of forecast models, and different levels of reliability.

Table 2.7 Types of Electricity Demand Forecasts and Major Applications (Al-Alawi and Islam 1996)

Forecast Types	Forecast Horizons	Applications
Long-term	5 to 25 years in future	System expansion planning and financial analysis
Medium-term	Few months to few years in future	Fuel procurement, maintenance scheduling and diversity interchanges
Short-term	Few hours to few weeks in future	Determining unit commitment and economic dispatch

The thesis focuses on the long-term load forecast because capital investments associated with electricity supply systems are extremely expensive and the construction of power generation plants requires up to five years to complete.

2.4.1 Forecast Methods

Neural Networks (NN) are connected structures including simple elements. The simple elements are called neurons, and the structure is parallel. Neurons are organized in parallel layers and are connected together like biological neuron systems. NN models typically have at least three layers as input, hidden, and output layers. The number of neurons in each layer depends on different items. For instance, the nature of the problem defines the number of neurons in the input and output layers. The values of the connections, known as weights, are important factors in NN systems. Essentially, by adjusting weights between neurons, most of the difficult functions can be accomplished by training. The training process enables model to lead from particular input to specific target output. The training process (considering the comparison of the output and target) continues until the output and target match (Entchev & Yang, 2007).

2.4.2 Forecast Evaluation

Forecast evaluation is accomplished by employing mean absolute error (MAE), mean absolute percentage error (MAPE), and mean square error (MSE) are used to measure the forecast accuracy as follows:

$$MAE = \frac{\sum_{t=1}^{n}|e_t|}{n} = \frac{\sum_{t=1}^{n}|y_t - \hat{y}_t|}{n} \tag{2.1}$$

$$MAPE = \frac{100}{n}\sum_{t=1}^{n}\left|\frac{e_t}{y_t}\right| \tag{2.2}$$

$$MSE = \frac{\sum_{t=1}^{n} e_t^2}{n} \tag{2.3}$$

where:

e_t	=	the error term
y_t	=	the observed value
$\hat{y}_t$	=	the estimated value
n	=	the total number of observations
t	=	time index

2.5 Basic Concepts of Optimization

Optimization is the scientific method for analyzing complex models. The best solution for finding the available optimized value of a real function is indicated by developing specialized techniques. Three main requirements are defined for optimization (Edgar and Himmelblau 2001): objective functions, decision variables, and constraints. Depending on the objective function, the optimized value can be a minimum or maximum amount of the function in the specified domain.

The mathematical model of the objective function is:

Objective function $\quad \min/\max_{x,y} f(x, y, v)$ (2.4)

Equality Constraint $\quad h(x, y, v) = 0$ (2.5)

Inequality constraint $\quad g(x, y, v) \leq 0$ (2.6)

where x is explanatory variable like electricity generation, CO_2 emission, capacity factor, etc. and y is a binary variable that shows existence or nonexistence of power plants units for instance fuel selection, new power plants, etc., and v is a parameters.

The equality constraints consist of process model equation, for example, satisfaction of demand or cost model of new plants. The inequality constraints may refer to quality, feasibility, logical and binary constraints. The CO_2 emission target is the quality constraint. It states that the CO_2 emission should be equal to or less than a specific percent of a target year by a certain time. An example of logical constraint is the total generated power should be equal to or greater than the Ontario electricity demand. The capacity factor of each power plant is a feasibility constraint. New power plants choice and fuel selection are binary constraints.

In addition, mathematical models are categorized in three general classifications:
Linear Programming, LP
Nonlinear Programming, NLP
Mixed Integer Programming, Linear and Nonlinear, MILP and MINLP

2.5.1 Linear Programming

LP consists of a linear objective function and linear constraints. The constraints should include only linear equalities and inequalities. LP is the most effective optimization technique and it is used extensively. The solution must satisfy all linear constraints and find the minimum or maximum of the defined linear objective function. Currently, LP mathematical models with thousands of constraints and variables can be solved by optimizer packages.

2.5.2 Nonlinear Programming

NLP consists of linear and nonlinear objective functions and constraints. The constraints or objective function must at least involve a nonlinear term. In problem solving, both the theoretical and practical features of NLP problems are considered. Studying the algebraic and geometric situations that distinguish the solution involves theoretical issues. Mathematical formulation, algorithms development, and the analysis of a specific problem are practical issues. One method of solving NLP problems is removing the variable with the nonlinear term from the formula by solving explicitly.

2.5.3 Integer Programming

The integer programming model consists of one or more integer variables. These variables are discrete and have integer values, such as the existence or nonexistence of power plant units as binary variable termed zero-one. Another example is tray of distillation columns, with terms one, two, three, etc. In general, if the objective function depends on two type of variables (continuous and integer), the problem would be a MIP model. If only the integer variables are used, the problem would be an Integer Programming (IP) model. Finally, if only variables with the amount of 1-0 are used, the problem would be a Binary Integer Programming (BIM) model.

Moreover, the MILP model consists of only linear equalities and inequalities, and the MINLP model includes linear and nonlinear ones. In this study the MIP model is employed to optimize energy planning of Ontario energy sector.

2.6 Journal Reviews

Several studies have been conducted to model energy planning optimization, address the MINLP, and analyze the wide spread adoption of PHEVs penetration on energy generation planning systems.

2.6.1 Energy Planning Optimization Models

A deterministic multi-period MILP model for power generation planning was developed with respect to meeting electricity demand and CO_2 emissions targets at minimum cost (Mirzaesmaeeli et al., 2010). Some of the time dependent decision variables that comprised the objective function included expected energy demand, fuel prices, construction lead time, and variability in operational and maintenance costs. The model was applied to two case studies, one without a CO_2 emissions target (case I) and another with the Kyoto Protocol's emissions reduction target (case II). It was found that case I required the building of several new high emissions power plants without CCS technology while case II required the building of low emissions power plants with CCS technology. It was also found that case II would cost approximately 11.4% more to implement than case I.

Benjamin F. Hobbs (1995) reviewed optimization models for electric utility planning. It is an exploration of how the needs of utility planners have changed due to changes in electricity demand, environmental issues, competition, and overall uncertainty. Various models are presented in response to the challenges stated and the gaps these models contain are addressed.

Jebaraj and Iniyanb (2006) studied various emerging issues related to energy modeling. These included energy planning models, energy-supply demand models, forecasting models, renewable energy models, emission reduction models and optimization models. In addition, neural network models and fuzzy theory models were also explored. In the linear programming models considered, it was determined that factors such as income, output, profit, energy quantity, energy performance and energy production were important for finding energy utilization levels. Technology, efficiency, supply, demand, employment and resource availability were found to be constraints in these models.

A MILP optimization model under CO_2 emissions constraints was discussed (Lee and Hashim, 2014). Using the case study of Iskandar, Malaysia, the model is able to determine the combination of the most economical and lowest CO_2 emitting solution to meet electricity demands through 2025. Some of the decision variables involved in this model include fuel switching, use of renewable energy power generation and carbon capture and storage technology. Various CO_2 emission limits were used for the model. It was determined from sensitivity analysis that the resultant combination of energy generation types were significantly affected by CO_2 emission limits.

Arnette and Zobel, (2012) developed a model used in the energy planning decision making process focusing on increased use of renewable. A MOLP model was used to determine the optimal combination of existing fossil fuel power plants and the addition of renewable energy sources. A clear trade-off between the electricity generating costs and greenhouse emissions can be extrapolated from this paper's findings. A case study using this model was applied for the greater southern Appalachian Mountains in the eastern US. Findings from the optimization model indicate that the costs of implementing renewable energy generating sources are not as high as previously assumed.

Computational methods in optimizing energy generation from renewable and sustainable sources are reviewed (Banos et al., 2011). Through the review of over two hundred papers, it was concluded that the quantity of research papers that use computational optimization methods to solve renewable energy problems has increased dramatically. Large numbers of researchers are using heuristic optimization, Pareto-optimization methods and parallel processing to solve these problems.

Cong (2013) developed a REOM to analyze the effect of three sources (wind, solar and biomass). From this model, the maximum capacities of the three renewable energy sources were found for 2020. In addition, the growth patterns of the three renewable energy sources were determined, and the cost of using solar power was found to decline significantly in the coming years.

Cristobal et al. (2012) suggested a systematic tool using a MINLP model that minimizes the cost of electricity for a specific trading price of CO_2. A case study was explored for retrofitting an existing coal-fired power plant with respect to generation quantities and carbon management solutions. It was concluded that the selection of the minimum cost option greatly depended on the prices of CO_2 emissions on the market. A trigger price for CO_2 was determined that would make carbon capture and storage technology profitable.

A method is proposed to help design carbon capture and compression processes retrofitted to existing power plants by combining simulation, automated heat integration and multi-objective optimization (Harkin et al., 2012). Specifically, this model was applied to coal fired power plants using a potassium carbonate based solvent absorption system. The efficiency of power plants can be reduced 14-38% after the installation of a carbon capture and storage system. Results from this model will be useful for early stage process design and optimization of operating values for solvent carbon capture plants for their respective power plants.

Bazmi and Zahedi (2011) addressed a literature review on power and supply sector developments, the role of modeling and optimization in this field and future uses of optimization modeling for decision making for sustainable energy systems. A discuss of the current state of power generation technologies, optimization models related to power generation and the impact of optimization in future power sector decision making are explored. Small-scale decentralized power generation systems are becoming an appealing alternative to large centralized power generation. It was concluded that optimization modeling is allowing researchers to find optimal and sustainable solutions to the complicated problems of power generation, supply and distribution.

Elkamel et al. (2009) developed a fleet-wide model of energy planning for determining the optimal structure to meet CO_2 reduction targets while maintaining power to the grid. A mixed-integer program is used to optimize an existing fleet with the addition of new generating stations (hydroelectric, wind, nuclear, fossil fuels) while considering carbon capture technology at the minimum total cost. This model was applied for the system operated by OPG. Four future electrical demand scenarios, various CO_2 reduction levels and six additional power generation technologies were considered. Fluctuations in natural gas prices were found to significantly affect model results as well as the cost of electricity.

MILP model for the planning of optimal electrical generation systems while meeting a specified CO_2 reduction target for a country is presented (Muis et al., 2010). The model was applied using the software GAMS in the Peninsular Malaysia area. To halve the current CO_2 emissions, the model determined that IGCC, NGCC, nuclear, biomass and palm oil residue electrical generation technology must be implemented. In addition, it was also found that Malaysia could currently generate up to 9% of its electricity from renewable sources.

Pekala et al. (2010) identified a general modeling methodology for the planning of optimal energy generating networks with respect to CO_2 emissions and land footprint. Two technologies of liquid biofuels used in transportation and carbon capture and storage with power generation are explored within the flexible and expandable model framework. Case studies were used to demonstrate the variations in the different technology implementations.

The Finnish EFOM was employed to support policy planning for the sustainable use of resources (Lehtila and Pirila, 1996). The common modeling framework was comprehensively adapted into the Finnish energy network along with a submodel of the energy intensive pulp and paper industry. Results from the model determined that reductions of CO_2 emissions strategies are difficult to implement, though the model has provided useful results for policy making.

Carapellucci and Giordano (2012) assessed economic and energy performances of renewable energy islands integrated with a hydrogen storage system by a simulation tool. The electrical generating technologies in these energy systems include solar power, wind power and micro-hydroelectric generators. The approach for optimizing the energy island is hybrid geneticsimulated annealing algorithm and minimizes the cost of electricity. A farm in central Italy is used as a case study for this optimization model.

Rajab Khalilpour (2014) focused on the carbon-management strategy at the enterprise level using PCC technology and carbon credits. A multi-period MILP which maximized net present value was developed to find the best investment decision for the enterprise. Dynamic elasticity and carbon market prices over the planning time are incorporated into the model. Power generation levels and carbon capture rates are adjusted within this model to find the best operating conditions of a power plant and PCC process. The model was applied to several case studies with differing prices of CO_2 emission credits.

A dynamic interval-parameter optimization model (DIP-REM) developed for long term energy planning along with GHG mitigation (Liu et al., 2013). The energy system in the Liaoning province of China was the focus of this study. Two different GHG mitigation levels are considered with respect to energy, socio-economic and environmental effects in Liaoning. The findings from this model provide optimal energy resource, service allocation and capacity expansion plans, and also helps policy makers determine the most cost effect method to mitigate CO_2 emissions. The results of this model can be used to formulate GHG reduction levels and the economic implications associated with those decisions.

A multi-period MILP model for planning the operations of a steam power system was provided (Luo et al., 2012). The objective functions of this model are minimized for both economic and environmental costs. Optimal operation schedules were obtained from the model at various environmental charge standards (carbon emission credits). Total cost savings and pollutant reductions were optimized using this model. It was found that the model results were quite sensitive to environmental charge standards.

Lin et al. (2014) presented an interval-parameter mixed-integer power management systems model (IMPMS) for supporting sustainable power systems under uncertainty. Uncertainties captured within this model can include interval values and capacity expansion issues. The model was applied to a Canadian power system case study which yielded results that may help develop strategies for sustainable energy development under uncertainty. It was found that a combination of wind and hydroelectric power would reduce system costs, conserve energy and carbon emissions as well as diminish the intermittency of renewable energy sources on power grids. The development of an inexact power management systems tool which integrated renewable and conventional power generating sources into an optimization model were the main results of this paper.

A RISO method for planning energy systems and trading CO_2 by incorporating interval-parameter programming within a RO network was studied (Chen et al., 2012). The model is applied to large scale electric power system planning under the constraint of a CO_2 trading scheme. Various solutions were generated from this model and can be used to adjust allocation plans of energy resources, prepare local energy policy, analyze the effectiveness of the CO_2 trading scheme and analysis of the trade-off between system cost and CO_2 reduction levels.

Dongjie et al. (2013) developed a multi-period superstructure optimization planning model of the Chinese power sector under uncertainty. A levelized optimal pathway demonstrated that with the presence of a carbon tax, carbon emissions from the power sector would drastically be reduced as low-carbon emitting technologies such as nuclear, renewable power and carbon capture and storage would be implemented. Decision variables in this model included the power demand, plant efficiency, plant capital cost, fuel costs and the carbon tax levels. From the model, it was shown that if a carbon tax were to be implemented, the construction of new coal plants would slow drastically and the development of nuclear and renewable would increase in a corresponding manner.

2.6.2 Summary of MINLP Models

To summarize the most important works on modeling of optimization problems using MIP since 1979; Grossmann and Sargent (1979) developed a MINLP model to maximize the profit of a multi-product batch plant. Furthermore, Suhami and Mah (1982); Papageorgaki and Reklaitis (1990a; 1990b); Fletcher (1991), Barabosa and Macchietto (1994), Ravemark and Rippin (1998)(1995), Xia and Macchietto (1997), Orcun et al. (2001), Janak et al. (2007) proposed different MINLP models to address design, production planning, and scheduling with the same objective function and application as Grossmann et al. (1979). From the literature review, several

MIP models have been applied in different applications, for instance, a toluene process (Diwekar and Madhavan, 1991), an ethylene plant (Diaz and Bandoni, 1996), a reactor network (Pahor, 2000), distillation (Floudas and Paules, 1988), energy planning, etc.

In the energy sector, Godoy et al. (2011) employed a NLP model to minimize specific annual cost values, capital investment, and operating costs in combined cycle gas turbine power plants. They tried to simplify the resolution of the optimization problem based on the economic optima distinctive characteristics. Optimal complex combined cycle power plants are distinguished by Kocha et al. (2007). They minimize the product costs by optimizing the design configuration and process variables at the same time by means of a MIP model. Savola et al. (2007) presented a MINLP model for the scheduling and planning of CHP plants on a small scale. In addition, power production was formulated to be increased over time. A single-period deterministic MINLP optimization model was developed to minimize costs while satisfying electricity demands and CO_2 emission targets by Hashim et al. (2005). Mirzaesmaeeli et al. (2010) developed a multi-period MINLP to indicate the optimal mix of energy supply sources meeting the yearly peak and base load demand, and the CO_2 emission target by minimizing the overall cost of electricity.

2.6.3 PHEVs Penetration

Yabe et al. (2012) forecasted the rate of EV/PHEV market penetration and its effect on carbon emissions. Factors such as battery learning curves, geographic distribution of daily travel distances and an optimal power generation planning model for charging electric vehicles were used to determine the rate. The forecast shows that only a quarter of the vehicles shares in 2050 will be EV/PHEV in Japan. This market share forecast is sensitive to battery development and initial prices of vehicles. In addition, carbon emissions reduction rates are also predicted in the forecast as a result of EV/PHEV penetration.

Wu et al. (2012) explored regional growth patterns of light-duty passenger vehicles in three developed areas in China. In addition, several scenarios for the penetration of HEV, PHEV and EV were developed for the 2010-2030 time period. Factors such as petroleum consumption, fossil fuel use and carbon emissions were employed to evaluate various technologies that could be implemented. It was found that HEV penetration reduced carbon emissions more in coal electricity producing intensive regions, while PHEV and EV were better suited for regions with cleaner electricity production methods.

Ahmadi et al. (2012) studied PHEVs Penetration and its impact on Ontario's Electricity Grid. For this purpose, long-term regression models, both linear and non-linear ones, of electricity load demands were forecasted for the years 2012-2030. For the forecasting models various variables in the climate, economic, and demographic sectors were considered. Number of PHEV's was calculated based on different penetration levels. The PHEVs' charging electricity of different PHEVs' penetration scenarios was estimated. Effect of them on base and peak load demands was analysed. Moreover emission reduction as a result of PHEVs penetration was determined. Finally, additional electricity load demand considering PHEVs penetration was identified for energy planning purposes.

A resource dispatch and emissions model was developed with respect to changing electric grid demand due to the penetration of electric vehicles for western US grid (Jansen et al., 2010). Results from the model were compared to historical data to validate the model. Impact between EV penetration and the western grid was found based on correlations between historical dispatch and system load data. Findings from this study showed that dispatch planning can be assisted using the model, charging scenarios affect the emissions intensity and type, and ideal charge profiles can be found using hourly model resolution of changes in emissions intensity.

Current progress in PHEV technology, economic constraints, market trends, research requirements and challenges ahead for the integration of PHEVs into the electric grid was assessed (Anurag et al., 2010). Policies required for the implementation of vehicle-to-grid operation and the advantages of PHEVs for consumers and power producers were also explored. A PHEV can be charged from a utility and a vehicle-to-grid capable vehicle can reverse the direction of electricity back to the grid.

Waraich et al. (2013) introduced an iterative approach that integrates PEV electricity demand and a power system simulation to expose inadequacies in the energy system due to increased

PEV electricity demand. The main goal of this study was to understand the potential impact of PEV charging on the electrical grid. An agent-based traffic demand model along with an interconnected multiple energy carrier system was used to trend electricity demand and production. It was found that charging patterns are very sensitive to electricity pricing.

Richardson et al. (2013) reviewed current literature on different types of EVs, the electric grid and renewable energy integration. Main ideas such as key methods and assumptions from literature were discussed and the economic, environmental and grid impact of electric vehicles were assessed. Capability of EVs to integrate intermittent and renewable energy sources (especially wind power) were reviewed from various papers. Literature indicates EVs might reduce the amount of excess electrical energy produced under specific conditions.

A comprehensive survey of various research problems and their solutions with respect to PHEV integration to a smart grid was demonstrated (Hota et al., 2014). Many aspects of PHEV to grid integration have been addressed recently, such as charging and control strategies of PHEVs, vehicle-to-grid technology, and application domains. Mathematical models were formulated based on artificial intelligence methods, intelligent methods and agent based computing methodologies to resolve these problems.

The effects of PHEV penetration on the fuel consumption of coal, natural gas and oil, and on pollutant levels were explored (Valentine et al, 2011). Specifically, this study focussed on the New York Metropolitan Area undergoing two battery charging scenarios on a normal summer and winter day. Network constraints were incorporated into an economic dispatch model in addition to battery charging pattern models based on commuter transportation. Findings show that network-constrained economic dispatch penetration of PHEVs was much more realistic than unconstrained scenarios, and that fuel consumption were on the margins. In addition, regulated PHEV charging produced lower night-time emissions than unregulated charging. It was found that models combining network constrains and economic dispatch can optimize the performance of PHEV penetration in energy systems.

Falvo et al. (2011) created the design of sustainable urban mobility systems through the integrated metro-lines with surface PEVs. This study is a review of the planning criteria of urban mobility system in large cities with respect to transportation power systems. A case study was applied in terms of power systems architecture and business models which identified energy savings, environmental sustainability objectives and cost savings. The integration of the metro transit system and electric vehicles connected by a smart grid would minimize economic and environmental impact while optimizing the performance of both systems.

An investigation into the systems and processes required to implement vehicle-to-grid technology is presented (Kempton and Tomic, 2005). Vehicle-to-grid uses the high power capacity, low utilization and low capital cost of vehicle power along with long operating life and low operating costs of power generators to complement one another. Business models and strategies are suggested to optimize the electricity utilization, power production and electricity costs in a vehicle-to-grid energy system. In addition, vehicle-to-grid can provide storage for intermittent renewable energy sources especially wind power.

Mullan et al. (2012) reviewed the most common variants of the vehicle-to-grid theme using the case study of Western Australia is presented in this paper. Western Australia is an energy isolated geographic location that cannot import or export electricity with no hydroelectric storage capabilities. There is already an underutilization of generation and transmission capacity in this region. The study concludes that vehicle-to-grid technology operation in Western Australia would require too much infrastructure investment and can carry significant risk in implementation. However, it was found that simply charging electric vehicles can be added to the planned electricity demand without extra capital investment.

Goransson et al., (2010) investigated the costs and benefits of integrating electric vehicles in a power grid supplied by a quarter wind power and the remainder thermal energy electricity generation. Four different PHEV integration methods with varying impacts on total electric load were examined. It was found that a controlled PHEV charging system will reduce carbon emissions up to 4.7% while an uncontrolled charging system will lead to an increased in emissions. Reductions in emissions can be mostly attributed to a decrease in thermal power plant start-up and partial load operation conditions.

Kiviluoma and Meibom (2011) developed a generation planning optimization model for power plant portfolios to estimate the costs and benefits from EVs for future power systems. In the models formulated, the charging and discharging of EVs were integrated with the rest of the power system. A large difference was found in the power system cost for EVs with smart charging system compared to dumb EVs. Some findings from this study were that the price of electricity for electric vehicles was reasonable. In addition, the power system will benefit from a smart timing charging system for EVs and lower power plant portfolio cost

PHEV and EV penetration through 2030 was analysed for the five northern European countries of Denmark, Finland, Germany, Norway and Sweden (Hedegaard, 2012). Shares of private passenger EVs were assumed to increase 2.5%, 15%, 34%, 53% in 2015, 2020, 2025 and 2030 respectively. Results illustrate that a smart grid connection to the PHEVs and EVs will propagate wind energy investments and reduce reliance on new coal or natural gas power plants. If renewable do not compliment PHEV and EV penetration, fossil fuel sourced electricity will likely increase substantially. EVs will bring carbon emission reductions and total cost increases, although this result varies from country to country and is sensitive to fuel and carbon pricing.

A review of existing literature on power system integrated with electric vehicles and economic dispatches of PHEV in the electricity market is published (Peng et al., 2012). In addition, the joint scheduling problem considering renewable and intermittent energy sources and risk management of PHEV-penetrated power grids are discussed. Due to government incentives, rapid development of PHEVs in the market has occurred recently. If PHEVs are randomly connected to the power grid in large quantities, this will bring great challenges to the power system operations.

Soares et al. (2012) developed a linear programming optimization tool for the modeling of electric power system expansion in northeastern Brazil, with a particular focus on the variable output of future wind farm production capacity. Disparity between the supply and demand of electricity was expected due to variations in power generation. As a result, PHEVs were considered in this study to assist in the moderation of power supply fluctuations. From this study, it was found that increasing the fleet of PHEVs (0.5 million to 1.5 million) over the next two decades would be able to regulate power loads generated from wind farms. Advantages of simultaneously optimizing power generation and transportation sectors as part of a “smart grid” were also explored.

A group of models based on light-duty PEVs fleets for national level planning studies of the transportation and energy sections was studied (Wu et al., 2013). Three case studies were performed over a 40 year period for the US transportation and energy sections based on the models. The results of the case studies indicate that penetration of PEVs along with investments in renewable energy sources can reduce total energy and transportation cost by 5%. Emissions and gasoline consumption can also be reduced, although 800TWh of extra annual electricity production will be required. It was noted that optimization of the entire electric vehicle fleet is unlikely to occur in a free market economy such as the US, and that these optimization results should rather be targets.

Brouwer et al. (2013) evaluated the performance of four types of CHP plants to PEVs compared to using electricity from the grid. Simulation of CHP plant performance was achieved by integrating the composition of a future power system, the demand for heat and electricity, and specifications of EVs and CHP plants. It was found that there were no significant added benefits of a combined deployment of CHP plants and EVs. Timing of electricity supply and demand as well as abatement costs was not improved.

An integrated optimization model used to find the most economic and environmentally sustainable plans for future smart electricity systems with intermittent renewable energy sources and electric vehicle penetration was demonstrated (Zhang et al., 2013). Two goals of this model were to find the ideal power generation and capacity combination to meet future electricity demands, and to obtain a detailed model of hourly operations of power plants and controllable electric devices. This model was applied to a case study in the Tokyo area in Japan with a time horizon of 2030. Results found the paths towards the ideal energy generation combinations based on fossil fuels, hydroelectric power, nuclear and renewable energy.

A mixed integer linear programming model for capacity expansion, plant dispatch and PHEV charging was introduced (Weis et al., 2014). The cost savings from controlling PHEV charging and the trade-off between a controlled charging program or increased power system generation capacity was also explored. It was found that by controlling PHEV charging, the integration costs of PHEV into the power system were cut in half. In addition, wind generation intense systems and system that require capacity expansion benefit greatly from controlled charging.

From the literature review, there are no publications on studying the energy planning through multi-period optimization model for electricity generation considering the effects of wide spread of PHEVs penetration.

CHAPTER 3: Methodology

3.1 Introduction

The quality and quantity of vehicle emissions are a major concern in the design and production of new automobiles. PHEVs have a significant potential to reduce GHG emissions and also to increase fuel economy and fuel flexibility because PHEVs are propelled by the energy from both gasoline and electric power sources. The penetration of PHEVs into the automobile market and its increased demand on the existing electrical grid has not been fully investigated.

The main objective of the thesis is to develop a multi-period optimization model for the amount of electricity needed considering the anticipated PHEV penetration.

The model considers electricity load demands and a corresponding number of light-duty vehicles expected to be operating. The number of projected PHEVs is based on three different levels. Once the number of PHEVs is determined, the charging amount is calculated to ascertain the total electricity load demand. The deficit in electricity is identified by modelling the power plant optimization adding new power plants and retrofitting them by using fuel switching. Finally, the optimal solution with the minimum electricity cost is identified.

3.2 General Methodology

The general methodology can be divided into six main steps. The flowsheet for the general methodology is illustrated in Figure 3.1. The details of each step are discussed in subsequent sections.

Electricity Demand: Forecast the load demand without considering the PHEVs to find the amount of electricity needed to be generated in Ontario.

PHEV's Consumption: Forecast the number of new vehicles and the number of PHEVs based on different scenarios. Calculate the charging amount to estimate how much more electricity the PHEVs need for charging in Ontario.

New Demand: Add the existing demand by PHEVs electricity consumption to find the new demand.

Current Generated Power Satisfies Demand: Compare the supply generation to assess if available generated electricity is sufficient or not.

Optimization: Optimize the current power plants and add new power plants if generated power is unsatisfactory.

Optimal Solution: Identify the optimal solution where the optimal electricity generation is a mix of the minimum costs.

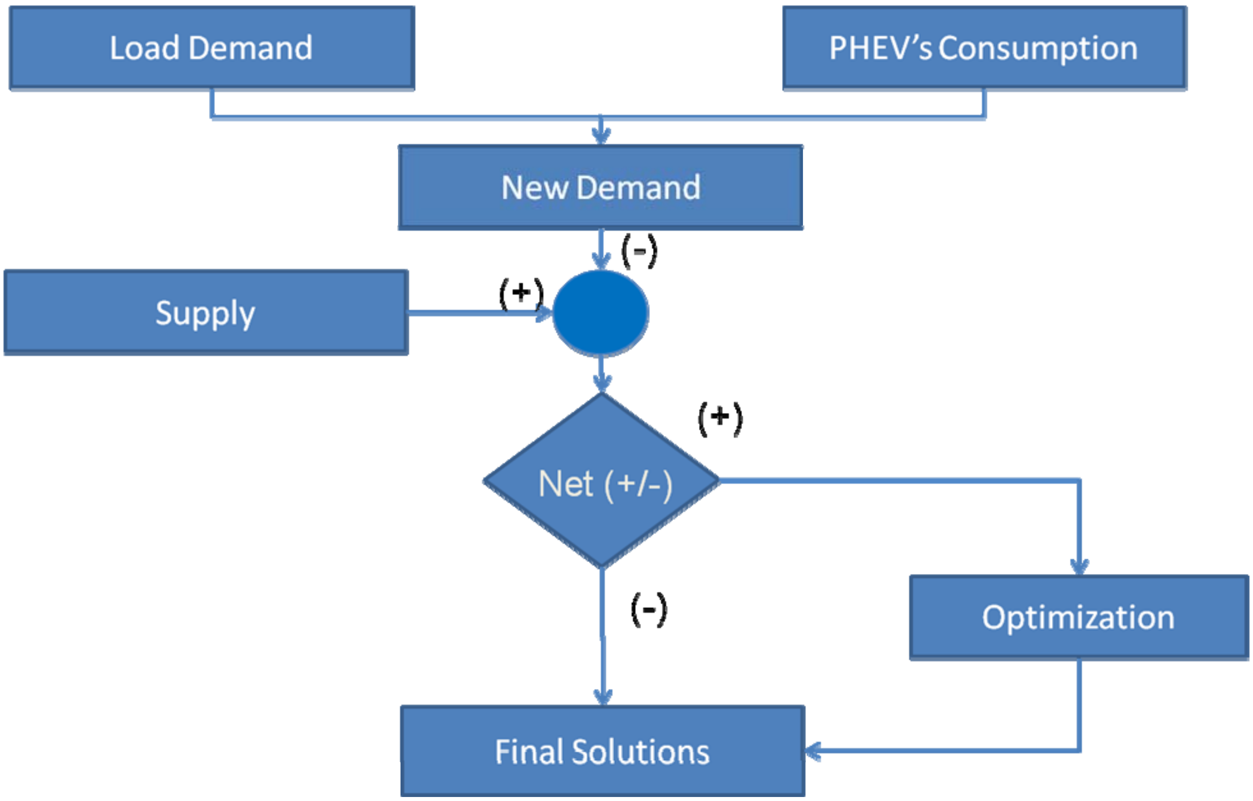


Figure 3.1 Flowsheet of General Methodology.

3.2.1 Load Demand Forecasting

- The calculation for the anticipated load demand from 2014 to 2030 has two principle components: forecasting the base and peak load demands, forecasting typical daily load curves

Different forecast techniques and model selection criteria are studied to choose a suitable method. Both LR and NLR techniques are employed to create proper forecast models. Dependent variables are peak and base load demands (*PEAK* and *BASE*) and light-duty vehicles sold (*VEH*). Peak load demand is the maximum demand in each day normally occurring between 9 a.m. and 9 p.m. For base load demand, it is defined as the minimum amount of power that power plants must make available to customers. It can be calculated by averaging daily demands in a weekday. Explanatory variables that may impact the PEAK and BASE models are broadly divided into three groups: (I) weather variables such as temperature (*T*), relative humidity (*RH*) and wind speed (*WS*), (II) demographic variable such as population size (*POP*), income (*INC*), number of employments (*EMP*), and (III) economic variable which is gross domestic product (*GDP*).To forecast *VEH*, the number of new graduated students (*EDU*) is also an important factor. People who get degrees at the undergraduate and graduate level tend to buy new cars more than others. Therefore, the number of graduated students is one of the explanatory variables to forecast the number of light-duty vehicles sold.

Historical data of dependent and explanatory variables are collected to fulfill the required data for developing the models. Before achieving historical data of peak and base load demand, outlier determination is an important step in order to avoid poor forecasting results. In this study, Statistics Package for Social Science (SPSS) version 20.0 was used to develop the forecast models. SPSS also has a feature to identify outliers among inputs by using boxplot. All outliers are omitted from the data and replaced by the values at the closest boundary. An important possible issue with explanatory variables is multicollinearity problems. Multicollinearity occurs when two or more explanatory variables are highly correlated. As a result, regression procedures may not be able to distinguish between the separate contributions of these variables to the dependent variable, and the estimation of unknown parameters may be unreliable. Ordinary multicollinearity is the situation in which there is a close, but not perfect, linear relationship between some of the explanatory variables in the sample data. Multicollinearity is usually considered to be a data or sample problem. The principle of parsimony (using the simpler model when greater complexity does not provide significant benefits) suggests that when two or more variables are highly correlated, one of them should be omitted from the model. Matrix scatter in SPSS is used for detecting multicollinearity. The scatter that presents linear relationship between two explanatory variables indicates multicollinearity problem.

Model Development and Selection

In this step, models for forecasted peak and base load demands and light-duty vehicles sold are developed using LRMs and NLRMs. Historical data of peak and base load demands are monthly data from 1994 to 2010. Those data and hourly load demand in 2010 were obtained from the Independent Electricity System Operator (IESO). To simplify the forecasting, four months representing each season were used as input in the model development. Hence, eight models were developed to represent peak and base load demands for the four selected months. Four of them are used for forecasting peak load demand and the rest are used for forecasting base load demand.

For historical light-duty vehicles sold, information was provided by season. Therefore, one model was formulated to represent light-duty vehicles sold in all seasons, with only some model parameters being changed to distinguish the four seasons. The seasonal periods are identified in Table 3.1.

Table 3.1 Period of Season

Season	Months
Winter	January to March
Spring	April to June
Summer	July to September
Autumn	October to December

Linear Regression with SPSS

To formulate a LRM in SPSS, dependent and explanatory variables need to be defined. Details of these variables were discussed in the first step. A list of variables used as input of SPSS is summarized in Table 3.2, where *PEAK, BASE, VEH* represent peak and base load demand and light duty vehicles sold. *T, RH, WS, POP, INC, EMP, EDU, GDP* are temperature, relative humidity, wind speed, population size, income, number of people employed, number of new graduated students and gross domestic product respectively. But some of these explanatory variables are highly correlated to each other. For example, when there are more new graduate students, there will be a higher number of people employed. Also wind speed and relative humidity are highly correlated for some temperatures (in particular for the extreme high and low ones).

Table 3.2 Input Variables for Linear Regression

Dependent Variables	Explanatory Variables
PEAK, ln(PEAK)	T, RH, WS, POP, INC, EMP, GDP, ln(T), ln(RH), ln(WS), ln(POP), ln(INC), ln(EMP), ln(GDP)
BASE, ln(BASE)	

To determine which combination of explanatory variables provides the best fit to the data, SPSS has an automated process for variable selection called “stepwise regression” in which the regression equation is automatically estimated several times.

Non-Linear Regression with SPSS

NLR in SPSS does not have a tool to choose the best combination of explanatory variables unlike LR. Therefore, selecting a set of explanatory variables should be done manually. To reduce complexity, only multiple NLRMs were considered which means only two explanatory variables were used as input of the models. In addition, pairing of explanatory variables which are highly correlated must be omitted to prevent the multicollinearity problem. Logarithm terms of both dependent and explanatory variables were not included. Possible combinations of explanatory variables are illustrated in Table 3.3.

Table 3.3 Possible Explanatory Variables Combination for Non-Linear Regression

Dependent variables	Combination of explanatory variables		
PEAK	T vs RH T vs WS T vs POP T vs INC T vs EMP T vs GDP	RH vs WS RH vs POP RH vs INC RH vs EMP RH vs GDP	WS vs POP WS vs INC WS vs EMP WS vs GDP
BASE			

After finding all possible LRMs and NLRMs, the next step is model selection. Mean Absolute Error, MAE, Mean Squared Error, MSE, and Mean Absolute Percentage Error, MAPE, were employed as a criterion for selecting the best model. The model that has the lowest MAE, MSE and MAPE were chosen to represent the historical data and also forecast future data. The equation of *MAE*, *MSE* and *MAPE* can be written as follows:

$$MAE = \frac{\sum_{t=1}^{n}|e_t|}{n} = \frac{\sum_{t=1}^{n}|y_t - \hat{y}_t|}{n} \tag{3.1}$$

$$MSE = \frac{\sum_{t=1}^{n}(e_t)^2}{n} = \frac{\sum_{t=1}^{n}(y_t - \hat{y}_t)^2}{n} \tag{3.2}$$

$$MAE = \frac{\sum_{t=1}^{n}(100 * |e_t|/y_t)}{n} = \frac{\sum_{t=1}^{n}(100 * |y_t - \hat{y}_t|/y_t)}{n} \tag{3.3}$$

where e_t is the error term, n is the total number of observations and t is time index. y_t and $\hat{y}_t$ are the observed and estimated values, respectively.

Projection of Forecast Variables

The best models for forecasting peak and base load demands and light-duty vehicles sold were used for projecting the future value of those dependent variables from 2014 to 2030. Future values of all explanatory variables shown in the selected models were substituted into those models in order to predict values of the dependent variables.

Forecasting Typical Daily Curves

A neural network model is developed to predict hourly load demand. The dependent variable is the hourly load demand (HRL) and the initial explanatory variables are indicated in Table 3.4. As mentioned in Table 3.4 the day of the week (DOW) is defined as a new explanatory variable. DOW is specified by programming in MATLAB. By specifying the DOW, the effect of weekdays and weekends is considered in the predicted hourly load.

Table 3.4 Initial Variables for Hourly Load Forecasting Model

Dependent Variables	**Explanatory Variables**
HRL, Ln(HRL)	T, RH, WS, POP, INC, EMP, GDP, ln(T), ln(RH), ln(WS), ln(POP), ln(INC), ln(EMP), ln(GDP), DOW,

Data clustering will be done after finding the hourly load demand because of large data. Essentially, data clustering divides a large set of data into smaller groups. A typical daily curve represents the group. In this work, all data are categorized into four groups corresponding to four seasons per year. There are different methods for data clustering. Marton et al. (Martona, Elkamel, Duever 2008) clustering tool is selected to identify the typical daily curves.

3.2.2 PHEVs Penetration and Charging Pattern

Since PHEVs were not commercially produced before January 2014, this study assumes that there is no PHEV in January, 2014. Variables that are used for vehicle forecasting model are presented in Table3.5.

Table 3.5 Variables for VEH Forecasting Model

Dependent Variables	Explanatory Variables
VEH, ln(VEH)	POP, INC, EMP, EDU, GDP, ln(POP), ln(INC), ln(EMP), ln(EDU), ln(GDP)

Three transition models of PHEVs penetration in the light-duty vehicles sold, named low, medium and high, are shown in Figure 3.2 assuming 10%, 30% and 50% of PHEVs penetration by December, 2030, respectively. These equations are used because of being more straightforward than the exponential equations during mentioned time period. For all models a constant penetration rate for any given scenario is assumed:

$$PHEVs = k \times t^2 \tag{3.4}$$

where *PHEVs* is the number of PHEVs, k is the constant rate and t is time. In this study, only new light-duty vehicles are considered. Before studying charging patterns, it is necessary to identify which type of PHEVs will penetrate into the transportation sector. To choose appropriate types of PHEVs that match people's lifestyle in Ontario, commuting distance must be considered.

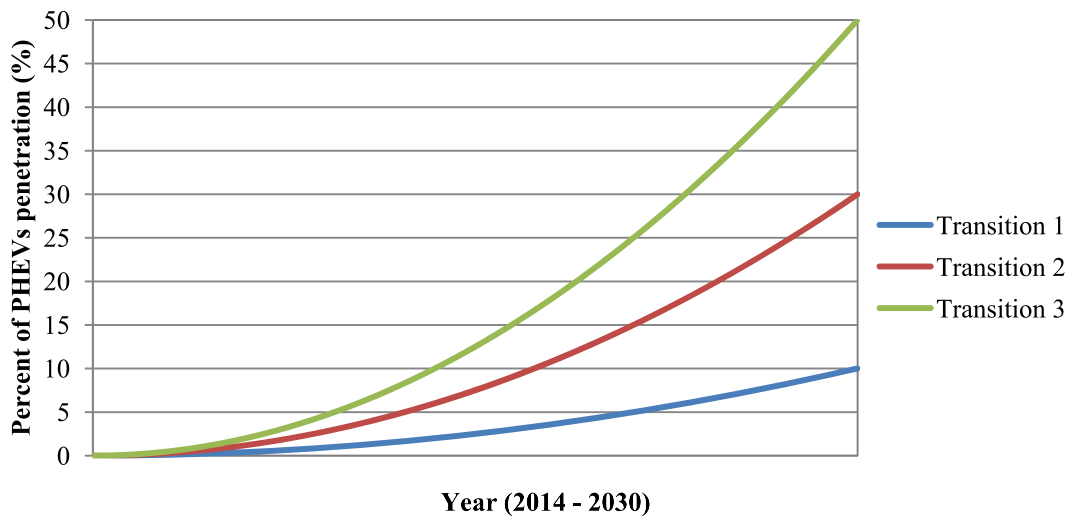


Figure 3.2 Assumed PHEVs Transitions in Ontario.

Table 3.6 compares commuting distances in Canada and Ontario [20]. The average commuting distance in Ontario is 12.9 km (= 8 miles). This implies that PHEV-20, which can travel twenty miles without using its combustion engine, is appropriate for a majority of people in Ontario. Therefore, this study assumes that only PHEV-20 penetrates into the light-duty vehicles sold. Another assumption is that no PHEVs are retired during the period under study. Since most household outlets already contain 120 V/15 A outlets, it is assumed that all PHEV-20 will be recharged through this circuit every day. Charger requirements of PHEV-20 with 120 V/15 A outlets are summarized in Table 3.5.

Table 3.6 Average Commuting Distance in Canada and Ontario (Statistics Canada 2006)

Commuting Distance (km)	Commuters (people)	
	Canada	**Ontario**
Less than 5 km	4,741,630	1,672,260
5 to 9.9 km	2,962,810	1,101,410
10 to 14.9 km	1,738,750	672,685
15 to 19.9 km	1,095,465	475,410
20 to 24.9 km	693,645	318,960
25 to 29.9 km	461,250	213,460
30 km or more	1,376,340	640,470
Average commuting distance (km)	11.9	12.9

Table 3.7 Charger Requirements for PHEV-20 under 120 V/15 A Outlets (Statistics Canada 2006)

Vehicle Type	**Rated Pack Size (kWh)**		**Charging Size[a] (kW)**	**Charger Rate[b] (kW)**	**Charging Time (hour)**
	20 miles	8 miles			
Compact Car	4.10	1.64	1.44	1.18	4
Mid-Sized Sedan	4.70	1.88	1.44	1.18	4.7
Mid-Sized SUV	6.30	2.52	1.44	1.18	6.3
Full-Sized SUV	7.40	2.96	1.44	1.18	7.4
Average	5.63	2.25	1.44	1.18	5

Note: [a] An 80% required safety factor for continuous charging is used.
[b] Charger efficiency is assumed to be 82%.

PHEVs can be recharged in both peak periods and off-peak periods. Details of each scenario are illustrated in Table 3.8. Scenario 1 represents the worst case of charging scheme since all PHEVs are assumed to be recharged during the peak period whereas Scenario 4 represents the best case which all PHEVs are recharged during the off-peak period.

Table 3.8 Charging Scenarios

Scenario	**Name**	**Period**
1	After work	17:00-22:00
2	Three hours after work	21:00-2:00
3	In the morning	8:00-13:00
4	During the night	24:00-5:00

3.2.3. Total Demand

New peak, base, and hourly load demands represent PHEVs charging in peak, off-peak, and specific periods, respectively. They can be calculated by adding the amount of PHEVs charging in each period with the peak, base, and hourly load demands obtained from regression models and a neural network model. Equations for calculating the new peak, base, and hourly load demands are

$$\mathrm{Peak}_{n,i} = \mathrm{Peak}_{r,i} + \mathrm{CR} \times \mathrm{PHEVs} \tag{3.5}$$

$$\mathrm{Base}_{n,i} = \mathrm{Base}_{r,i} + \frac{\mathrm{BS} \times \mathrm{PHEVs}}{24\ \mathrm{hrs}} \tag{3.6}$$

$$\mathrm{Hrl}_{n,i} = \mathrm{Hrl}_{r,i} + \mathrm{CR} \times \mathrm{PHEVs} \tag{3.7}$$

where $Peak_{n,i}$, $Base_{n,i}$,and $Hrl_{n,i}$ are the new peak, base, and hourly load demands after adding the amount of PHEVs charging, respectively. $Peak_{r,i}$, $Base_{r,i}$, $Hrl_{n,i}$ are peak, base, and hourly load demands obtained from the regression models. CR is the charger rate, PHEVs is the number of PHEVs charging, and BS is the battery size or rated pack size.

3.2.4. Comparison of Total Demand with Generated Electricity by Ontario Power Plants

In this step, the worst case of penetration level and charging scenario is chosen as the case study. The demand of the worst case is compared to available resources in Ontario to see whether there can be enough supply to the increasing demand from PHEVs charging.

3.2.5 Optimization Methodology for Energy Planning

The methodology that is used to find the optimal solution of energy planning of power plants electricity generation contains six different steps as indicated in Figure 3.3. The details of each step are provided in subsequent sections.

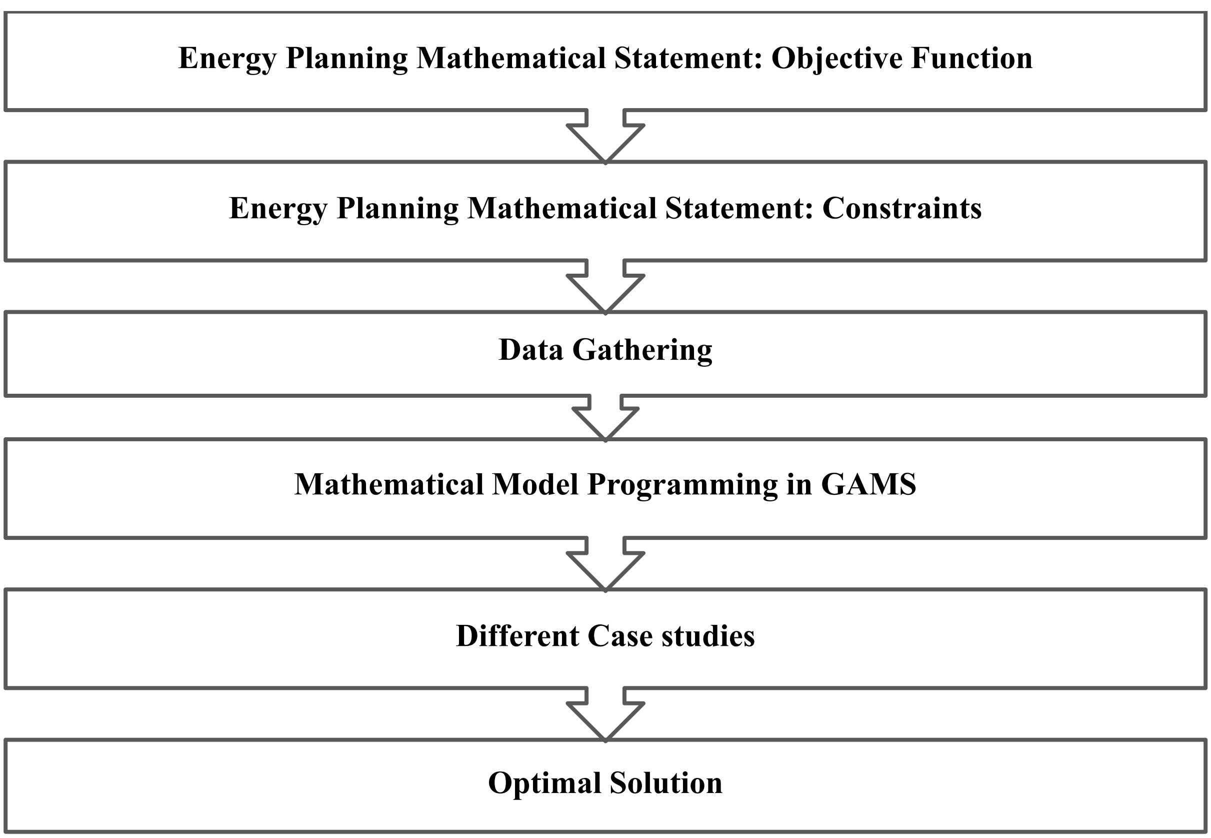


Figure 3.3 General Optimization Methodology.

3.2.5.1 Objective Function Mathematical Statement

As a first challenge after calculating the difference between load demand and generated power, an LP model will be formulated for the existing electricity fleet for load demand satisfaction. Furthermore, the optimization model will be a MILP model which identifies discrete decision variables for fuel switching of each power plant. In the next step, the binary variables of existence or nonexistence of different types of new power plants are defined. As a final step, CO_2 emission target is considered.

The objective function of the energy planning optimization model is to minimize the present value of the cost of electricity over a sixteen year period (2014-2030). The overall costs consist of the fuel costs, fixed and variable operating and maintenance costs, the capital costs for a new power plant, and the retrofit costs of existing power plants (associated with fuel switching from coal to natural gas for coal-fired stations). The total discounted present value is minimized by considering the electricity demand as an effect of PHEV penetration, as well as, in the last stage of this work, satisfying CO_2 emission target.

The mathematical model of the previously mentioned objective function is:

$$\begin{aligned} min f(i,j,n,N,H,W) = &\sum_{i \in FF} \sum_j F_{ij}^{FF} Opr_{ij} F_{ij} F_{FF}^D + \sum_{N \in NUCLEAR} F_N^{NUCLEAR} Opr_N F_N^D + \\ &\sum_{H \in HYDRO} F_H^{HYDRO} Opr_H F_H^D + \sum_{W \in WIND} F_W^{WIND} Opr_W F_W^D + \\ &\sum_{i \in CMAX,C} \sum_j Rcost \left(\frac{F^{CMAX}}{Optime}\right)(AF)\left(F_{i,ng}^C\right) + \sum_{n \in NEWMAX} Cap_n \left(\frac{F_n^{NEWMAX}}{Optime}\right)(AF)(F_n^D) + \\ &\sum_{n \in NEWGEN} (Opr_n + (P_n\, Hr_n))(F_n^{NEWGEN}) \end{aligned} \tag{3.8}$$

where i is the index of all of the Fossil Fuel Generators in Ontario, j is the fuel used, Opr are the associated operating and maintenance costs for each Power Plant (\$).$Cap_n$is the capital cost for new power plants. n, N, H, and W are the index of all of the new possible, Nuclear, Hydro and Wind Power Plants in Ontario. F^{FF}, $F^{NUCLEAR}$, F^{HYDRO} and F^{WIND} are electricity generated (MWh) by the Fossil Fuel, Nuclear, Hydro, and Wind Power Plants in Ontario. F_{FF}^D, F_N^D, F_W^D, $F_H^D$and F_n^D are binary variables (0-1) for existence or not existence, operating or not of unit related to identified indices at the time. F^{CMAX} is the set of the maximum power generation of all the current coal generation plants in Ontario, and F^C is the set of the adjusted power generation of the current coal plants in Ontario. Optime is a maximum operation time in a year which is 8760 hours. AF is the Annual factor. F^{NEWMAX} is the set of the maximum power generation possible for the possible new Power Plants, and F^{D} is the decision variable to build a new power generation plant. P is the index of the price of the fuel used at each plant; Hr is the heat rate (efficiency of each type of fuel) at each new possible Power Plant, and F^{NEWGEN} is the amount of Power Generated at each new Power Plant.

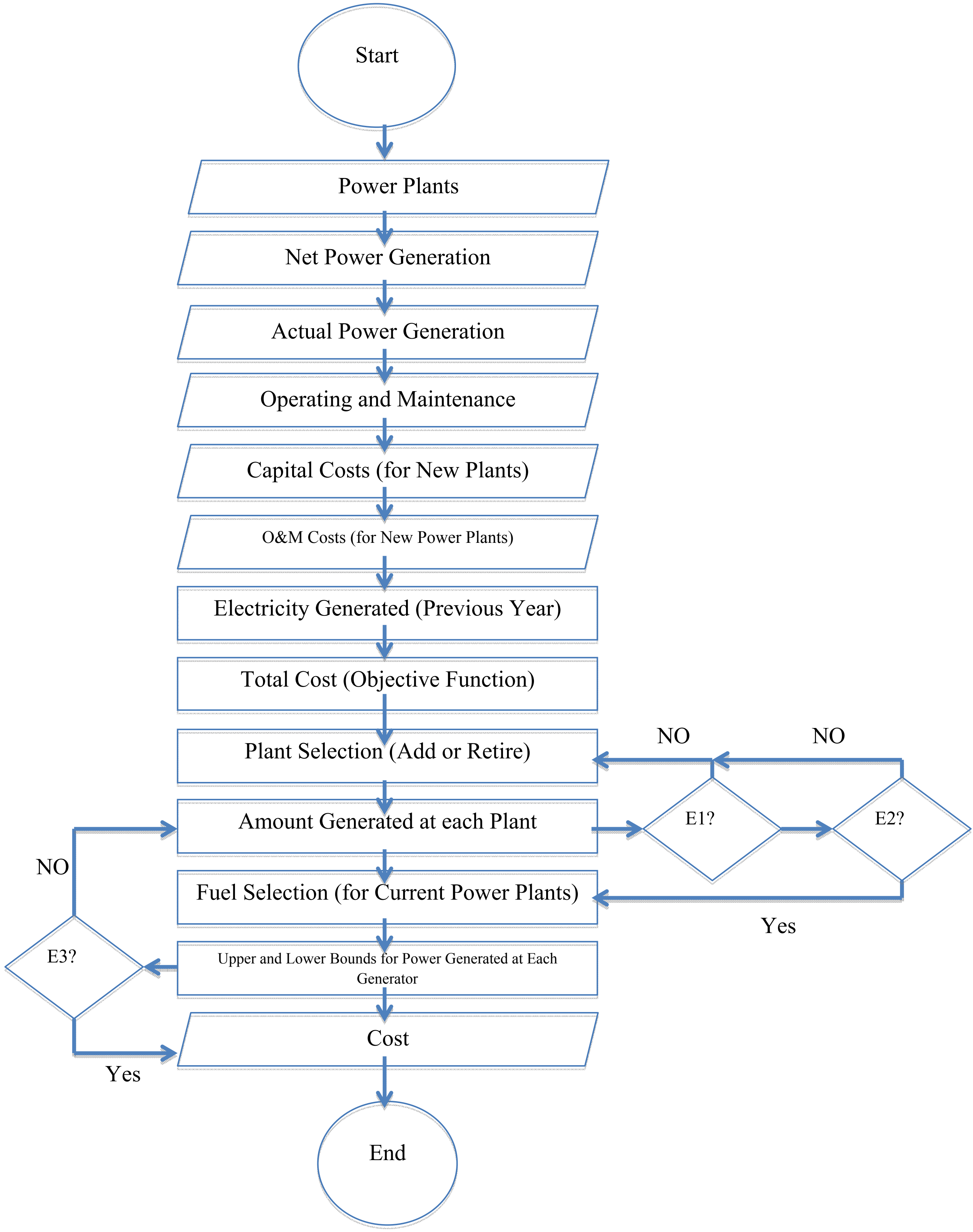


Figure 3.4 Optimization Modeling Flow Chart.

This function will be minimized through the constraints laid out by the equations that follow; Total electricity generated, Fuel selection and Plant Shutdown, Fuel switching constraints, Non-Fossil plant constraints, constraints on the amount of power can be produced by the new plants, Upper bound of amount of electricity that can be produced by a new plant in that year, lower bound on the amount a current plant can produce, and selection of new plants.

The structure of the programming code is indicated in Figure 3.4. First the sets for all of the power plants are listed, and then the scalars are listed. The maximum possible generation for all of the power plants is inputted, along with the same variable for the possible power plants. Actual generation for all of the power plants in Ontario is listed, along with two different operational costs for all of the fossil fuel power plants (one for Coal, the other Natural Gas). The capital costs and operating costs are stated for the new possible power plants. Variables for the optimal amount of electricity generated by each power plant, electricity generation for the possible new power plants, adjusted generation based on fuel switching (for fossil fuel plants) are initialized, along with binary variables for fuel selection at each plant and decision variables for the possible new power plants.

3.2.5.2 Constraints Mathematical Statement

The equations are initialized, with the objective function, total electricity generated, fuel switching equations, equations that set certain plants to be natural gas, total electricity generation for each plant, capacity constraints, new plant capacity constraints, upper bound on generation for new plants, and a lower bound for generation of current plants, and a cap on additional new plants being created as functions. The equations of constraint are presented as outlined below;

E1

$$\sum_i \sum_j F_{ij}^{P} \leq \sum_i \sum_j F_{ij}^{PMAX} F_{ij}^{DP} \qquad (3.9)$$

where F^{PMAX} is the power generation of a Power Generation Plant in Ontario, and F^{PC} is the binary decision variable to keep the current Power Generation Plant in Operation. This is repeated for all Power Generation Plants in Ontario, including the possible new plants, meaning the output of a power plant must be less than its maximum possible output multiplied by either a 1 or 0 (if the plant is in operation (1) is will produce less than or equal to its production level, or if retired (0) no electricity will be produced there).

E2

$$\sum_n F_n^{NEW} \leq \sum_n F_n^{NEWMAX}(ACF) \tag{3.10}$$

where F^{NEW} is the set of new possible power plants, and F^{NEWMAX} is the set of maximum possible power generated at each new possible Power Plant, and ACF is the Annual Capacity Factor for new Stations, which is 75%, meaning that all new Stations, for the first year of the code, must operate at less than 75% capacity.

E3

$$\sum_i \sum_j F_{ij}^{FF} \geq \sum_i \sum_j F_{ij}^{FFMAX}(LOWER)F_{ij}^{DFF} \tag{3.11}$$

where F^{FF} is the set of Electricity Produced at Fossil Fuel Stations, F^{FFMAX} is the maximum amount of electricity produced at each Fossil Fuel Station, LOWER is the Annual Capacity Factor Lower Bound, which is 1%, and F^{DFF} is the decision variable to keep a current Fossil Fuel Plant in operation. In this technique the model makes all Operational Plants operate at over 1% Capacity, if not the Plant would be shut down.

The total generated power should be equal to or greater than the Ontario electricity demand.

$$D^T \leq \sum_{i \in FF} \sum_j F_{ij}^{FF} F_{ij} F_{FF}^D + \sum_{N \in NUCLEAR} F_N^{NUCLEAR} F_N^D + \sum_{H \in HYDRO} F_H^{HYDRO} F_H^D + \sum_{W \in WIND} F_W^{WIND} F_W^D + \sum_{i \in CMAX,C} \sum_j F^{CMAX}\left(F_{i,ng}^C\right) + \sum_{n \in NEWMAX} F_n^{NEWMAX}(F_n^D) \tag{3.12}$$

An initial guess for cost is made (integer value of 1) and the model is set to solve the problem with the CPLEX solver for Mixed Integer Programming (MIP) minimizing cost. The CPLEX solver was selected because of its numerous options for MIP, as the CPLEX solver takes less time on larger programs and automatically sets the best values for specific problems.

3.2.5.3 Data Gathering

The following data are gathered from OPG and IESO:

Installed capacity of power plants

Net electricity generation

Capacity factor of power plants

Operating cost

Retrofit cost

New power plants economic evaluation

3.2.5.4 Mathematical Model Programming in GAMS

A mathematical model is applied in the software Generalized Algebraic Modeling System (GAMS). Linear, nonlinear, mixed integer linear, and nonlinear optimization problems can be solved by the GAMS modeling system. Because of high level programming language to solve the compact version of complicated and large models, and of the possibility for the quick and safe modification in the model and formulating obvious algebraic terms, GAMS is one of the best options for optimization applications.

In GAMS, users can state the relations among objective functions, constraints, variables, parameters, and scalars. A Language compiler and a solver are two main operating stages for an input file in GAMS. LP, NLP, mixed integer linear programming (MILP), and mixed integer nonlinear programming (MINLP) can be solved by GAMS different solvers. In this study the followings steps are accomplished:

Define Set: indices in the mathematical models are called Set in GAMS. In this study, the set of different types of power plants, such as fossil fuel, hydro, nuclear, wind power plants, are defined. Then all the equations including the objective function and constraints are indicated. All the variables, parameters, scalars are defined. Variables are continuous and binary variables. Parameters are all the data that mentioned in the previous section that has been gathered from IESO and OPG. Next, minimizing or maximizing objective function is decided. Applicable solver to optimize model based on the problem formulation is selected. Table 3.9 indicates the list of solvers for different problem formulation. Moreover, the solution is established by the optimization algorithm, and the optimum value of the objective function is found as an output by changing decision variables.

Table 3.9 List of GAMS Solvers

Problem Formulation	Solver
LP	MPSWRITE, CPLEX, LAMPS, OSL
NLP	CONOPT, MINOS5
MIP	CPLEX, LAMPS, OSL
MINLP	DICOPT, BARON

In this study, the programming code is developed that accepts set inputs of all of the fossil fuel power plants (Coal, Natural Gas) in the Ontario power generation grid as individual sets with their own generators described as indices for that set and each of the renewable energy resources (Wind, Hydro, Nuclear) as its own set. This allows for easier manipulation of the fossil fuel plants compared to the renewable resource plants so that CO_2 emissions would be easier to manage. In this technique, the Province of Ontario's goal of phasing out all coal generation plants could be more accurately projected and accounted for with minimal alteration to the base code.

The next part of the programming code inputs the operating costs of each fossil fuel plant using both coal and natural gas, which allows the program to choose between coal and natural gas for each power plant, thus allowing for complete control over which fuel is used in each plant. The code then contains the capital costs and operating costs associated with each of the possible new power stations. This makes for the most control in the event the program decides a new power plant should be built, as the code will be able to make the best possible choice for the remaining power needing to be generated.

GAMS then initializes a number of variables to be used in the later linear equations. Some of the variables initialized by the program are adjusted electricity generation for all of the current power plants, decision (binary) variables to build new power plants, and fuel switching options for all of the current power plants.

Chapter 4: Forecasting Results

4.1 Introduction

This chapter considers historical data of electricity demand and demonstrates the results of developed models by SPSS and neural network. Results from linear, non-linear, and hourly regression models are presented and compared. In addition, the models that best describe forecast variables are chosen by using MAE, MSE, and MAPE as criteria. The projection of forecast variables is presented in this chapter, and different PHEVs penetration transitions and charging scenarios are developed. A comparison of the increased demand from PHEVs charging and Ontario's electricity supply are discussed.

4.2 Model Development

This section is divided into four parts based on four forecast variables: (i) peak load demand; (ii) base load demand; (iii) hourly load demand; and (ix) number of light-duty vehicles sold. Linear and non-linear regression models for the peak, base and hourly load demands and light-duty vehicles sold were developed using the methodology described in the previous chapter. For the peak and base load demands, the development of the regression models uses weather, demographic, and economic variables as previously mentioned. For hourly load demand the same explanatory variables as peak and base load demands and also DOW were applied. Demographic and economic variables were employed in the development of regression models for light-duty vehicles sold. The general forms of linear and non-linear regression models are shown in eq. (2.1) and eq. (2.2). The set of variables used for developing linear, non-linear and non-parametric regression models is listed in Table 3.2, Table 3.3 and Table 3.4, respectively.

Several models were generated after employing different sets of variables. In order to select the most appropriate models, the models with the lowest MAE were chosen. The results of the best models for linear and non-linear regression models are discussed in the following section.

4.2.1 Peak Load Demand Models

Using the selection approach mentioned previously, linear regression models for peak load demand forecast in January, May, August and October are chosen to be:

January: $$\ln(PEAK_i) = 9.7 + 5 * 10^{-7}\, GDP_i - 9.1 * 10^{-3}\, T_i \tag{4.1}$$

May: $$PEAK_i = -36{,}900 + 4{,}100\, ln(GDP_i) \tag{4.2}$$

August: $PEAK_i = -79{,}890 + 6{,}400\, ln(GDP_i) + 5{,}200\, ln(T_i)$ (4.3)

October: $PEAK_\text{i} = -42{,}000 + 4{,}590\, \ln(\text{GDP}_\text{i})$ (4.4)

The peak load demand in January and August are a function of temperature and GDP, while the peak load demand in May and October are a function of *GDP* only. Temperature has a significant effect for the winter and summer months. In winter (eq. (4.1)), the temperatures are always less than zero degree centigrade; therefore, the lower the temperature, the higher the peak load demand because people need more electricity for space heating. Alternatively, in the summer (eq. (4.3)), electricity consumption increases with increased temperatures because more electricity is required for space cooling. The GDP is the only explanatory variable which affects peak load demand in all four months. The GDP reflects the direction of economic growth. From eq. (4.1) to eq. (4.4), all coefficients for the GDP are positive; hence, the greater the GDP, the greater the peak load demand. The best non-linear regression models for the peak load demand in four selected months are:

January: $PEAK_i = 46{,}835 - 24{,}930(\exp(8 * 10^{-3}\, T_i)$

$+\exp(-6.2 * 10^{-6}\, GDP_i))$ (4.5)

May: $PEAK_i = 17{,}900 - 73{,}141\, exp(-10^{-5}\, GDP_i)$ (4.6)

August: $PEAK_i = 23{,}000 - 42{,}600(exp(-0.2\, T_i)$

$+exp(-7 * 10^{-6}\, GDP_i))$ (4.7)

October: $PEAK_i = 19{,}900 - 18{,}570\, exp(-4.8 * 10^{-6}\, GDP_i)$ (4.8)

The same trends are found for the linear regression models. Temperature affects the peak load demands in January and August (the seasons corresponding to the highest peaks), while *GDP* affects base load demand in all four months. All coefficients of NLRMs follow the law of diminishing returns. The models increase quickly with the increasing temperature and GDP, and then they gain slowly. For eq. (4.5), the coefficient of temperature is positive; however, when multiplying with temperature in the winter which is always negative, this term will be negative which follows the law of diminishing returns. All temperatures are given in °C. Note that although the January and August peaks depends on temperatures, those temperatures are assumed constant from one year to the other year and thus the changes in peak demand over the years are due solely to changes in *GDP*.

4.2.2 Base Load Demand Models

Using the same selection approach as in the case of peak load demand, the best LRMs and NLRMs of base load demand in January, May, August, and October are shown below:

Linear regression models:

January: $$BASE_i = 13{,}500 - 177\, T_i + 9.4 * 10^{-3}\, GDP_i \tag{4.9}$$

May: $$BASE_i = -37{,}000 + 4{,}000\, ln(GDP_i) \tag{4.10}$$

August: $$BASE_i = 73{,}200 + 5{,}650\, ln(GDP_i) + 5{,}650\, ln(T_i) \tag{4.11}$$

October: $$BASE_i = -36{,}510 + 4{,}050\, \ln(\mathrm{GDP_i}) \tag{4.12}$$

Non-linear regression models:

January: $$BASE_i = 57{,}750 - 22{,}430(\exp(8.3 * 10^{-3}\, T_i) + \exp(-5.5 * 10^{-7}\, GDP_i)) \tag{4.13}$$

May: $$BASE_i = 17{,}260 - 20{,}680\, exp(-5.8 * 10^{-6}\, GDP_i) \tag{4.14}$$

August: $$BASE_i = 21{,}080 - 43{,}000(exp(-0.1\, T_i) + exp(-7.4 * 10^{-6}\, GDP_i)) \tag{4.15}$$

October: $$BASE_i = 17{,}640 - 16{,}270\, exp(-5.4 * 10^{-6}\, GDP_i) \tag{4.16}$$

Trends for base load demand forecast are similar to those of peak load demand forecast. Both LRMs and NLRMs of base load demand forecast in January and August depends on the temperature and GDP and those of base load demand forecast in May and October depend only on GDP.

4.2.3 Hourly Load Demand Models

Using a neural network approach, non-parametric regression models for hourly load demand forecast in January, May, August and October are chosen.

Based on peak and base loads models, hourly load demands for all seasons are assumed to be a function of temperature, GDP and DOW. However, temperature is a more important factor for the winter and summer months; the effect of temperature is considered for autumn and fall too. In addition, hourly load demands of all seasons are affected by the GDP and DOW. Investigation of historical data shows the peak period of hourly demand is not the same in weekdays and weekends. Therefore, day of the week is another explanatory variable affects the hourly prediction. As a training network function, Newff was chosen to create feed-forward network based on (Li and others 2009; Mohamed and others 1998). Seventy percent of input data was used for training purpose and thirty percent for testing. The results of the neural network models of the hourly load demand in four typical seasons and year 2000 (as a sample) are plotted in Figure 4.1 to Figure 4.5.

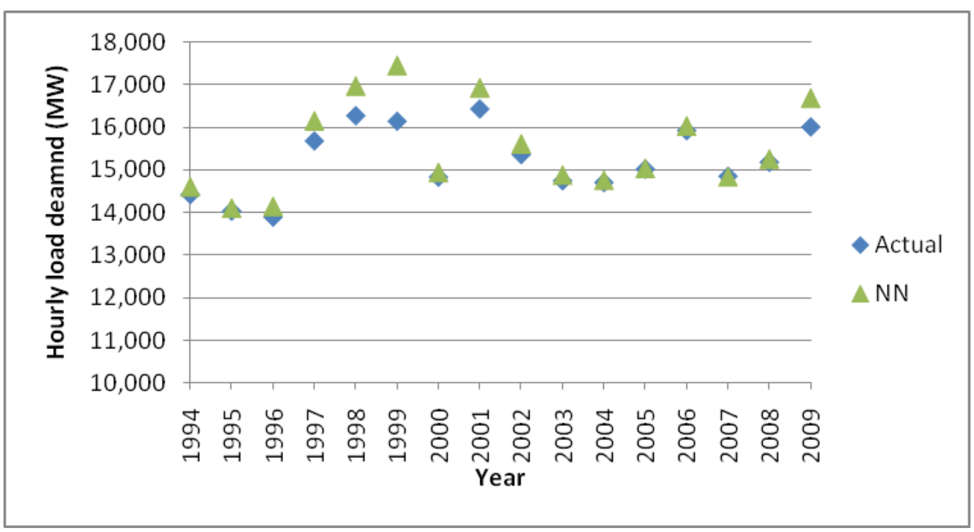


Figure 4.1 Results of NN Models for Hourly Load Demand in First Day of January.

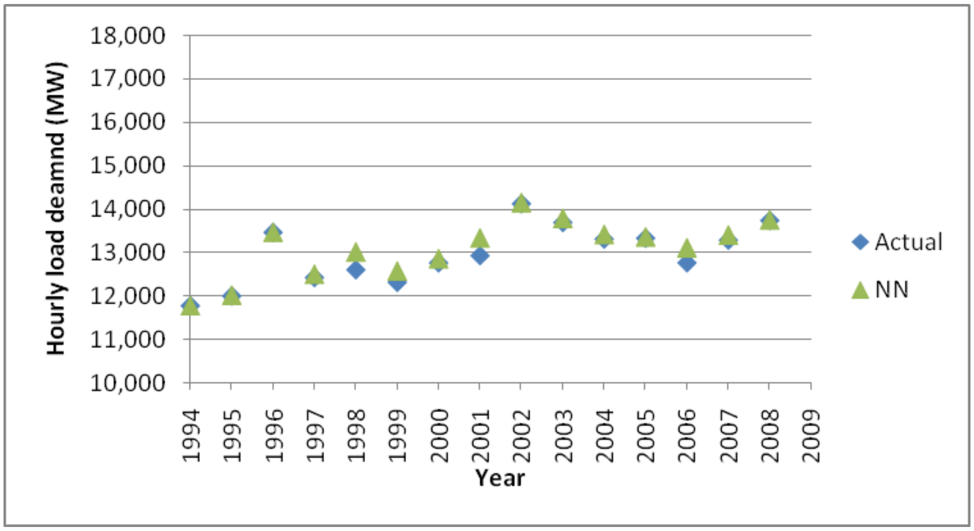


Figure 4.2 Results of NN Models for Hourly Load Demand in First Day of May.

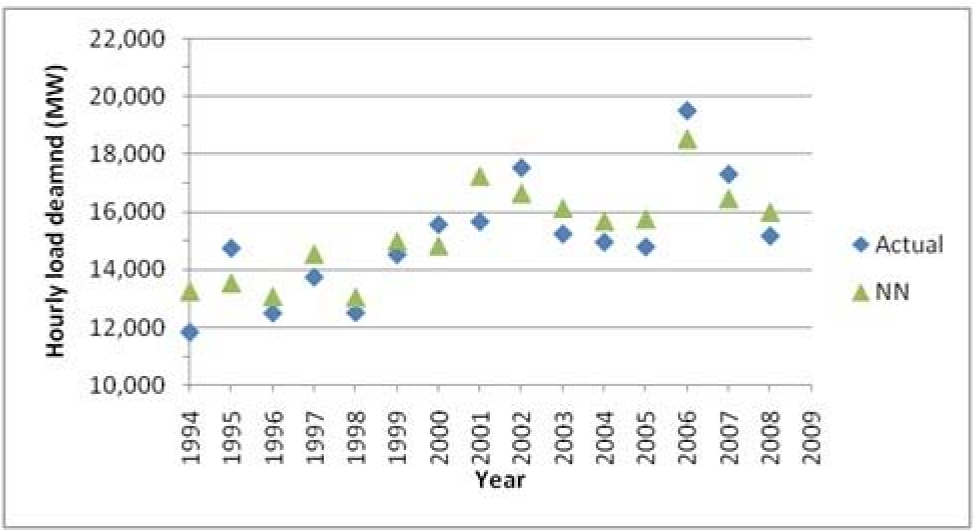


Figure 4.3 Results of NN Models for Hourly Load Demand in First Day of August.

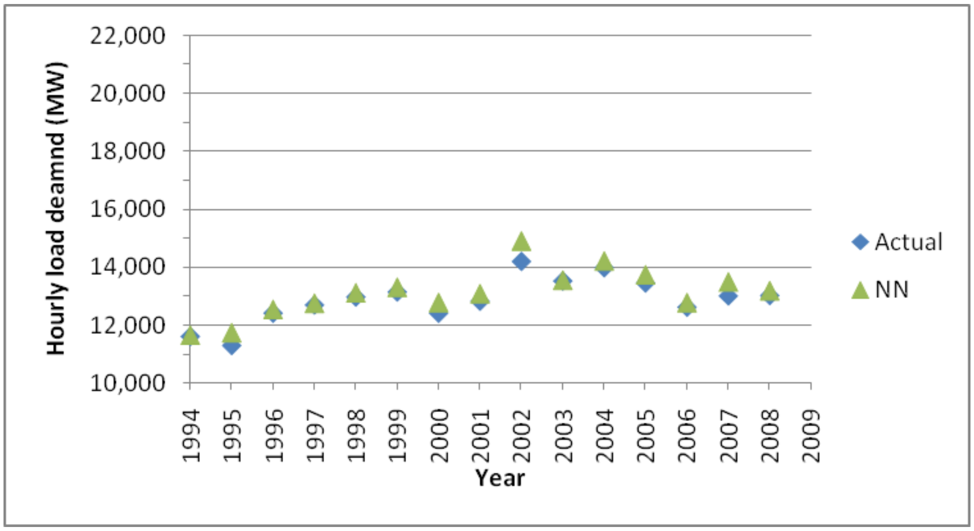


Figure 4.4 Results of NN Models for Hourly Load Demand in First Day of October.

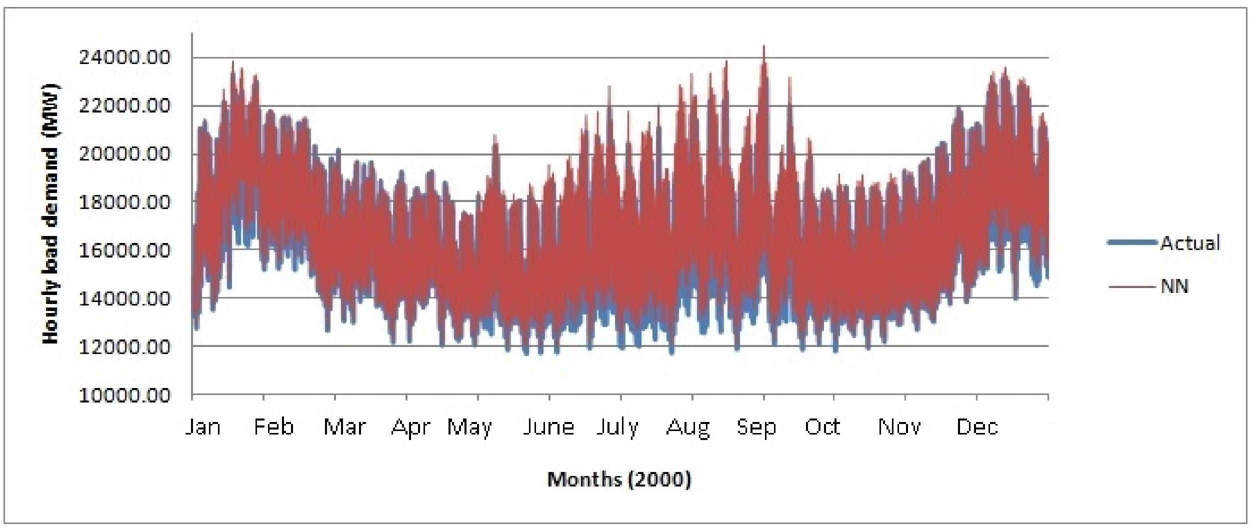


Figure 4.5 Result of NN Models for Hourly Load Demand Year 2000.

4.2.4 Light-Duty Vehicles Sold

The best linear and non-linear regression models are:

Linear regression models:

$$\ln(VEH_i) = 11.1 - 0.1\,x_1 + 0.3\,x_2 + 0.1\,x_3 + 2.1 * 10^{-7}\,GDP_i \quad (4.17)$$

Non-linear regression models:

$$VEH_i = 75{,}840 - 6{,}850\,x_1 + 24{,}370\,x_2 + 7{,}780\,x_3$$

$$-39{,}580 \exp\left(-6.1 * 10^{-6}\, GDP_i\right) \tag{4.18}$$

where x_1=1 and x_2=x_3=0 for winter, x_2=1 and x_1=x_3=0 for spring, x_3=1 and x_1=x_2=0 for summer and lastly x_1=x_2=x_3=0 for autumn. Both linear and non-linear regression models of light-duty vehicles sold forecast consist of these integer valued and GDP. From eqs. (4.17) and (4.18), the number of light-duty vehicles sold increases when increasing GDP because people have more potential to buy new vehicles when the economic growth is positive.

4.3 Model Selection

Comparisons were made among LRMs and NLRMs. MAE, MSE and MAPE were employed as the criterion to determine which model yields the most accurate results. MAEs, MSEs and MAPEs of all regression models of peak and base load demands and light-duty vehicles sold are compared in Table 4.1.

For peak load demand, NLRMs of all four months yield lower MAEs, MSEs and MAPEs than LRMs. Therefore, NLRMs represented in eq. (4.5) to eq. (4.8) were selected to represent peak load demand in January, May, August, and October, respectively.

When comparing between LRMs and NLRMs for base load demand, NLRMs in May, August, and October gives smaller MAEs. The opposite result is found in January. The LRM for January yield lower MAE, MSE and MAPE than NLRM. However, the difference between MAE, MSE and MAPE of LRMs and NLRMs is very small (approximately 1.8%). Therefore, the LRM represented by eq. (4.9) was employed to represent base load demand in January and NLRMs represented by eq. (4.14) to eq. (4.16) are used to illustrate base load demand in May, August, and October, respectively.

For light-duty vehicles sold, the LRMs gives better results than NLRMs, but there is only a slight difference between the MAEs for both regression models (approximately 0.4%). In this case, the LRM represented by eq. (4.17) was chosen to represent the number of light-duty vehicles sold due to lower mean absolute error of the model.

In summary, most of NLRMs yield lower MAE than LRMs. This implies that the relationship between forecast variables (peak and base load demands) and explanatory variables (temperature and GDP) are not always linear. In the few cases where LRMs give better results than NLRMs (base load demand in January and light-duty vehicles sold), the differences between MAEs, MSE and MAPE of both regression models are insignificant.

Table 4.1 Model Comparisons

Forecast variables	**MAE**		**MSE**		**MAPE**		**Selected models**
	LRM	**NLRM**	**LRM**	**NLRM**	**LRM**	**NLRM**	
1. Peak load demand							
- January	307.6	300.3	138965	124507	1.45	1.41	NLRM (eq. (4.5))
- May	323.7	273.0	181623	142217	1.90	1.60	NLRM (eq. (4.6))
- August	443.8	420.7	333226	301652	2.22	2.10	NLRM (eq. (4.7))
- October	415.2	391.4	269448	247339	2.34	2.21	NLRM (eq. (4.8))
2. Base load demand							
- January	327.6	333.4	158877	160983	1.71	1.74	LRM (eq. (4.9))
- May	336.4	308.9	208385	189852	2.16	1.98	NLRM (eq. (4.14))
- August	386.2	360.5	292767	254423	2.17	2.02	NLRM (eq. (4.15))
- October	390.3	372.9	211663	194546	2.40	2.30	NLRM (eq. (4.16))
3.Light-duty vehicles sold	6699.8	6848.9	74529858	7697788	8.62	8.87	LRM (eq. (4.17))

4.4 Projection of Forecast Variables

From the previous section, the best models of peak and base load demands and light-duty vehicles sold depend upon temperature and GDP. Using the temperature and GDP, the peak and base load demands and light-duty vehicles sold can be forecasted. The projections of peak and base load demands, without PHEVs, and light-duty vehicles sold until 2030 are shown in Figure 4.6 and Figure 4.7, respectively.

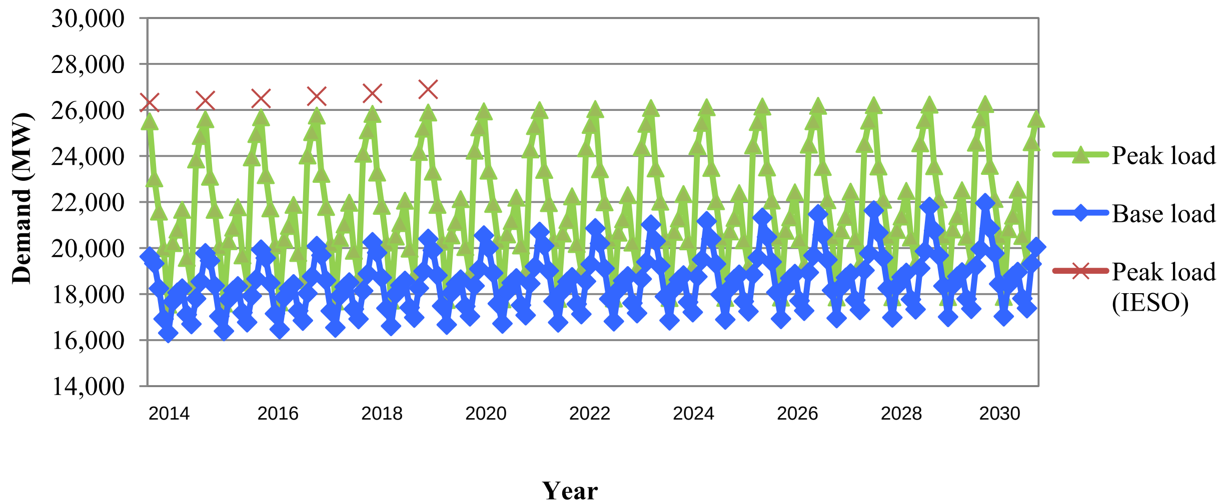


Figure 4.6 Load Demands Projection.

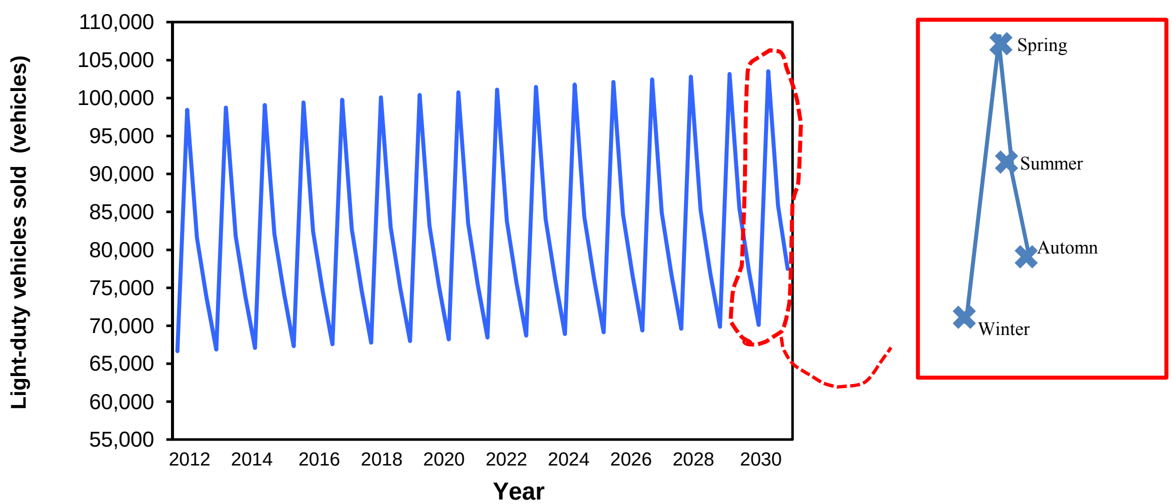


Figure 4.7 Vehicles Sold Projection.

As shown in Figure 4.6, the highest peak and base load demands of each year normally occur in January, which is approximately 26,000 MW and 21,000 MW, respectively. More electricity is required for space heating in the winter, resulting in a greater amount of peak and base load demands in January.

IESO also published a peak load demand forecast for Ontario from 2010 until 2020. Comparing peak load demand from the regression models with IESO forecast, there is an average difference of approximately 3%. Since the forecasting methodology from IESO is not known to us, it is impossible to explain these differences. Nonetheless, these differences are sufficiently small that both models are in reasonable agreement.

4.5 Effects of PHEVs Penetration

In the study of PHEVs penetration, three transitions, low, medium and high, are assumed to represent PHEVs penetration from 2014 to 2030, these were shown in Figure 3.2 Other assumptions used in PHEVs charging demand calculations are listed below:

- Only PHEV-20 penetrates into Ontario's transportation sector.

- No PHEVs are retired from 2014 to 2030.

- All PHEVs are recharged through the circuit during the peak period every day (worst case scenario).

Figure 4.8 represents model's results of accumulative numbers of PHEVs in the Ontario's transportation sector in various transitions of PHEVs penetration levels. The total number PHEVs at the end of 2030 for low, medium and high transition will be approximately 178,000, 534,000 and 890,000, respectively.

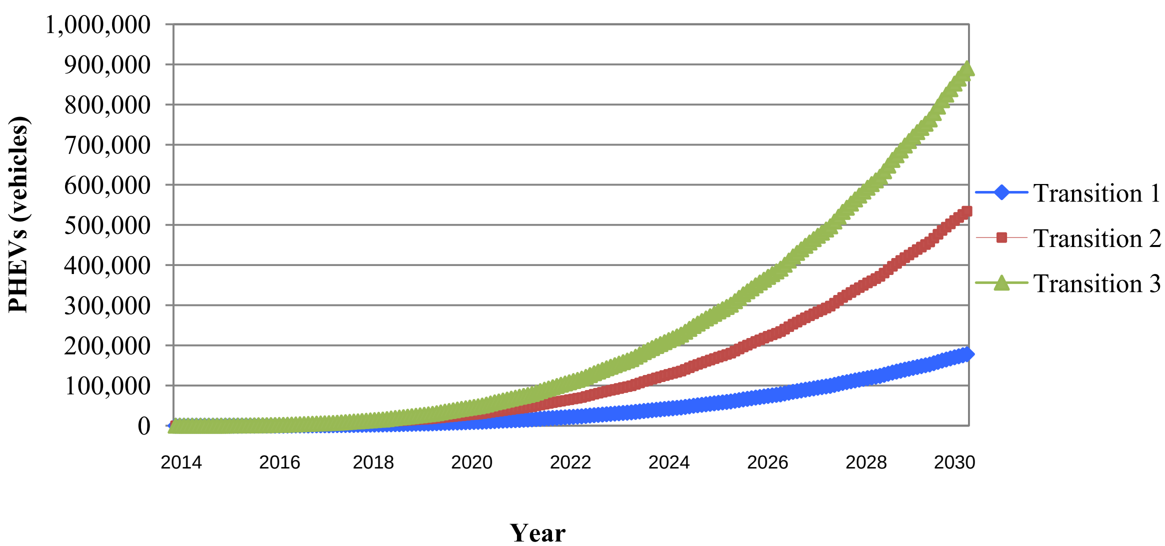


Figure 4.8 Accumulative Numbers of PHEVs in Ontario Transportation Sector.

New load demands after adding PHEVs into the transportation sector can be calculated from eq. (3.5), eq. (3.6) and eq. (3.7), respectively. As illustrated in Figure 4.9, the load demand of

PHEVs for high transition is the highest since this transition assumes the greatest amount of PHEVs penetration which is 50% of new vehicles in December, 2030. Additional peak load demands in December, 2030 from PHEVs charging for low, medium and high transitions will be 210.3 MW, 630.8 MW and 1,051.3 MW, respectively.

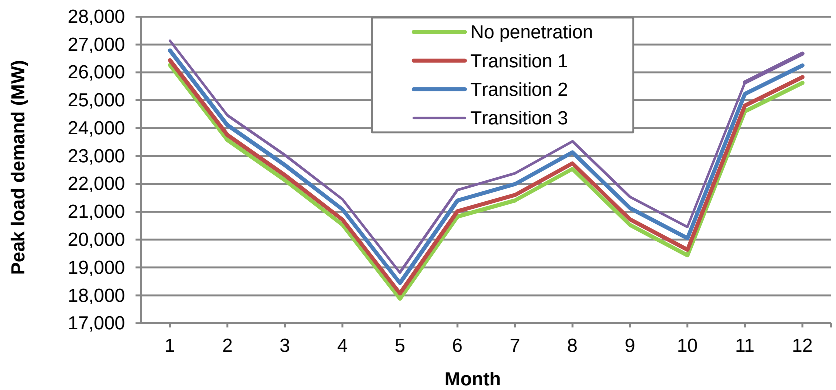


Figure 4.9 Comparisons of Peak Load Demand for Different Transition Levels in December 2030.

4.6 Effects of Charging Pattern

In the study of charging pattern, three assumptions used in PHEVs charging demand calculation are:

- Only PHEV-20 penetrates into Ontario's transportation sector with Transition 3 of penetration level.
- No PHEVs are retired from 2014 to 2030.
- All PHEVs are recharged through the circuit every day.

Four different charging scenarios are developed. Details for each scenario were illustrated in Table 3.8 and are shown again below.

Table 3.8 Charging Scenarios

Scenario	Name	Period
P1	After work	17:00-22:00
P2	Three hours after work	21:00-2:00
P3	In the morning	8:00-13:00
P4	During the night	24:00-5:00

Results of peak and base load demands for different charging scenarios after adding PHEVs into the transportation sector in 2023 (as an example) are shown in Figure 4.23. As indicated, the peak load demand from charging pattern in Scenario 1, which represents charging only during the peak period, is the highest among all scenarios. For Scenario 4, its peak load demand is similar to the peak load demand when there is no PHEVs penetration because the number of PHEVs being recharged in the peak period in Scenario P0 is assumed to be zero. Additional peak load demands in December 2023 from PHEVs charging in Scenario P1 to Scenario P4 will be 1,051.3 MW, 788.5 MW, 525.7 MW, and 0 MW, respectively.

For the base load demand, Scenario P4 in which all PHEVs are recharged during the off-peak period has the highest base load, while base load demand for Scenario P0 in which no PHEVs are recharged during the off-peak period is similar to the base load demand with no PHEVs penetration. The base load demand in all scenarios is not much different. Additional base load demands in December, 2023 from PHEVs charging in Scenario P1 to Scenario P4 are 0 MW, 20.9 MW, 41.7 MW, and 83.5 MW, respectively.

When comparing additional peak and base load demands in all scenarios, it was found that PHEV charging pattern has more effect on the peak load demand than on the base load demand.

4.7 Comparisons of Highest Transition with Scenario P1 with Ontario's Available Resources

Values of all transitions with 10%, 30% and 50% of PHEVs penetration in December 2030 and all scenarios for end of each year from 2014 to 2030 are indicated in Table 4.2. High transition on Scenario P1, in which all PHEVs are assumed to be recharged in peak period, has the highest value. All transitions and Scenario 1 are selected as the case study to compare with Ontario's generator availability at peak. As illustrated in Figure 4.10, in the beginning of 2014 where there is no PHEVs penetration into the transportation sector, the generator is more than the average peak load demand by about 2,228MW. At the end of 2030 in which the total number of PHEVs is 890,362 vehicles per highest transition, peak load demand is greater than the supply by about 1,466 MW. Therefore, it can be concluded that available resources in Ontario cannot afford the increasing demand from charging PHEVs between 2014 and 2030. In addition, since Ontario exports electricity to nearby province and USA, the increasing amount from PHEVs charging can reduce the quantity of electricity exported from Ontario.

Table 4.2 Peak Load Prediction of all Scenarios and Transitions at end of each Year (MW)

Year	Low_ P1	Low_ P2	Low_ P3	Low_ P4	Med_ P1	Med_ P2	Med_ P3	Med_ P4	High_ P1	High_ P2	High_ P3	High_ P4
2014	24872	24872	24872	24872	24872	24872	24872	24872	24872	24872	24872	24872
2015	25131	25129	25127	25122	25148	25142	25135	25122	25166	25155	25144	25122
2017	25211	25207	25203	25194	25246	25233	25220	25194	25280	25259	25237	25194
2018	25282	25275	25267	25252	25342	25319	25297	25252	25402	25364	25327	25252
2019	25354	25342	25330	25306	25449	25414	25378	25306	25545	25485	25425	25306
2020	25428	25410	25392	25356	25571	25517	25464	25356	25714	25625	25535	25356
2022	25505	25480	25454	25403	25710	25633	25556	25403	25915	25787	25659	25403
2023	25587	25552	25517	25446	25869	25763	25657	25446	26151	25974	25798	25446
2024	25670	25623	25575	25481	26046	25905	25764	25481	26423	26187	25952	25481
2025	25759	25698	25637	25514	26250	26066	25882	25514	26740	26434	26127	25514
2027	25857	25779	25701	25545	26483	26248	26014	25545	27109	26718	26327	25545
2028	25965	25867	25769	25573	26749	26455	26161	25573	27532	27043	26553	25573
2029	26082	25961	25840	25599	27049	26687	26324	25599	28017	27412	26808	25598
2030	26211	26064	25917	25622	27389	26947	26505	25622	28566	27830	27094	25622

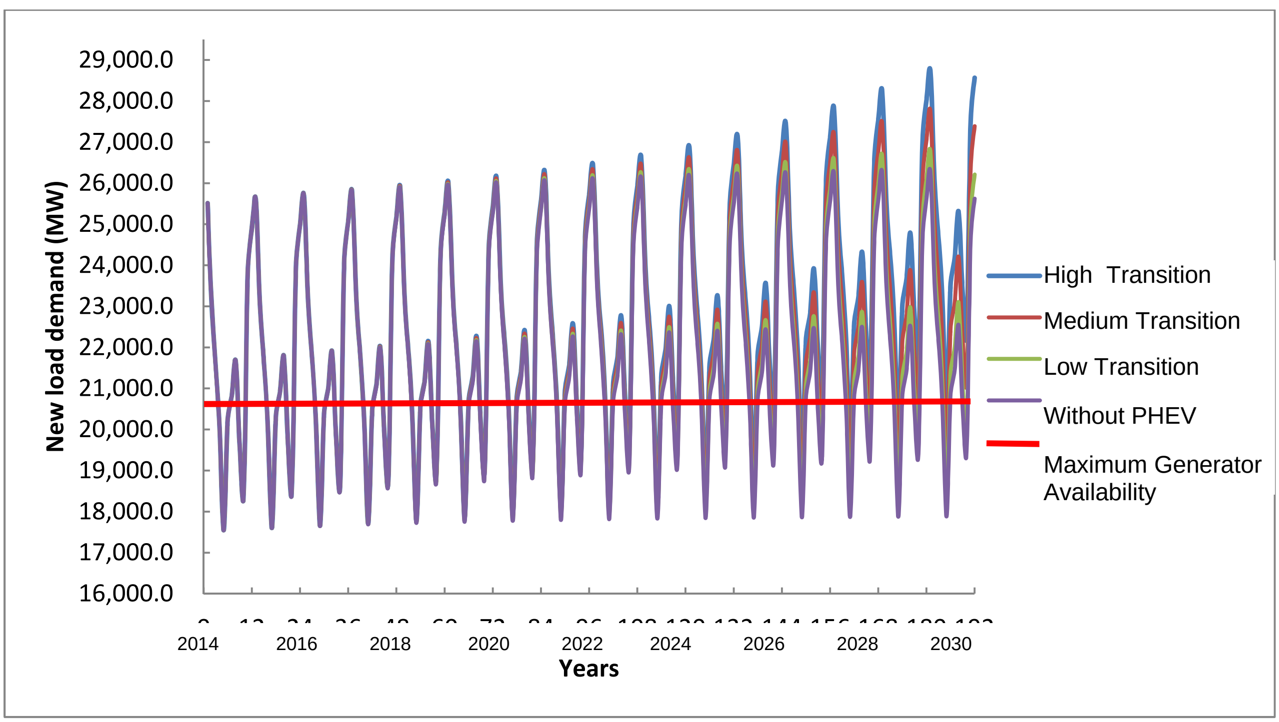


Figure 4.10 Comparisons of Peak Load Demand with Ontario Available Resource through Scenario 1.

4.8 Conclusions

Number of PHEVs is forecasted through consideration of three scenarios of penetration levels, and the maximum number of PHEVs would be 890,362 vehicles at the end of 2030 in Ontario. There are different factors effecting on PHEVs penetration. Moreover, four different scenarios of the charging pattern are developed. Additional peak load demands in December 2030 from PHEVs charging in different scenarios are 1,051.3 MW, 788.5 MW, 525.7 MW, and 0 MW. Also, additional base load demands in December, 2030 from PHEVs charging are 0 MW, 20.9 MW, 41.7 MW, and 83.5 MW. After PHEVs penetration, peak load demands and base load demands in December 2030 would be increased by ~13% and 4% compared to the 2013 demand. Consequently, supply is less than the peak load demand. The additional electricity demand on the Ontario electricity grid from charging PHEVs is incorporated for electricity production planning purposes. Therefore, we need more power plants if PHEVs are widely adopted.

Chapter 5: Effect of Socio-Economic Factors on PHEVs/EVs/HEVs Penetration

5.1 Introduction

Transportation sector contributes approximately 25% to Greenhouse Gas (GHG) Emissions in Canada as published by Canada's action on climate change website. As a response, Electric Vehicles (EVs) which operate solely on electricity have been penetrated to the market (Zhang et al., 2013). Hybrid Electric vehicles (HEVs) are also another type of low emission vehicles which comprise of two or more power sources (Emadi et al., 2008). Plug-in HEVs (PHEVs) include battery packs of high density which allow them to run longer than the HEVs and can be recharged via cable plug-ins (Emadi et al., 2008). For people who need more range coverage of up to 500 km sometimes, Extended Range Electric Vehicles (EREV) are perfectly suited. These type of vehicles run on their internal combustion engines when the battery is depleted and close to reach minimum state of charge, in order to recharge it (Eberle and Helmolt, 2010; Tuttle and Baldick, 2012). According to Table 5.1, HEVs are much more popular than EVs in Canada (IA-HEV, 2008 and IA-HEV, 2012). The main reason of this is most likely due to the fact consumers tend to have range anxiety regarding EV adoptions (Daziano, 2013).

Table 5.1 Number of EV and HEV Units Sold in Canada (2005-2009)

Year	2005		2006		2007		2008		2009	
Vehicle Type	Evs	HEVs	Evs	HEVs	Evs	HEVs	Evs	HEVs	Evs	HEVs
Units Sold	11	6053	18	13253	21	25783	29	45703	41	59541

GoodCarBadCar auto sales data sources present the sales of some of the more popular models of EVs and HEVs over the recent years as indicated in Table 5.2 and 5.3. Nissan Leaf is having the most sales as a popular EVs brand in Canada, since it's the first all-electric car built by large amounts with an affordable price. Among HEVs, Prius V stands out, mainly because of its high fuel efficiency which is 4.5L/100km mentioned in Toyota official website. As for PHEVs, several automobile manufacturers have only just started producing them commercially in 2010 (Ahmadi et al., 2012) with Toyota Prius Hybrid having the most sales in Canada at 193 units from 2012 Sep to 2013 May. As for the EREVs, Chevrolet Volt is having more sales than others. In Ontario, Considering the fact that the government is supporting EVs and PHEVs adoption by giving incentives of up to 8500$ to their customers, and also because Ontario Ministry of Transportation is envisioning a future that one out of every twenty vehicles in Ontario's roads would be electric vehicles, EVs and PHEVs will have a significant popularities in near future. This chapter focuses on analyzing EVs, HEVs and PHEVs adoption rate through various socio-economic factors in Ontario from the year 2012 to 2050.

Table 5.2 Units of EVs Sold in Canada

	Electric Vehicles	
Vehicle Brands	**I - miev (Nov 2011 - May 2013)**	**Nissan Leaf (July 2011 - May 2013)**
Units Sold	300	645

Table 5.3 Units of HEVs Sold in Canada

	Hybrid Electric Vehicles				
Vehicle Brand	**Ford C-max Hybrid (Sep 2012 – May 2013)**	**Honda CR-Z (Aug 2010 – May 2013)**	**Honda Insight (Jan 2010 – May 2013)**	**Toyota Prius C (Jan 2010 – May 2013)**	**Toyota Prius V (Oct 2011 – May 2013)**
Units Sold	883	1104	2299	3658	5717

Estimating the adoption of innovations has been the subject of academic and practical interest since 1960s (Eggers, 2011). Factors influence adoption rates include the risk the consumer believes he/she might be taking, the methods of the innovator's marketing and the innovation's cultural effects (Eggers, 2011). For the purpose of this chapter, the innovation of EVs, HEVs and PHEVs vehicles is the subject of interest. Studies have shown that economic factors such as the costs of purchasing the vehicle, its fuel and electricity and external factors such as government incentives affect the MV adoption rate. In addition, the households and target group of MVs' characteristics such as their age, income level and their environmental consciousness, plus the vehicle attributes also affect the adoption rate (Eggers, 2011; Musti and Kochelman, 2011). Even though MVs reduce dependence on fossil fuels which decreases GHG emissions as a result, there are still barriers preventing these innovations to be adopted on a large scale (Egbue, 2012). These challenges include the consumers' tendency to resist adopting new unknown technologies and therefore federal policy decisions addressing their concerns have major impacts. The economical factor of cost was shown to be ranked ahead of the sustainability and environmental factors when it came to adopting EVs, HEVs and PHEVs (Egbue, 2012; Tran et al., 2013).

Forecasting the penetration of MVs, is more complicated than the usual market forecasts due to various reasons. First fact is that EVs and PHEVs have only been introduced to the market in the recent years, and not enough sales data are available for study. Another reason is that to adopt

EVs and PHEVs, a behavioral change in the consumers would be required, which is refueling their vehicle at a gas station and/or charging by plugging in it and only a few studies have attempted to see how much consumers are willing to accept these change. Furthermore, the change in fuel type creates controversy regarding the use of past CV and HEV sales data (Al-Alawi and Bradley, 2013). According to (Alawi and Bradley, 2013), the three major modeling techniques have been used by researchers to represent the market interactions in their models for MV penetrations, including Agent-based models, Consumer choice models and Diffusion rate and time series models.

An agent based model is a computer simulation which has a virtual environment with agents in it. Each agent has a set of characteristics which determine their actions. This technique is applied to fields such as population dynamics, consumer behavior and vehicle traffic. Consumer choice models have been used in numerous studies to estimate vehicle sales and are usually derived from past vehicles sales data and consumer demographic data. The diffusion rate and time series models' goal is to find the "life cycle of new products over time". Diffusion is the rate at which product spreads in the market and it is usually presented as a normal distribution over time. Diffusion rate models are commonly associated with S-shaped curves and the impact of social influence in the innovation adoption rates are presented in them. This type of model is meant to present the acceptance of a product over time (Al-Alawi and Bradley, 2013).

For the purpose of this chapter, based on the diffusion rate model, a novel model is developed presenting the socio-economic factors affecting the EVs, HEVs and PHEVs adoption rates in Ontario.

5.2. Methodology

The Methodology used in this chapter consists of modeling of light duty vehicle sold, same as previous chapter, and penetration function of diffusion rate and socio-economic factors.

5.2.1. Light Duty Vehicles Sold Modeling

To predict the number of Light Duty Vehicles (VEH) sold in the future, a long-term forecast of Canada's Gross Domestic Product (GDP) is needed. To find the GDP, initially, a long term GDP forecast released by the PricewaterhouseCoopers firm (PwC) is considered (Elliot, 2011; PWC, 2011)). The forecast continued until year 2050, which is needed for this chapter. But since the GDP amounts are derived from Purchasing Power Parity (PPP) calculations, they are multiplied by a coefficient "k" in order to convert them to real GDP. The coefficient "k" is obtained by referring to Ontario's long-term report on the economy forecasted GDP until year 2030 and is released by Ontario's Ministry of Finance (Ontario Long term report, 2013). PPP, according to The World Bank Group and an article from the Climatic Change journal, is used for comparing the economy of different countries, by first picking a specific basket of goods and services that has an equivalent worth in all nations. By using the ratios of the prices of the goods and services, conversion to common currencies can be done. With this method, the negative impacts caused by differences in price levels are removed (Manne and Richels, 2005)). After converting the GDPs taken from PwC, the numbers are compared to the GDP numbers given in Ontario's Ministry of Finance report. The mean absolute errors which can be observed in Table 5.4 are negligible.

Table 5.4 Conversion and Comparison of GDPs from PwC and Ontario's Ministry of Finance

Year	GDP at PPP (PwC)	Real GDP (PwC)	GDP by applying growth rate (Ontario's Ministry of Finance)	Mean Absolute Error
2012	1,403.06	676855.3446	676855.3446	4.9921E-11
2013	1,440.95	695130.4389	697837.8602	0.00389484
2014	1,478.41	713203.8303	716679.4825	0.00487329
2015	1,517.11	731872.3532	731747.1299	0.0001711
2016	1,556.82	751029.5355	750901.0344	0.0001711
2017	1,593.87	768903.6892	770556.3035	0.00214931
2018	1,631.02	786825.0793	788895.1851	0.00263096
2019	1,668.26	804788.1542	807282.5314	0.00309942
2020	1,705.57	822786.9466	824103.0699	0.00159959
2021	1,742.94	840815.0741	842533.8333	0.00204416
2022	1,780.29	858834.1315	860994.6359	0.00251562
2023	1,817.69	876873.4888	879446.1506	0.0029339
2024	1,855.11	894926.1337	897918.4526	0.00334365
2025	1,892.54	912984.6407	915509.4348	0.00276543
2026	1,929.97	931041.1684	933983.2875	0.00316003
2027	1,972.55	951583.036	952455.1153	0.00091645
2028	2,016.24	972656.1117	973469.4458	0.0008362
2029	2,061.04	994269.2908	995027.2022	0.00076228
2030	2,106.98	1016431.538	1017137.484	0.00069453

The amount of light duty vehicles sold season by season (VEH) is forecasted by Eq (4.17):

$$\ln(VEH_i) = 11.1 - 0.1x_1 + 0.3x_2 + 0.1x_3 + 2.1 \times 10^{-7} GDP_i$$

According to the gathered historical vehicles sales data, the GDP factor and the seasons of the year affect the units of light duty vehicles sold. The seasons are taken into account by assigning integer numbers of 0 and 1 to the dummy variables, x_1, x_2 and x_3 in the model. Table 5.5 indicates what combination of numbers present which seasons.

Table 5.5 Season Representations

Seasons	Winter	Spring	Summer	Fall
x_1	1	0	0	0
x_2	0	1	0	0
x_3	0	0	1	0

As GDP increases, so does the number of light duty vehicles sold, due to the fact that when there's growth in the economy, more people would have the potential to buy new vehicles.

Initially, to find the best forecasting model, both of the Linear Regression (LR) and Non-Linear Regression (NLR) techniques are deployed by using the software called Statistical Package for Social Sciences (SPSS) (SPSS, 1987). At the end, it is observed that the forecasting model derived by LR has the least mean absolute error, and therefore it is concluded that it is the most convenient option to find VEH.

5.2.2. Penetration Function Modeling

To find out the number of EVs, HEVs and PHEVs in Ontario over time, a penetration function, representing diffusion rate and socio economic factors simultaneously, is modeled. All steps are discussed on the following sections in detail.

5.2.2.1. Diffusion rate

To find out what fraction of the new light duty vehicles would be made up of Modern Vehicles an exponential penetration functions are commonly used. The following penetration function, PF(I) is developed for diffusion rate part (Jochem et al., 2013)

$$PF(I) = \frac{1}{A+Be^{Cx+D}} \tag{5.1}$$

Where A, B, C and D represent related coefficients and x represents number of seasons.

The next step is to determine the coefficients. With the purpose of having more accuracy, this process considers some key facts regarding the amount of EVs, HEVs and PHEVs in different times, like Ontario Ministry of Transportation planning to have 1 out of every 20 vehicles on the province's roads to be EV, HEV or PHEV by 2020. Also, roughly around 200 EVs, HEVs and PHEVs were sold in the year 2012. Additionally, according to the Ministry of Environment, by

2050, the government of Ontario is planning to reduce the Greenhouse Gas Emissions by 80% below the 1990 emission levels; therefore at least 50% of the vehicles on the road need to be MVs by that year.

5.2.2.2. Socio-Economic factors

For the purpose of increasing the accuracy of the EVs, HEVs and PHEVs penetration function, a second part which represents the socio-economic impacts on the MV adoption rate, is developed considering the total cost of a vehicle ownership, driver's age, gender, location, community distance, traffic, vehicles production year, type and model. Vehicles with higher All-In Costs, AIC, would have a less penetration than vehicles with lower AIC. I, AIC is determined by Price My Ride [Pricemyride, 2013]. With more than 20,000 vehicles in their database, the Price My Ride team employs the intricate approaches of maintenance, insurance fees and fuel costs to find out how much it would cost to run the vehicle. According to the team, their AIC are found from purchase prices, insurance estimates and fuel costs, and the results are reliable. Purchases prices of new vehicles are based on prices suggested by car companies to their dealers and are acquired from a company called Autodata. The estimation of insurance is done by using the same rate of insurance companies which are filed by with regulators in Canada. It must be noted that if a vehicle is already owned, it is assumed that the consumer will be staying with his/her current insurance provider. As for fuel costs, the calculation is done by the procedure which the government has approved and is based on fuel economy data provided by vehicle manufacturers. In the next step, the methodology of finding the AIC by Price My Ride is explained. As presented in Fig. 5.1, initially an input of gender, age and location is required.

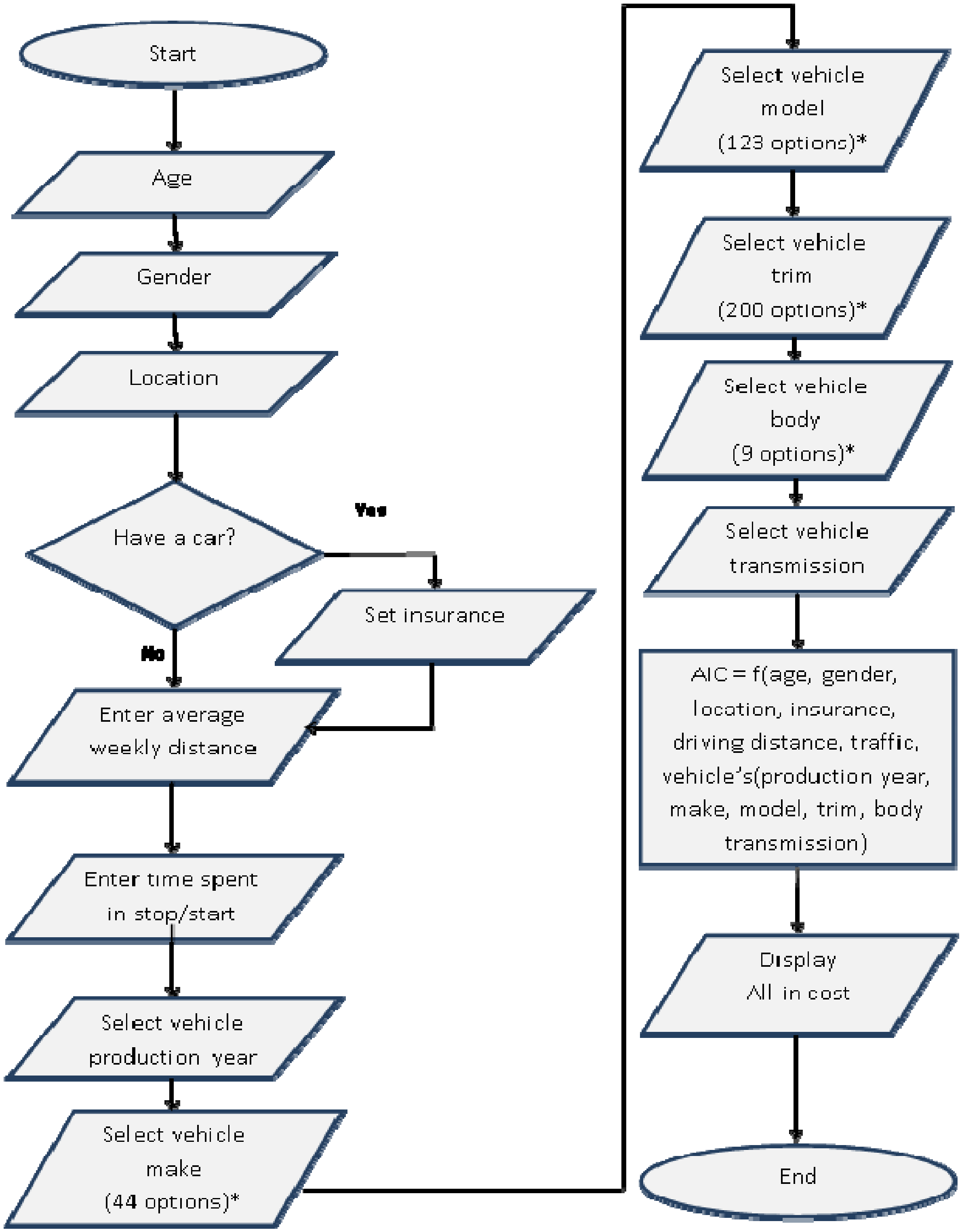


Figure 5.1 Calculation Procedures.

For more accuracy, all of the procedure is done two times, to have data for both females and males. The location is selected to be Toronto. For the insurance rates, if a vehicle is already owned, it is required for the users to select their insurance rates per month. For the result to be more accurate, the users can enter more details regarding their insurance, such as selecting the company, its bodily injury coverage, accident benefits and property damage. Because of developing penetration function on new vehicles sold in Ontario in this study, it is assumed that no vehicle is currently owned for calculating AIC, therefore the insurance estimate is considered to be based on current averages of the industry, with the assumption of no tickets and accidents. Next the model considers the travelling distance in an average week. According to Table 5.6, data are provided by Statistics Canada, for the age span of 25-54, the distance is approximately 119 kilometers per week for females and 154 kilometers per week for males.

Table 5.6 Commuting Distances

Commuting distance	Commuters (people with age 25-54)	
	Male	**Female**
Less than 5 km	466020	608235
5–9.9 km	370340	409875
10–14.9 km	243265	247430
15–19.9 km	181720	172080
20–24.9 km	126930	114370
25–29.9 km	88020	74550
30 km or more	289805	187230
Total average distance (km/day)	22	17
Total average distance (km/week)	154	119

Due to limitations existing in the selection of the distance on Price My Ride, for females, the average distance is selected to be 100 kilometers and for males, 150 kilometers. The next required input is the percentage of time that would be spent in stop-and-start traffic. By referring to Natural Resources Canada and Statistics Canada, the fraction is estimated to be roughly 10%. The vehicle selection process is divided into six parts. First the users have to select the production year of their vehicle. Next, the users indicate if their vehicle is leased or purchased. Also, if they are not planning to keep the car, they should indicate if they will be selling or trading it. In the final step, the users select the car that they are planning to get. Then the make, model, trim, body and finally transmission are selected as are indicated in Table 5.7, and based on all of the information that is submitted in the previous steps, the car's all-in costs are presented. In this study, more than 800 all-in cost samples are obtained, using Price My Ride's calculation system and are employed with the GDP trend to create the second part of the penetration function.

Table 5.7 Price My Ride Selections

Select vehicle make	Select vehicle model	Select vehicle trim	Select vehicle body	Select vehicle transmission
Acura	TL	Base (A6)/(A5), 3.2	Sedan	AWD AT6/AT5, FWD AT5/AT4
Audi	A3/A4	2.0 TDI Progressiv (S tronic) Diesel, 2.0 TDI (S tronic) Diesel, 2.0TSportsback (S-tronic),2.0T,Base (A5)Sportsback(M6),1.8T(EOP Nov/03)(A5),1.8T(A5),	Hatchback/ Sedan	FWD AT6/MT6/AT5 AWD AT5
BMW	Active Hybrid,7L/ X6,323,320,318	Base,i,i (A4)	Sedan/ Sport Utility	RWD AT6/MT6/ AT4,AWD AT7
Buick	LaCrosse,Enclave, Allure,Century	Base,CX,Custom,Special	Sedan Sport Utility	FWD AT6/AT4 AWD AT6
Cadillac	Escalade /Hybrid ,Catera,DeVille	Base	Sport Utility Sedan	4x4 CVT4/AT4 AWD AT6/AT4 RWD AT4,FWD
Chevrolet	Tahoe,Hybrid, Cavalier Silverado1500/ Hybrid	Base,LT,LS	Regular Side, Sport Utility,Sedan	4x2CVT4/CVT/AT4/MT5, FWD MT5
Chrysler	200,300,,300M, ,Sebring	Limited,Base,JX	Sedan Convertible	FWD AT6/AT4 AWD AT5
Daewoo	Lanos	S	Sedan	FWD MT5
Dodge	Journey Grand , Caravan	R/T Rallye,CV Base, Sport	Sport Utility, Cargo & Passenger Van	AWD AT6 FWD AT4/AT3
FIAT	500	Lounge	Hatchback	FWD MT5
Eagle	Talon	Base,ESi	Hatchback,Coupe	FWD MT5
Ford	Fusion Hybrid, Escape /Hybrid,Focus,F-150	Hybrid,Base,Limited Duratec,XLS,LX,Standard, Special Styleside	Sedan Sport Utility Regular Side	FWD CVT2/ MT5 4x4 CVT2/ AT4/ MT5, 4x2 MT5
Geo	Metro	base	Coupe	FWD MT5
GMC	Sierra 1500,Safari Hybrid,Yukon, Hybrid,Jimmy,	Base,SLE,SL	Regular Side, Sport Utility, Cargo Van	4x2 CVT4/ AT4 AWD AT4
Honda	Civic /Hybrid	Base,DX /(A5)/(A4)	Sedan, Hatchback	FWDCVT2/ AT5/AT4
HUMMER	H3 SUV	Base	Sport Utility	4x4 MT5
Hyundai	Elantra	GL /(A4),GLS 1.8L (A4)	Sedan	FWD MT6/ MT5/ AT4
Infiniti	G25/37/35/20,I30	Luxury /(A4)/(A7),Base /(A5)/(A4),Sport (A4)	Sedan	RWD AT7/ AT5 FWD AT4
Isuzu	Trooper	LS	Sport Utility	4x4 AT4/MT5
Jaguar	X F/K/J8/J6, S-TYPE	Base,3.0L /V6 (A6)/V6,Base 4.0L	Sedan, Coupe	RWD AT6/AT5/AT4

Jeep	Wrangler, Grand Cherokee	Rubicon, Laredo	Sport Utility	4x4 MT6/ AT5/ AT4 4x3 AT4,4x2 AT4
Kia	Rio, Sephia	EX(A6)/(A4),LS(A4),Base(M5)	Hatchback, Sedan	FWD AT6/ AT4/ MT5
Land Rover	LR4,LR3,Discovery,Range Rover	Base,V6 /SE,HSE,Series II /Kalahari Edition,LE,4.0 SE	Sport Utility	4x4 AT6 4x4 AT4
Lexus	ES /300/330/350	Base	Sedan	FWD AT6/AT5/AT4
Lincoln	MKZ /Hybrid,LS Continental	Hybrid,Base,V8 Sport,V6 /Auto/AutoBase/AutoLuxury	Sedan	FWD CVT2/AT4 AWD AT6,RWD AT5
Mazda	CX-7,MX-5 Miata, Protégé	GX,3rd Generation Limited (M6),GS /(M6),1.8 (A4),Base (A4),LX (A4)	Sport Utility Convertible Sedan	FWD AT5/AT4/MT5 AWD AT6 RWD MT6/AT4
Mercedes-Benz	S-Class	Base	Sedan	AWD AT7/AT5 RWD AT5
MINI	Cooper	Base	Hatchback	FWD MT6/MT5
Mitsubishi	Lancer	GT,SE,GTS,ES /(A4)	Sedan	FWD MT5/MT4
Mercury	Grand Marquis	GS	Sedan	RWD AT4
Nissan	Altima /Hybrid	2.5 S /(CVT)/(A4), S (A4), XE (A4)	Sedan	FWD CVT2/AT4
Oldsmobile	Silhouette, Achieva	GL SC	Extended, Coupe Passenger Van,	FWD AT4/MT5
Plymouth	Breeze	Base	Sedan	FWD MT5
Pontiac	G 5/6, Aztek, Grand Prix	Base,GT,SE	Sedan, Sport Utility, Coupe	FWD MT5/AT4 AWD AT4
Porsche	Cayenne /Hybrid, Boxster, 911	S,V6,Base /(M6),Carrera	Sport Utility, Convertible,Coupe	AWD AT8/ MT6/ AT6 RWD MT5/MT6
Ram	1500	Laramie	Regular Side	4x2 AT6
Scion	tC	Base (M6)	Coupe	FWD MT6
Saab	9-5, 900	Base Automatic, Aero w/1SC,Aero,S	Sedan,Hatchback	FWD AT5/MT5
Saturn	VUE /Green, Saturn Line/Hybrid, LS, SL	Base,4 CYL (CVT)/(M5)/Automatic, Sport /(A4),SL	Sport Utility, Sedan	FWD AT4/MT5 AWD CVT1
smart	fortwo	BRABUS, passion /diesel	Coupe	RWD AT5/AT6
Subaru	Legacy	2.5 GT (M6)/(M5),GT (M5),L+ (M5)	Sedan, S Wagon	AWD NT6/MT6/MT5
Suzuki	Grand Vitara, Vitara,Esteem	Base,JX /(A5)/(A4), JA Base 1.6L (M5),GL Custom (A4)	Sport Utility, Sedan	4x4 AT4/ AT5/ MT5 FWD AT4
Toyota	Prius,Corolla	Base,CE (A4),DX (A3)	Hatchback,Sedan	FWD CVT2/AT4/AT3
Volkswagen	Golf, City Golf	2.5L Comfortline (A6), 2.0L (M5),CL (A4),GL (A4)	Hatchback, Coupe	FWD AT6/MT5/AT4
Volvo	S80,S60,S70,960	T5 Level 1,3.2 A,3.2,2.5T ,A SR,2.4T A SR,Base (A5),GLT (A4),Base	Sedan	FWD, AT6/AT5/AT4, AWD AT6,RWD AT4

Furthermore, to develop adoption rate model of the EVs, HEVs and PHEVs base on the impact of the socio-economic factors, the technique of regression analysis is deployed, using the software SPSS. Initially by taking numerous economic factors into consideration, regression models are created for each of them to find their impact on the dependant variable which is the AIC of vehicles during 1996-2012. In this step, the economic factors are the number people employed (EMP), population size (POP), income (INC), the number of graduated students (EDU) and the gross domestic product (GDP) (Table 5.8).

Table 5.8 Linear Regression Variables

Dependant variable	Economic factors
All-in Cost	EMP, POP, INC, EDU, GDP

Using the GDP give the lowest mean absolute error (MAE) when is compared to the historical data of AIC (Table 5.9).

Table 5.9 Mean Absolute Error of a Linear Regression Model Sample

Female all-in cost (average)				
Year	**GDP**	**F_ave_all-in-cost**	**Prediction**	**MAE**
1996	454868.46	510.72	448.9857	0.120876997
1998	494828.2	556.97	494.375	0.112384868
2000	538298.36	617.32	522.2122	0.154065639
2002	569972.38	675.97	609.0301	0.099027915
2004	603510.12	759.82	686.5294	0.096457845
2006	624737.99	903	825.57805	0.085738594
2008	632257.33	1106.18	1033.16935	0.066002504
2010	639867.18	1302.97	1240.3081	0.048091591
2012	676855.34	1423	1300.5553	0.086046873

5.2.2.3. Final penetration function

In the final stage, the exponential function representing the diffusion rate (PF(I)) and the regression model representing the socio economic factors' (PF(II)) impact on the EVs, HEVs and PHEVs adoption rate are combined to give the final penetration function:

$$PF = PF(I) + PF\ (II) \tag{5.2}$$

For the predictions of adoption rates to be more accurate, three scenarios are considered as three case studies (Table 5.10).

Table 5.10 Scenario Weights

Scenario	A	B
A	1	0
B	0	1
C	0.50	0.50

Scenario A represents a situation where only the impact of the diffusion rate is being considered, whereas in scenario B, only the impact of socio-economic factors is accounted for. In scenario C, the impact weight is equally balanced between the two factors.

The AIC function already has six different scenarios, and when combined by the three scenarios due to α and β, the adoption rate of EVs, HEVs and PHEVs can be estimated in eighteen different scenarios, using the final penetration function.

5.3. Results

5.3.1. Light Duty Vehicle Sold

It is found that the VEH in spring exceeds than that of the other seasons due to better weather and buying conditions. Winter has the least of light duty vehicle sales. The sales are depicted in Figure 5.2.

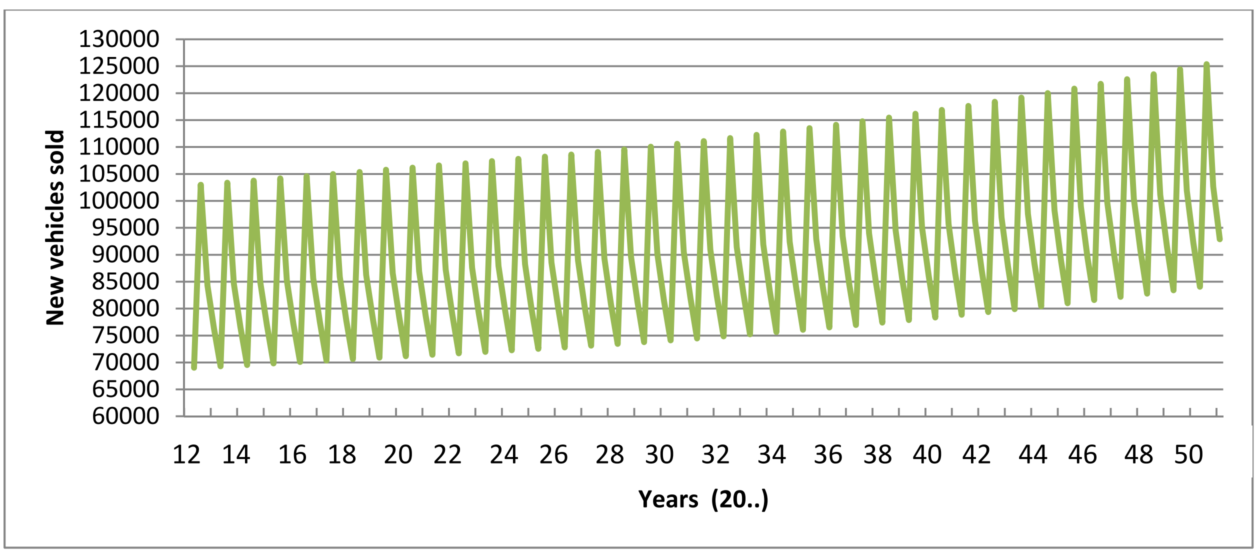


Figure 5.2 Vehicle Units Sold Seasonally During 2012-2050.

5.3.2. Penetration Function of Diffusion Rate

After doing all the calculations and analysis, all the coefficients of PF(I) are found as indicated in Table 5.11.

Table 5.11 Diffusion Function Parameters

Coefficient	Value
A	2
B	2
C	-0.08178
D	5.15214

By substituting the coefficients in the above equation, PF(I) which is presented below, holds true to all facts mentioned in section 2.2.1 . For example if we consider end of year 2020 the adoption rate would be 0.05, and therefore the first part of representing the diffusion rate of the final penetration function is the proper model.

$$PF(I) = \frac{1}{2+2e^{-0.08178(x-63)}} \quad (5.3)$$

Figure 5.3 presents the diffusion rate over time.

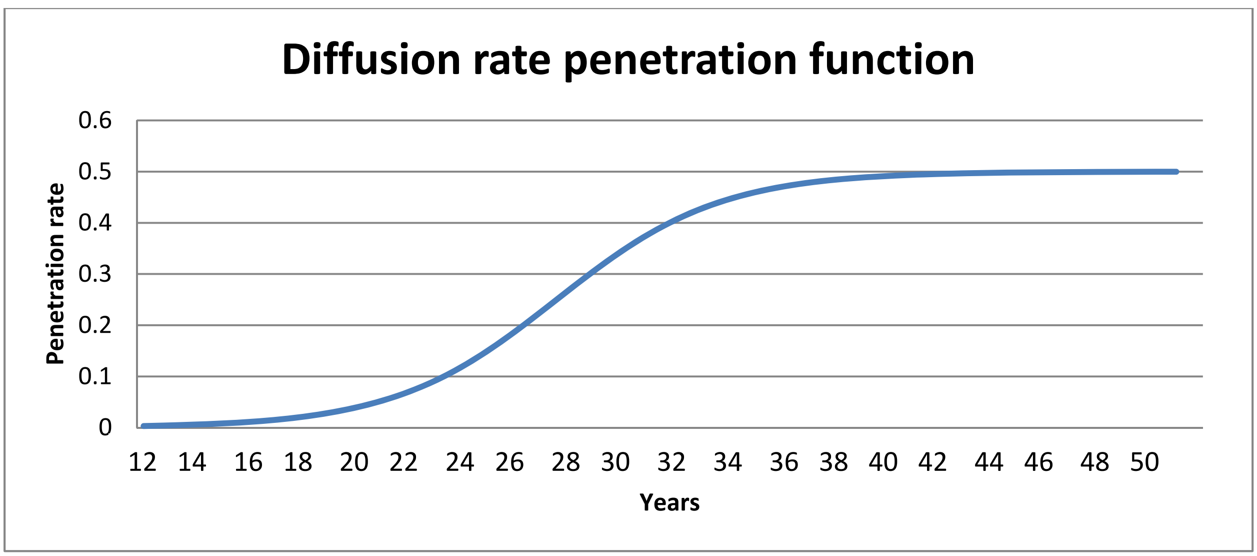


Figure 5.3 Diffusion Penetration Rate Function.

5.3.3. Penetration Function of Socio-Economic Factors

By employing the GDP historical trend, socio-economic forecasting models are created for males and females separately. In order to better analyze the socio economic impact on the EVs, HEVs and PHEVs adoption rate, for both males and females, three different scenarios are considered, regarding the AIC estimation data. The resulting formulas are as presented:

FEMALE

- Aggressive all-in cost forecast

$$PF(II) = (210.0890) - (0.1059 * YEAR) + (4.8359 * 10^{6} * GDP) \quad (5.4)$$

- Average all-in cost forecast

$$PF(II) = (56.8195) - (0.0282 * YEAR) + (1.15141 * 10^{6} * GDP) \quad (5.5)$$

- Mild all-in cost forecast

$$PF(II) = (22.5581) - (0.0108 * YEAR) + (2.3028 * 10^{7} * GDP) \quad (5.6)$$

MALE

- Aggressive all-in cost forecast

$$PF(II) = (209.7629) - (0.1057 * YEAR) + (4.8359 * 10^{6} * GDP) \quad (5.7)$$

- Average all-in cost forecast

$$PF(II) = (56.3289) - (0.0279 * YEAR) + (1.1514 * 10^{6} * GDP) \quad (5.8)$$

- Mild all-in cost forecast

$$PF(II) = (21.1650) - (0.0101 * YEAR) + (2.3028 * 10^{7} * GDP) \quad (5.9)$$

5.3.4. Final Penetration Function

After adding diffusion rate and socio-economic factors the following penetration functions present the total adoption rate of EVs, HEVs and PHEVs in Ontario.

FEMALE

- Aggressive all-in cost forecast

$$PF = (\alpha)\left(\frac{1}{2+2e^{-0.08178(x-63)}}\right) + (\beta)((210.0890) + (-0.1059 * YEAR) + (4.8359 * 10^{6} * GDP)) \quad (5.10)$$

- Average all-in cost forecast

$$PF = (\alpha)\left(\frac{1}{2+2e^{-0.08178(x-63)}}\right) + (\beta)((56.8195) + (-0.0282 * YEAR) + (1.1514 * 10^{6} * GDP)) \quad (5.11)$$

- Mild all-in cost forecast

$$PF = (\alpha)\left(\frac{1}{2+2e^{-0.08178(x-63)}}\right) + (\beta)((22.5581) + (-0.0108 * YEAR) + (2.3028 * 10^{7} * GDP)) \quad (5.12)$$

<u>MALE</u>

- Aggressive all-in cost forecast

$$PF = (\alpha)\left(\frac{1}{2+2e^{-0.08178(x-63)}}\right) + (\beta)\big((209.7629) + (-0.1057 * YEAR) + (4.8359 * 10^{6} * GDP)\big) \quad (5.13)$$

- Average all-in cost forecast

$$PF = (\alpha)\left(\frac{1}{2+2e^{-0.08178(x-63)}}\right) + (\beta)((56.3289) + (-0.0279 * YEAR) + (1.1514 * 10^{6} * GDP)) \quad (5.14)$$

- Mild all-in cost forecast

$$PF = (\alpha)\left(\frac{1}{2+2e^{-0.08178(x-63)}}\right) + (\beta)((21.1650) + (-0.01015 * YEAR) + (2.3028 * 10^{7} * GDP)) \quad (5.15)$$

where β and α represent the weight of the socio economic factors and the diffusion rate on the total MV adoption rates respectively. x is the number of seasons.

5.3.5. Number of EVs, HEVs and PHEVs of Different Case Studies

In this section, the results derived from the total adoption rates in various scenarios are analyzed.

<u>SCENARIO A:</u>

By referring to Figure 5.4, it can be observed that when considering only the diffusion (α=1, β=0), the EVs, HEVs and PHEVs adoption will start off in low sales in 2012 at approximately 215 unit sales. The diffusion penetration rate is increasing throughout the entire time span. The trend is fluctuating rapidly; as is the same with all the other trends due to the fact that the sales are being analyzed seasonally. The adoption rate picks up in 2020 and reaches an almost steady rate of increase in roughly year 2038. The reason of the slow start is that the early adopters are taking risks, and not everyone is willing to do so. After the initial adoptions, more people will realize the benefits of MVs and the product's popularity will rapidly increase until it reaches a certain saturation level and the increase in its adoption will reach a steadier rate.

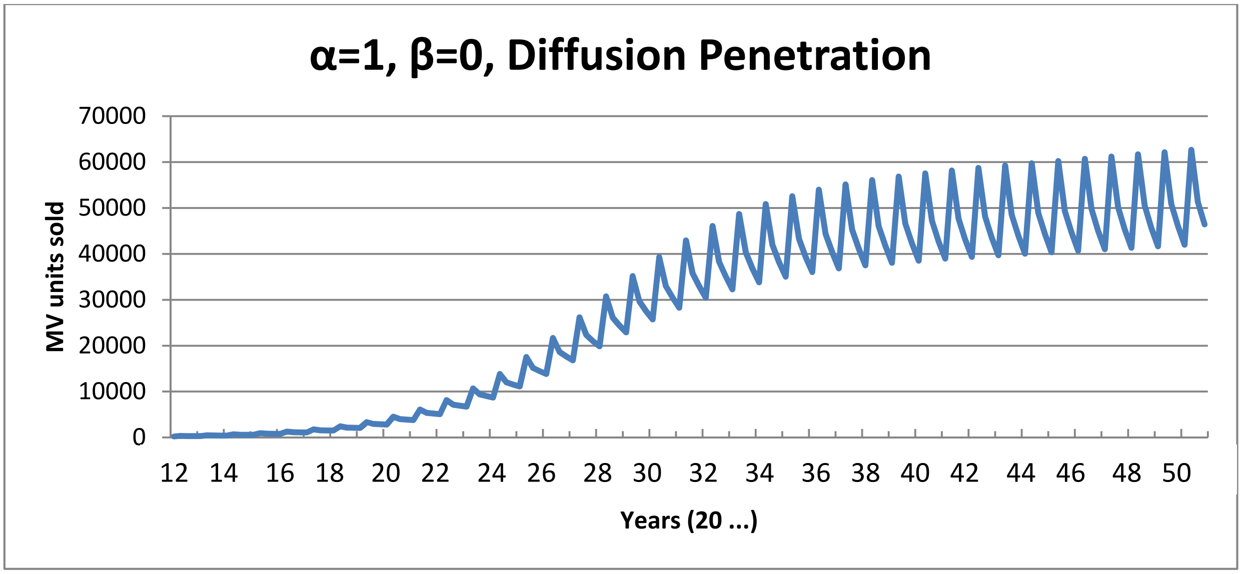


Figure 5.4 EVs, HEVs and PHEVs Sold in Scenario A.

<u>SCENARIO B:</u>

In this scenario, the only factor that is considered to impact the MV adoption rate is the socio-economic factors (α=0, β=1). When referring to a trend result for the Male/Female adoption rates in the average case (Figure 5.5), it is observed that the rate increases after roughly the year 2030. In all of the cases, the male and female behavior show a similar pattern with the male MV adoptions slightly exceeding the female MV adoption, due to the fact that men have a tendency to drive more (Table 5.6) and therefore are willing to invest more on their vehicles.

<u>SCENARIO C:</u>

When considering both the diffusion and the socio-economic factors for the EVs, HEVs and PHEVs adoption rates (α=0.50, β=0.50), as observed in Figures 5.6 and 5.7, the number of MV units sold in the aggressive case is generally lower than the other two, in both males and females, due to the high AIC of vehicles. As mentioned in section 5.2.2, high AIC have negative effects on the consumers' desire to purchase the EVs, HEVs and PHEVs. Until approximately year 2032, the aggressive case adoption rate, while still being lower than the other two cases, exhibits a behavior similar to them. After the mentioned year, the aggressive case unit sales will keep increasing with almost the same slope while the other two will have a decrease in their slope. As a result, in all the three cases for both males and females, the number of adopted MVs will become very close to each other near 2050.

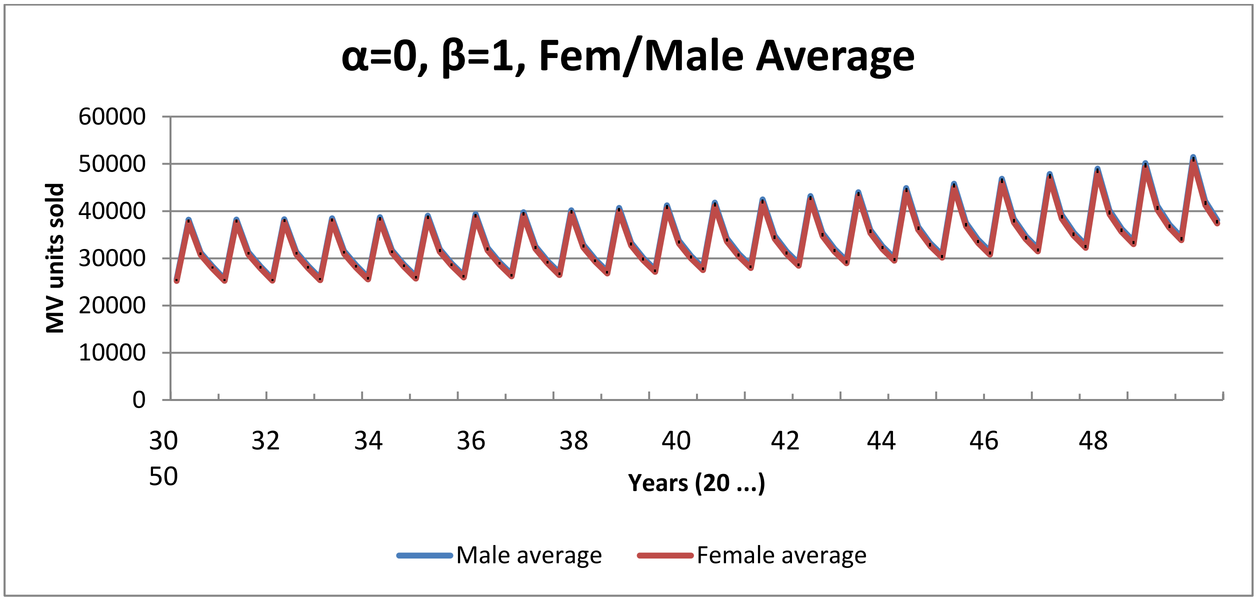


Figure 5.5 HEVs and PHEVs Sold in Scenario B, Average Case, Male/Female Comparison.

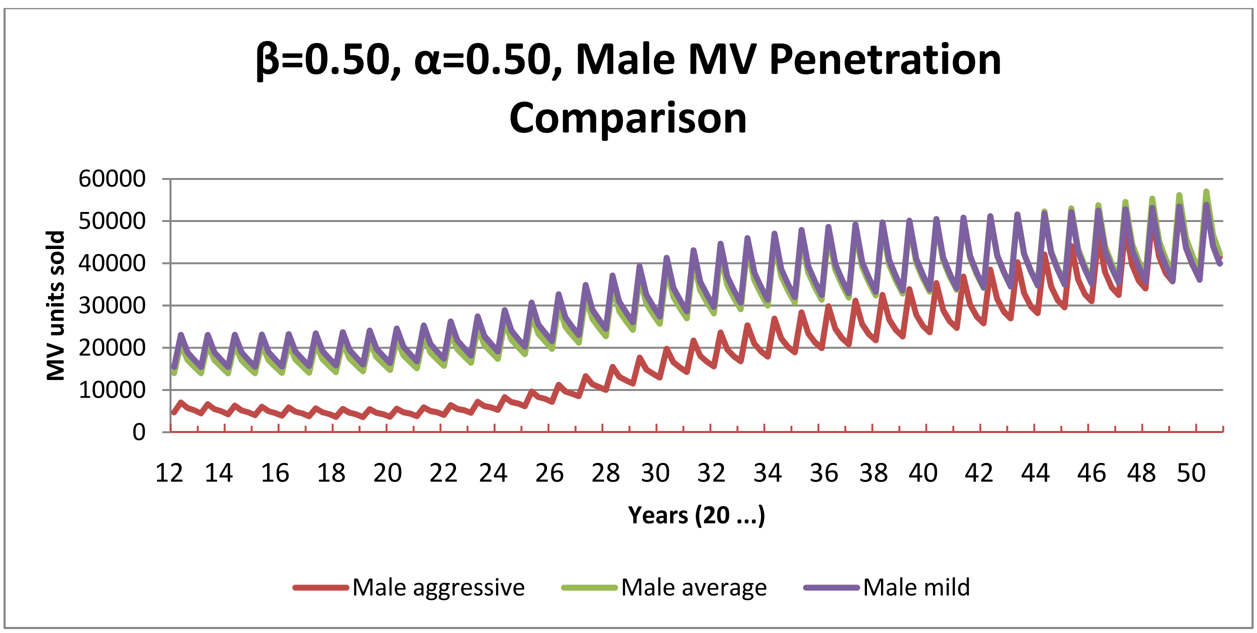


Figure 5.6 EVs, HEVs and PHEVs Sold in scenario C, Male Cases Comparison.

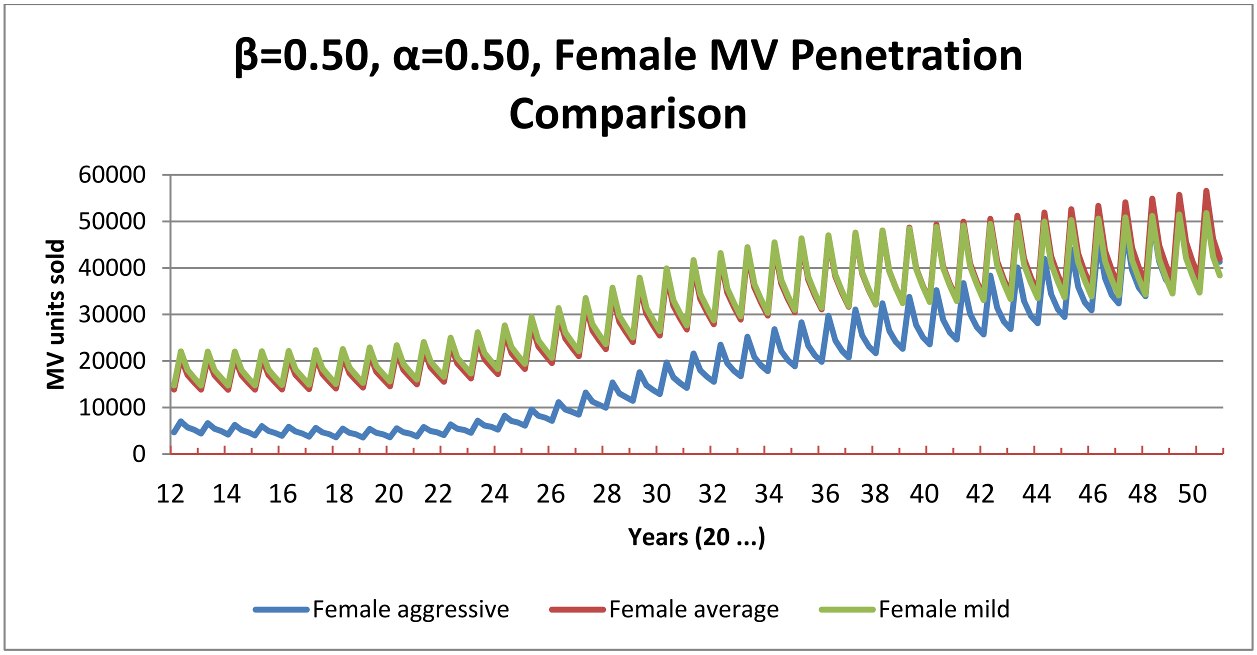


Figure 5.7 EVs, HEVs and PHEVs Sold in Scenario C, Female Cases Comparison.

When comparing the Male/Female MV adoption rates in the mild case, it is noticed that the number of MV units adopted by males exceeded the females' by the largest amounts, compared to their difference in the other cases (Figure 5.8).

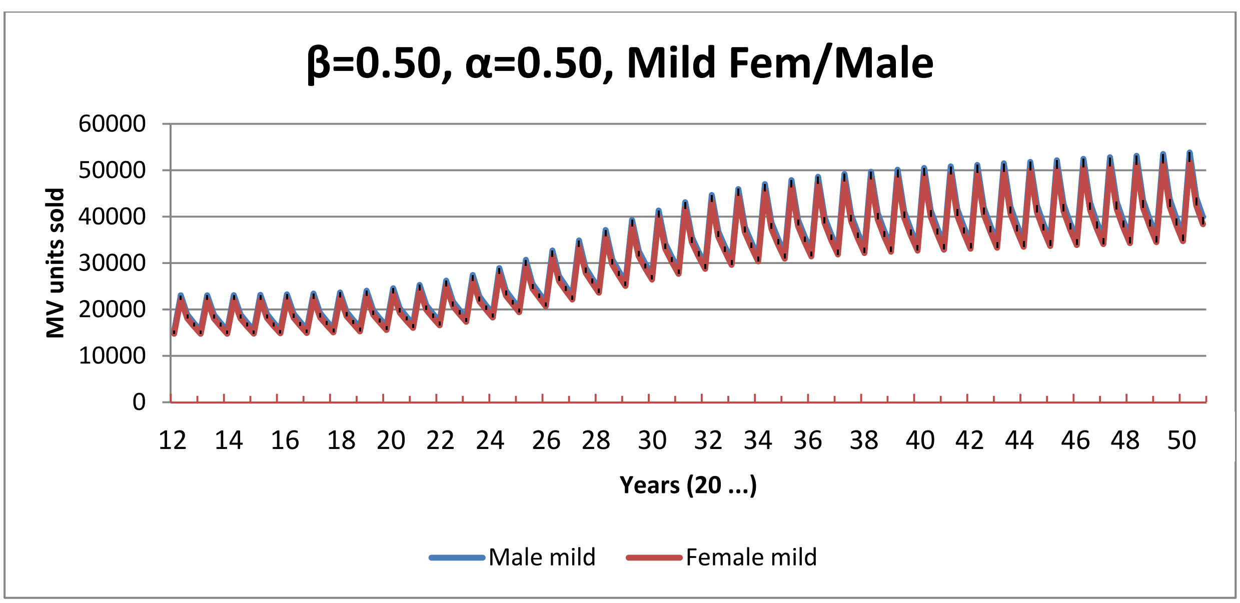


Figure 5.8 EVs, HEVs and PHEVs Sold in Scenario C, Male/Female Mild Case Comparison.

Table 5.12 presents the units of EVs, HEVs and PHEVs sold in Scenario C in all the three cases for both males and females from 2012 to 2050 of scenario C. According to the table, in 2050, the sales in the aggressive case will be significantly lower than the other two cases due to the higher AIC, while the mild case has slightly higher sales than the average case.

Table 5.12 EVs, HEVs and PHEVs Sold in Scenario C

Year	Male			Female		
	Aggressive	Average	Mild	Aggressive	Average	Mild
2012	7,012	20,861	23,048	7,009	20,705	22,054
2014	6,299	20,815	23,075	6,288	20,645	22,036
2016	5,907	20,961	23,261	5,887	20,777	22,177
2018	5,510	21,301	23,689	5,482	21,103	22,559
2020	5,592	22,114	24,587	5,555	21,901	23,411
2022	6,428	23,683	26,241	6,382	23,455	25,017
2024	8,297	26,291	28,933	8,242	26,047	27,662
2026	11,227	29,968	32,696	11,163	29,710	31,377
2028	15,478	34,444	37,122	15,405	34,170	35,753
2030	19,769	38,750	41,324	19,685	38,460	39,903
2032	23,606	42,283	44,669	23,513	41,976	43,193
2034	26,923	44,929	47,032	26,820	44,605	45,501
2036	29,836	46,874	48,616	29,722	46,532	47,027
2038	32,515	48,369	49,692	32,391	48,008	48,043
2040	35,342	49,680	50,498	35,207	49,301	48,787
2042	38,500	50,962	51,180	38,353	50,563	49,405
2044	42,115	52,309	51,824	41,956	51,891	49,982
2046	46,277	53,779	52,480	46,106	53,340	50,568
2048	50,783	55,329	53,144	50,600	54,868	51,161
2050	55,930	57,055	53,862	55,734	56,570	51,804

5.4. Conclusions

The goal of this chapter is to analyze the impact of the socio-economic factors on the adoption rate of Electric, Hybrid Electric and Plug-in Hybrid Electric Vehicles (EVs, HEVs and PHEVs) in the time span of year 2012-2050. In the first step, the number of light duty vehicles sold in the future in each season is found, with the slope being positive its graph having a fluctuating nature, showing that seasons greatly affect the number of the vehicles that are sold. In the next step, a penetration function is formed, comprising of two parts. One part represents the diffusion rate and the other presents the socio-economic factors. The socio-economic section which accounts for males and females separately, by itself is divided into three sections of aggressive, average and mild. Using the penetration function, the adoption rates are calculated in three different scenarios of A, B and C as three case studies. In scenario A, full weight is assigned to the diffusion rate, and the trend of the vehicle units sold resembles the shape of S, showing that initially people are hesitant to adopt modern vehicles, but over time they get more popular. In scenario B, full weight is assigned to the socio-economic section of the penetration function. It is observed that both of the males' and females' adoption behaviors are similar, with the male adoption rates being slightly higher during the time span. In scenario C, both of the diffusion and the socio economic factors are considered. The graphs show that in all of the cases of aggressive, average and mild, the number of EVs, HEVs and PHEVs adoptions reach to amounts which are close to each other near the end of the time span. The behavior of all the six trends is mostly similar, with the trend of the aggressive case being lower than the other two cases for the most part. It has been concluded, considering different scenarios of socio-economic factors on analyzing the adoption rates of the EVs, HEVs and PHEVs is very essential as the results indicate that when considering only the impact of socio-economic factors (scenario B) on the EVs, HEVs and PHEVs adoption rates, the unit sales by 2050 would improve by the average of roughly 18.9%, while when considering both of the diffusion rate and the socio-economic factors, the unit sales would improve by the average of approximately eight percent.

Chapter 6: Zonal Emission Analysis of PHEVs/EVs Penetration

6.1. Introduction

According to Canada's Action on Climate change, the transportation sector is the source of 25% of the total Greenhouse Gasses (GHG) emitted throughout the country. According to the International Energy Agency, the CO_2 emissions in Canada accounted for two percent of the global emissions in 2009 (Canada's Emissions Trends, 2012). As stated by the U.S. Environmental Protection Agency: Office of Mobile Sources, initially, when vehicles are analyzed individually, the amount of harmful emissions are not alarming. However, when gathering the volume of emissions from millions of those from the many cities in the country, personal vehicles become one of the greatest polluters (EPA, 2012). In order to mitigate the effects caused by these pollutants, Modern Vehicles (MV), namely in this chapter, Electric Vehicles (EV) and Plug-in Electric Vehicles (PHEV) are considered. EVs and PHEVs will have growing popularity in the future due to the Government of Canada's support to their users of incentives up to $8500 to their adopters. As mentioned in the previous chapter, the Ontario Ministry of Transportation also plans to have one out of twenty of the province's vehicles to be either EVs or PHEVs. The purpose of this chapter is to show that the adoption of MVs through 2012–2050 will greatly decrease the vehicle GHG and major non-GHG emissions in the future.

The pollutants known as GHG and major non-GHG are included:

- CO - carbon monoxide: The result of incomplete combustion and oxidation, this product reduces the flow of oxygen in the bloodstream (EPA, 2012).
- NOx - nitrogen oxides: Due to the high pressure and temperature of an engine, nitrogen and oxygen atoms react and create nitrogen oxides, and, as a result, ozone and acid rain are created (EPA, 2012).
- SO_2 - sulphur dioxide: This chemicals is the major component of acid rain (Nagase and Silva, 2007).
- VOC - volatile organic compounds: These compounds are the main reason of ground level ozone and particulate matter in the atmosphere (Geddes et al., 2009)

- PM (particulate matter): Airborne particles that are in solid or liquid form. The size of PMs determine the environmental and health impacts to a large extent; Environment Canada classifies them in to three sizes (Yan et al., 2011; Callen et al., 2011; Dongarra et al., 2011)

  TPM - total particulate matter less than 100 microns in diameter
  PM_{10} - particulate matter less than or equal to 10 microns in diameter
  $PM_{2.5}$ - particulate matter less than or equal to 2.5 microns in diameter

- GHG (CO_{2e}) - carbon dioxide equivalent: This emissions factor presents an estimation of all the GHG that are the result of fossil fuel combustion, expressed as an equivalent mass of carbon dioxide (CO_{2e}) (Workplace travel plans, 2010). An anthropogenic source of CO_2 is the activity of fuel combustion (Quadrell, 2007), and although this substance does not directly impact health, it traps heat inside the earth's atmosphere, which, as a result increases the potential for global warming (Zhang et al., 2013).

6.2. Methodology

To find the average amount of pollutants created by vehicles in a location, initially Emissions Factors (grams of pollutant per vehicle-kilometers) are needed. By referring to Workplace Travel Plans – Guidance for Canadian Employers prepared by ACT Canada and Noxon Associates Limited, for the ecoMOBILITY Program of Transport Canada, the average vehicle emissions factors for GHG and Major Non-GHG pollutants for different Canadian provinces can be found in a table with the name of Suggested Emissions Factors. The guide was prepared with the purpose of helping employers and property managers encourage their employees to find more sustainable ways to commute to work and mitigate traffic.

Three zones in Ontario were designated for study the Metropolitan Area of Toronto, Ottawa ON, and the Metropolitan Area of Hamilton. Table 6.1 identifies the emissions factors for the mentioned pollutants in Ontario:

Table 6.1 Ontario Pollutant Emissions Factors

Province	GHG (CO_{2e})	CO	NOx	SO_2	VOC	TPM	PM_{10}	$PM_{2.5}$
Ontario	258	11.3	0.601	0.00415	0.669	0.0169	0.0165	0.00799

The emissions factors are calculated by using Transport Canada's Urban Transportation Emissions Calculator (UTEC) (Transport Canada, 2013). These are the average vehicle emissions factors in Ontario, and depending on their driving costumes and vehicle fuel efficiency, actual emissions factors for each person will differ from each other. The emissions factors are calculated by assuming a ratio of 98.5:1.5 between gasoline powered vehicles and diesel powered vehicles existing in the provinces roads in 2006, for the purpose of the guide.

Figure 6.1 presents the steps taken to find the seasonal amount of major pollutants emitted from the consumption of gasoline by vehicles in specific zones. In short, this is done by multiplying the kilometers travelled (CD) (Stat Canada, 2013) (while they consume gasoline) by vehicles in a specific zone, by the pollutants' emission factors. Initially, the seasons in which the amount of emissions is desired to be presented are specified. The seasons start off from X = 1, representing the first season of the year 2012, then X = 2 representing the second season and so on until X = 156 which represents the fourth season of year 2050. Next, the zone of interest is selected. As mentioned before, three zones are available for selection, and consist of the metropolitan area of Hamilton, Ottawa ON and the metropolitan area of Toronto. After zone selection, two processes initiate. The first process (P1) calculates the total number of vehicles sold by seasons (VEH) in Ontario, using a formula with independent variables representing GDP and seasons. The next process (P2) finds the VEH in the selected region. In the next step, it is specified whether MVs, namely PHEVs or EVs will be penetrating or not. If no MVs are to be penetrated, the total seasonal commuting distance (CD) of zone specific VEH will directly be calculated.

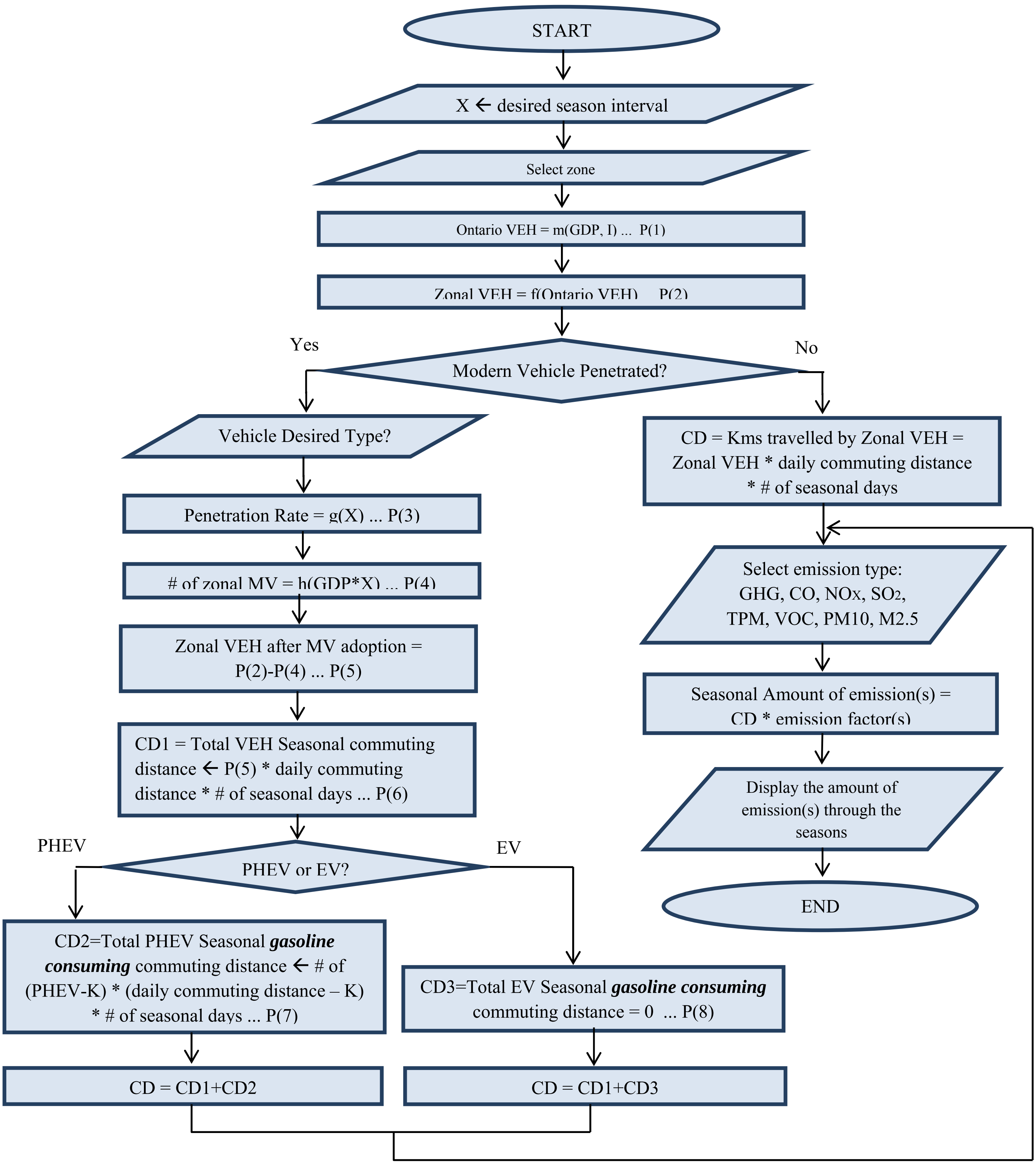


Figure 6.1 Flowchart of Zonal Emission Analysis of PHEVs/EVs Penetration.

The steps are more complicated if MV penetration is involved. First it is indicated whether PHEVs would be penetrating the zonal VEH or EVs. This affects the amount of gasoline consuming seasonal commuting distance of VEH in later steps. Then, in (P3), by using the diffusion rate from (Jochem et al., 2013) which has the number of seasons as its independent variable, the seasonal MV penetration rate is found. Using this penetration rate, the total number of zonal seasonal MVs sold by seasons is found in (P4). The number of zonal MVs sold then, is deducted from the zonal VEH to give the number of non-MV VEH in the zone in (P5). In (P6), the total seasonal commuting distance of the non-MV VEH is calculated, and is assigned to (CD1). Following (P6), if EVs are decided to penetrate, due to the fact that they have no tailpipe emissions, their gasoline consuming commuting distance (CD3) is zero. Therefore only the total commuting distance of non-MV VEH would be considered (CD = CD1). On the other hand, if PHEVs are decided to penetrate, first, the total gasoline consuming commuting distance (CD2) is calculated in (P7). The total gasoline consuming commuting distance of PHEVs is significantly less than that of the non-MV VEH, since they can travel a portion of their driving distances without using gasoline. In the case of this chapter, PHEV-10s are considered. The summation of the total seasonal commuting distances of the non-MV VEH and the gasoline consuming commuting distance of PHEVs is assigned to (CD).

By selecting the emission type in the following step, CD will be multiplied by its emission factor and the result(s), which is the grams of pollutants emitted seasonally, will be displayed.

6.3. Results and Discussion

Figure 6.2 indicates the amount of CO created in the three different zones, in the scenario where no MVs are penetrated. It can be appraised the amount of CO will rise rapidly in all the three zones, with Toronto's slope being much steeper higher than the other two. Toronto's CO emission in 2050 is seven times more than that of the other two zones. The amount of CO that Hamilton and Ottawa produce in 2050, is around the amount that Toronto produces in year 2018. This indicates that Toronto's situation in the case of contributing to emissions is significantly more serious than the other mentioned zones, and actions needs to be taken to mitigate it. Hamilton is producing the least emissions.

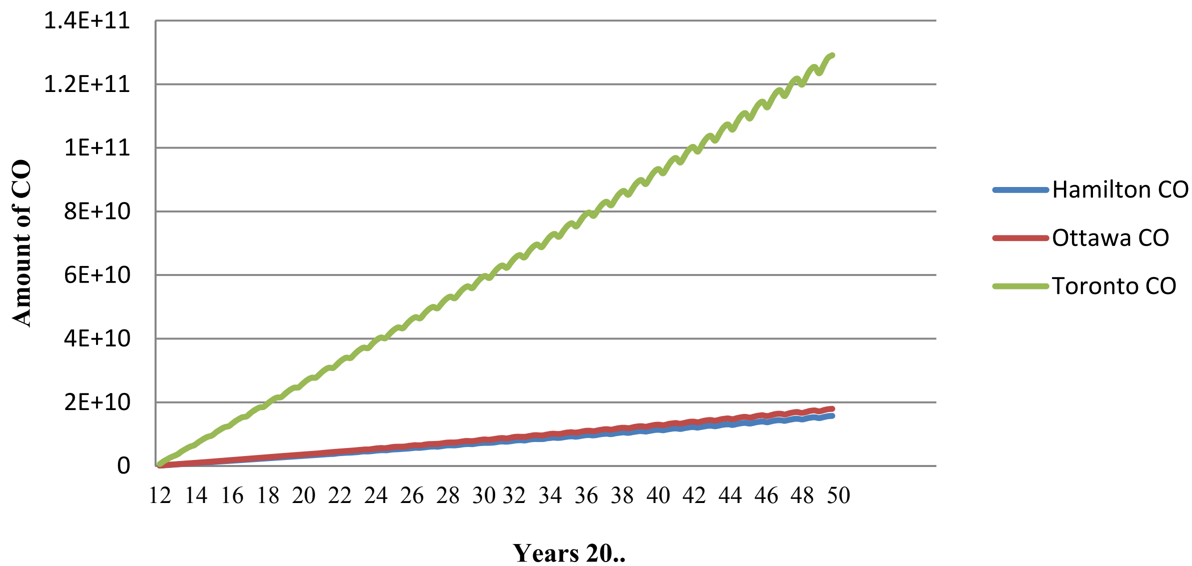


Figure 6.2 No-MV Zonal CO Comparison.

The amount of PM10 created in Hamilton, Ottawa and Toronto, in the scenario where PHEV10 is penetrated, are presented in Figure 6.3. At around year 2027 where the growth rate of the PHEVs penetration increases, the slope of the PM10 emission in Toronto decreases noticeably, while the other two zones' slope decrease are not as obvious. Ottawa and Hamilton's emissions are significantly less than Toronto's, with the two's amount being very close to each other.

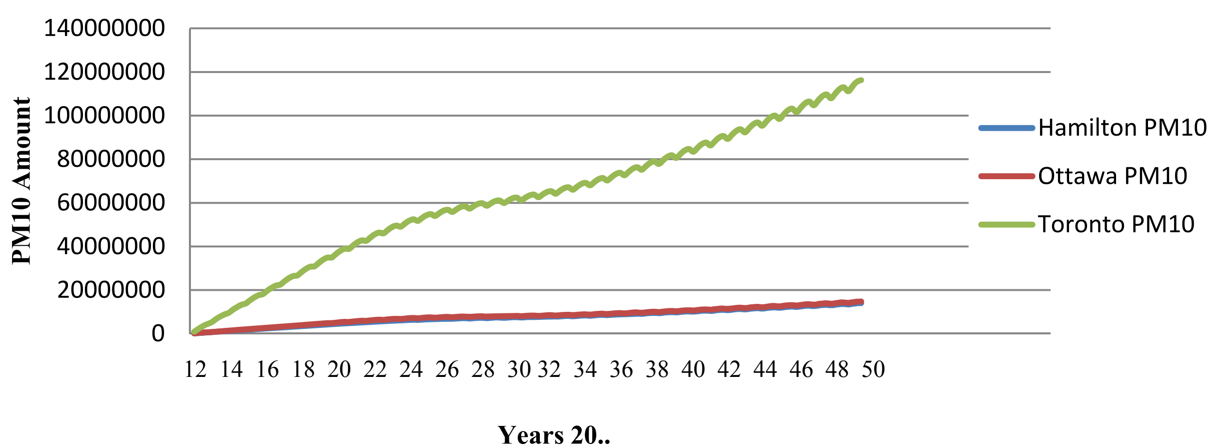


Figure 6.3. PHEV Zonal PM10 Comparison.

Figure 6.4 confirms that in the scenario where EVs are penetrated, Toronto's CO emissions greatly exceed the CO emissions of Ottawa and Hamilton. The emissions amounts of the aforementioned two zones are very close to each other, with the difference between them increasing as the years pass. The effect that the increase of the EV penetrations has on the Toronto emissions' slope is significantly more than its effect on the other two zones' slope.

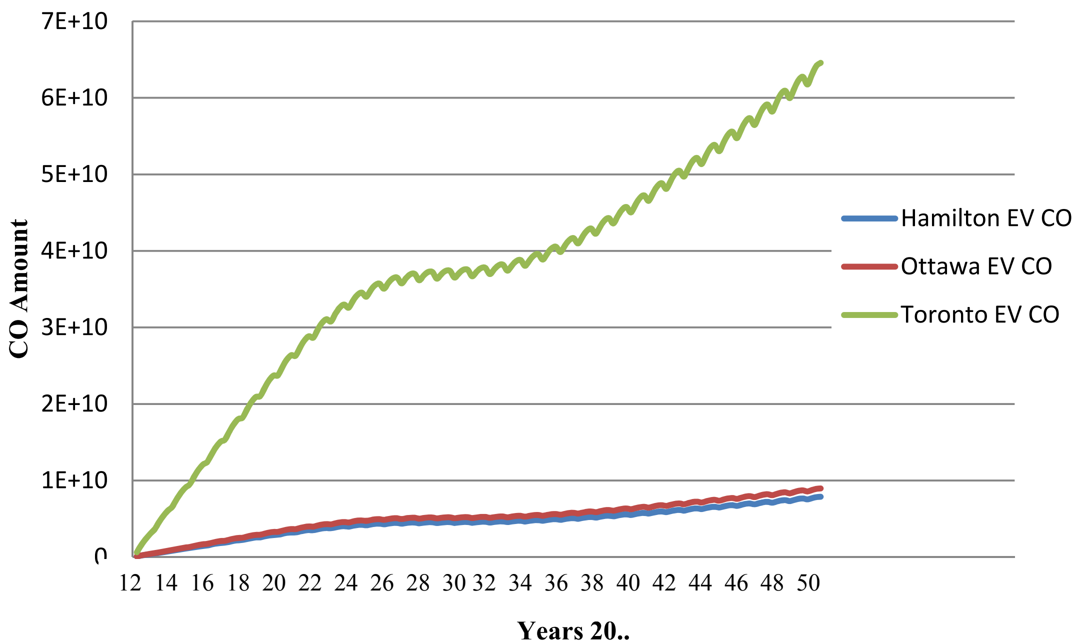


Figure 6.4. EV Zonal CO Comparison.

Figure 6.5 presents the quantity of GHG that is released into the air in Hamilton, in three different scenarios through 2012-2050. It is observed that at the beginning, the emissions quantities are very similar to each other in the three scenarios, and it's not until after the year 2022 where the penetration rate of the EVs and PHEVs increase, and as a result the emissions amounts deviate from the No-MV scenario's emissions amounts. In the scenario where no MVs are penetrated, it is shown that the GHG emissions increase rapidly, which is due to the rapid increase in the population and therefore the conventional vehicle sales. In the next scenario where PHEV-10s are penetrated, it is observed that the slope of the GHG emission's trend decreases noticeably after the year 2028. In the scenario where EVs are penetrated, the emissions drop to an even lower quantity, such that at year 2050, amount of GHG emitted is almost half of the emissions in the No-MV scenario.

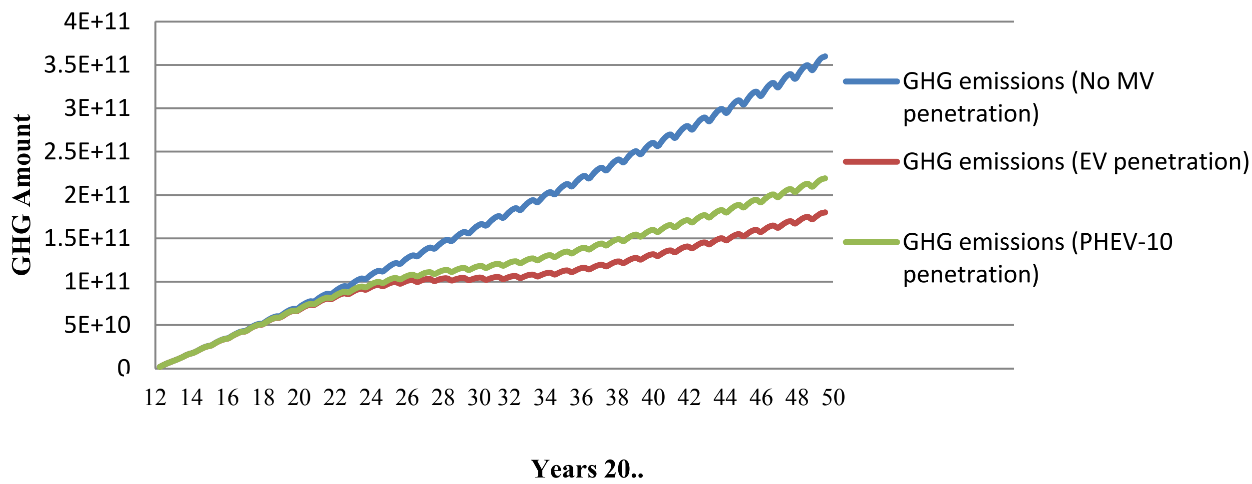


Figure 6.5. Hamilton GHG Comparison.

As observed in Figure 6.6 which presents the amounts of VOC and NOX emitted in Toronto in the scenario where EVs are penetrated, the emissions for both pollutants start off very close to each other. As the years progress, the emission quantity difference between them gradually increases and it gets relatively significant from approximately year 2020. Overall, VOC has a higher emissions rate than NO_X.

Figure 6.7 is comprised of the plots of the amounts of SO2, TPM, PM10 and PM2.5 emitted in years 2012 – 2050 in Toronto, when considering the scenario in which the penetration of PHEV-10 is involved. TPM and SO2's quantity of emissions are very close to each other, while both of their differences from the other two pollutants are significant. The mentioned two pollutants have higher emissions compared to the other two pollutants. PM10 and PM2.5 have a lower slope compared to SO2 and TPM, and while noticeable, the difference between PM10 and PM2.5's emissions is not as great their emission difference with the other two pollutants. PM2.5 has the least amount of emissions compared to the other three pollutants.

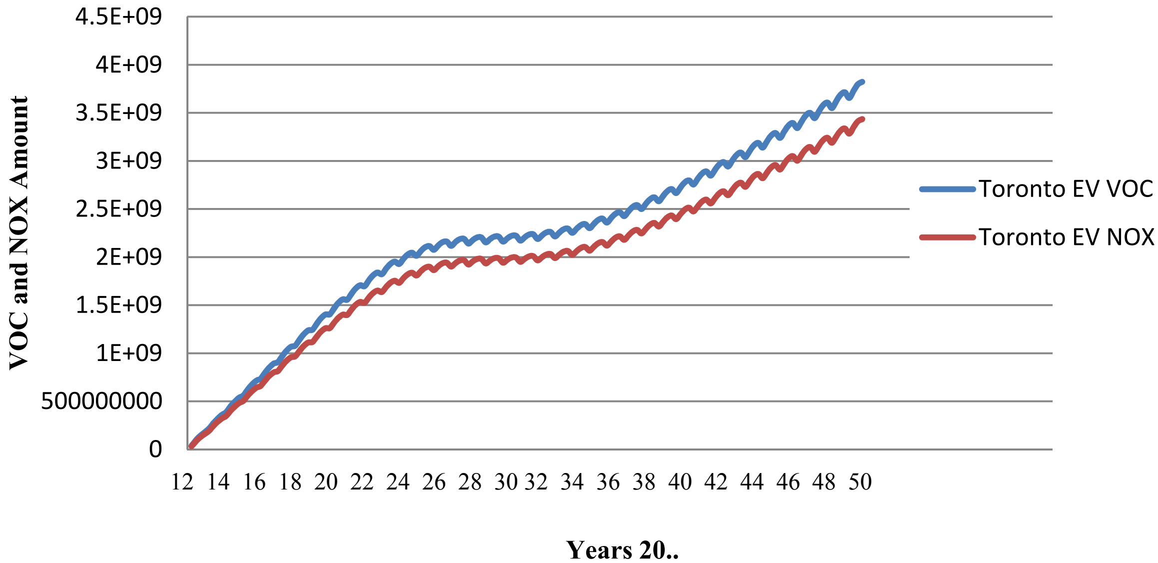


Figure 6.6 Toronto EV (VOC, NOX) Comparisons.

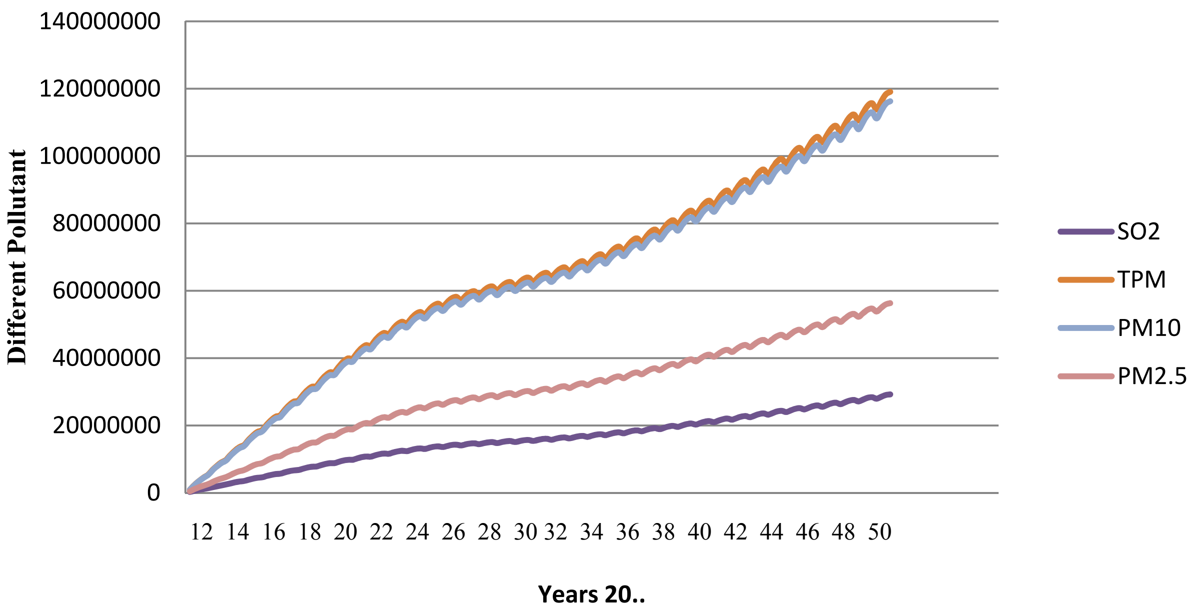


Figure 6.7. Toronto PHEV-10 Comparisons.

By referring to Figure 6.8, the amount of NO_X emissions in 2050 that Toronto, Ottawa and Hamilton contribute to the amount that Ontario emits when no MV is penetrated can be observed. When no MVs are penetrated, Toronto contributes to approximately 44% of Ontario's total NOX emissions, while Ottawa and Hamilton are roughly 7%.When EVs are penetrated, all of the three zones' emissions contributions drop by about half of what they were emitting in the previous scenario with Toronto now having a 22% emission contribution.

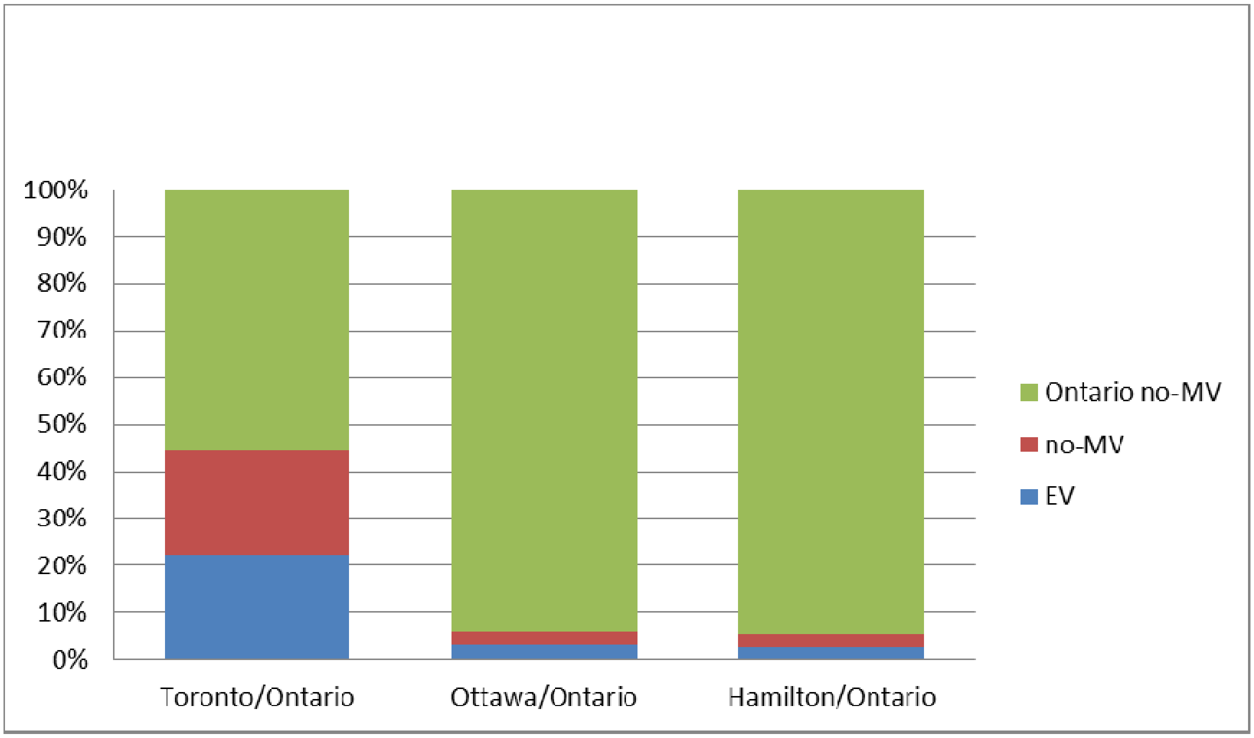


Figure 6.8. Zonal NOx Comparisons (with and without EV) in 2050.

Figure 6.9 presents the amount of CO that Toronto contributes to the amount of CO emissions that Ontario's vehicles produce in the scenario where no MVs are penetrated in 2012 – 2047. When no MVs are penetrated, Toronto contributes to roughly 44% of Ontario's CO emissions throughout the years. When EVs are penetrated, initially small drops in the contribution can be seen, and as the years progress, so do the drops in Toronto's CO emissions contributions, until it reaches a contribution rate almost 50% less than what it is producing in the scenario where no MVs are penetrated in 2047. This is due to the fact that as time passes, the penetration rate of the EVs increases.

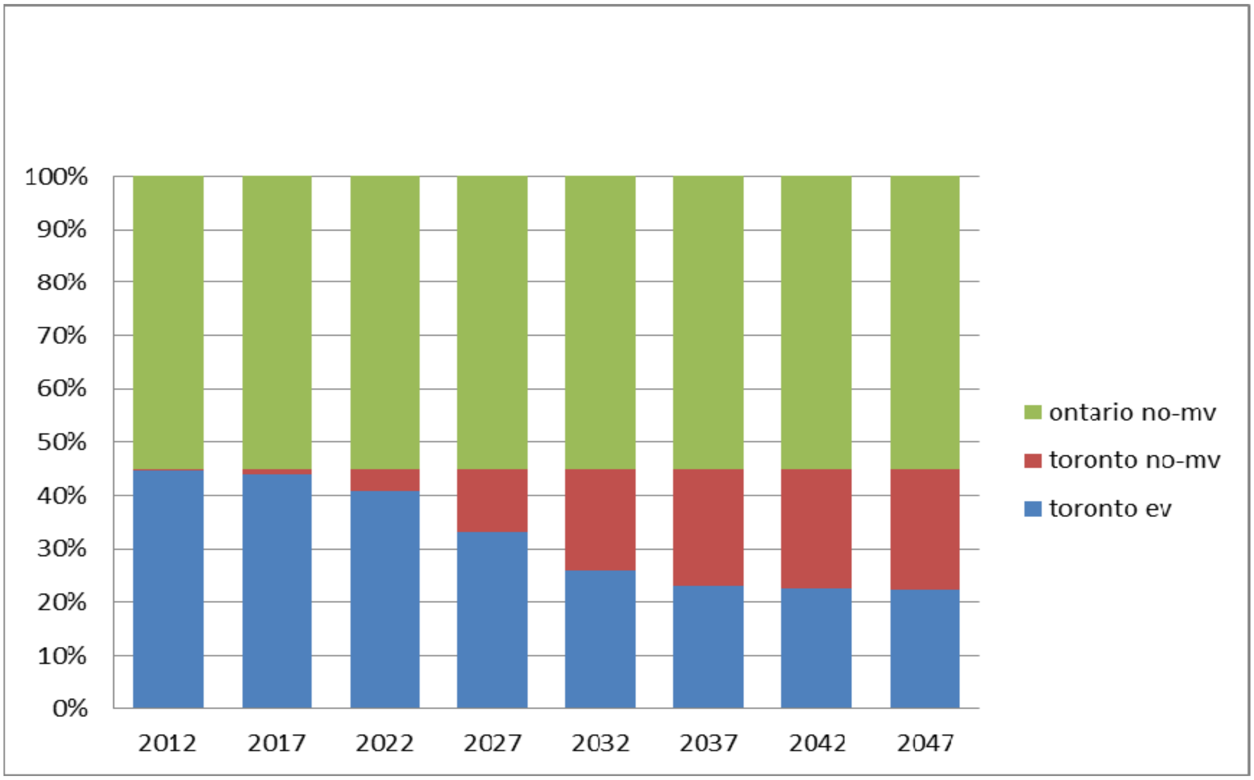


Figure 6.9. Zonal CO Comparisons (with and without EV), 2012 - 2050.

6.4. Conclusions

This chapter serves the purpose of presenting the decrease in vehicle emissions through years 2012 – 2050, when EVs and PHEVs are penetrated in the vehicle adoption market. Initially the emissions factor is found. Then the total seasonal commuting distances in the assumed scenarios are found. The scenarios comprise of a case where no EVs and PHEVs are penetrated, a case where EVs are penetrated and a case where PHEVs are penetrated. When combining the emissions factors with the total seasonal commuting distances, the seasonal vehicles emissions are presented through 2012 – 2050. The results show that when there are no MVs penetrated, the average emissions will decrease by approximately 210 times by 2050. When penetrating PHEVs and MVs, the average emissions quantities by 2050, will drop by roughly 40% to 50% when compared to the total emissions in the scenario where no MVs are introduced. It is observed that The Metropolitan area of Toronto makes the largest contribution of 40% to Ontario's total emissions when no MVs are penetrated, but when penetrating EVs in its adoption market, the contribution fall to approximately 20%. Overall, vehicle emissions in Ontario are rising exponentially, and it is concluded that penetrating the EVs and PHEVs will dramatically mitigate this situation.

Chapter 7: Optimization Results

7.1 Introduction

This chapter outlines results of the process, methods, and equations used to optimize the power generation plants in Ontario in order to minimize power generation cost. The results include outcome of the programming code in five different case studies (Table 7.1) on the base case situation with employing CO_2 emission constraints, PHEVs penetration, and ceasing the use of coal by the end of 2014. In the event of a surplus of power in the power grid, the program identifies which plants are ineffectual and recommend their closure, while in the event of a deficit of power in the grid, the program will recommend new plants to be built to meet the demand. The results represent the lowest electricity cost option, which should always be considered in solving problems of this magnitude.

Table 7.1 Different Case Studies

Case Study	PHEVs Adoption Rate	Type of Potential Power plants	CO_2 Limit
A: Base Case	Medium Penetration	All type of power plants except Coal power stations	No
B: Base case with increased NG prices	Medium Penetration	All type of power plants including NG double price	No
C: Base case with Coal	Low Penetration	All type of Power plants	No
D: Base case with 6% reduction in year 2018 CO_2	High Penetration	All type of power plants except Nuclear power stations	Yes
E: Base case without considering current load deficit	Medium Penetration	All type of power plants except Coal power stations	No

7.2 Case Study A (Base Case) & B (Base case with increased NG prices)

Base case considers PHEVs are penetrated with a Medium rate in Ontario. Therefore, load demand would be increased by vehicles charging amount of electricity. All coal power plants have been phased out according to the Environmental Protection Act (EPA) is engaged in the year 2014. In Case B the penetration is still with a medium rate but the price of natural gas is doubled starting in year 2018.

7.2.1 New Power Generating Stations

In base case, depicted in Table 7.2, new NGCC stations make up 68% of the total new installed capacity.

In base case with increased NG prices, when the natural gas price is double in Table 7.3, the fleet rely on more coal technologies making up 30% of the total new installed capacity, largest of any new supply technologies used, therefore PC is popular. In the early years, NG is used because of shorter construction time; however there are NG power plants later because of coal and nuclear capital expenditure constraint.

As it is shown in Tables 7.2 and 7.3 model adding new power plants have been suggested as soon as possible to satisfy current load demand deficit. The optimizer suggests building NG power plants because of coal capital expenditure constraint in the model. Highlighted area is the period of construction. The year thereafter is when electricity production commenced, except for the import option that we would import power from the beginning of the highlighted area. As total budget of building new power plants specified in the model, results indicate import by the end of the period.

Table 7.2 New Power Generating Stations and their Construction Time_ Base Case

	New Capacity (MW)	Year (20..)																
		14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30
NGCC	1080																	
NGCC	770																	
Wind	1000																	
Wind	1000																	
Nuclear	1080																	
NGCC	1040																	
Import	1300																	

Table 7.3 Detail Fleet Structure: Natural Gas Price Doubled in 2020_ Base Case with Increased NG Prices

	Capacity (MW)	Year (20..)																
		14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30
PC	420																	
PC	410																	
PC	410																	
PC	420																	
IGCC	440																	
NGCC	430																	
NGCC	500																	
Nuclear	1010																	
Import	1250																	
Wind	1000																	
Wind	1000																	

7.2.2 Economic and Emission Analysis

As indicated in Figure 7.1, both two cases follow a general trend where a peak during 2014 is observed. The base case, where no new or existing coal is available after 2014, has a particularly high cost of electricity during the early years. A large capacity of existing coal power supply has gone offline, forcing the model to purchase a large amount of new supply technologies to prepare the fleet for this urgent lack of generating capacity.

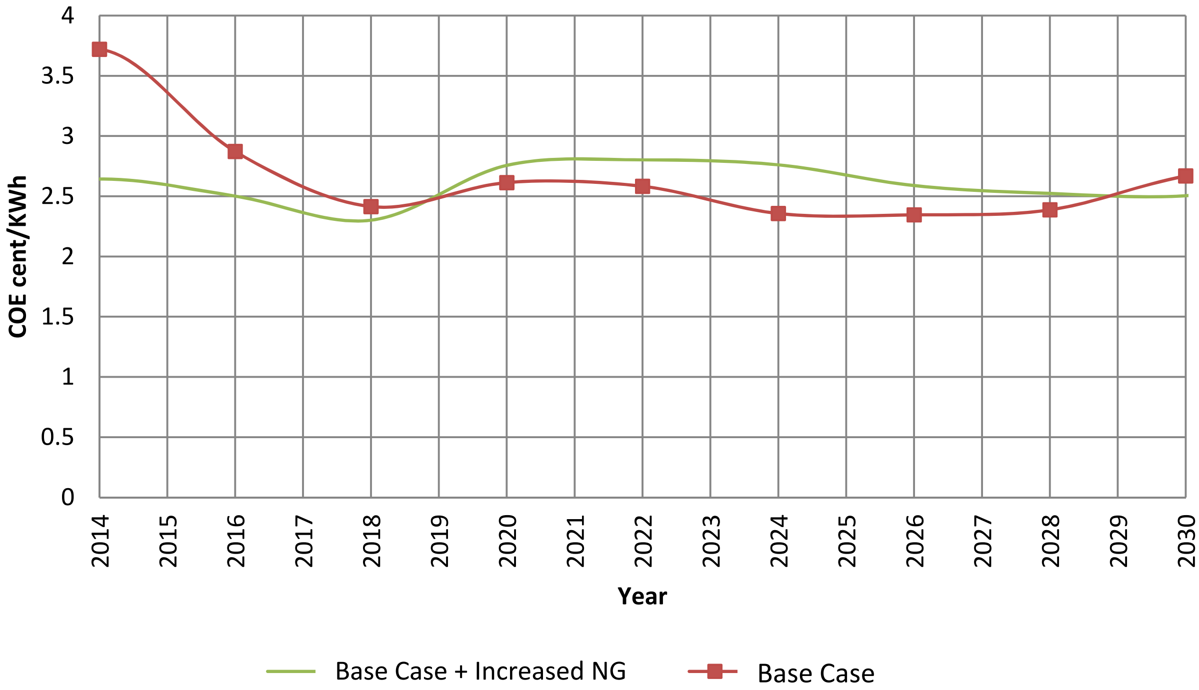


Figure 7.1 Overall Cost of Electricity.

A different building strategy is employed in Figure 7.2 and Figure 7.3. Total expenditure is higher for the case with the double natural gas price, since there would be more investment on nuclear power plants.

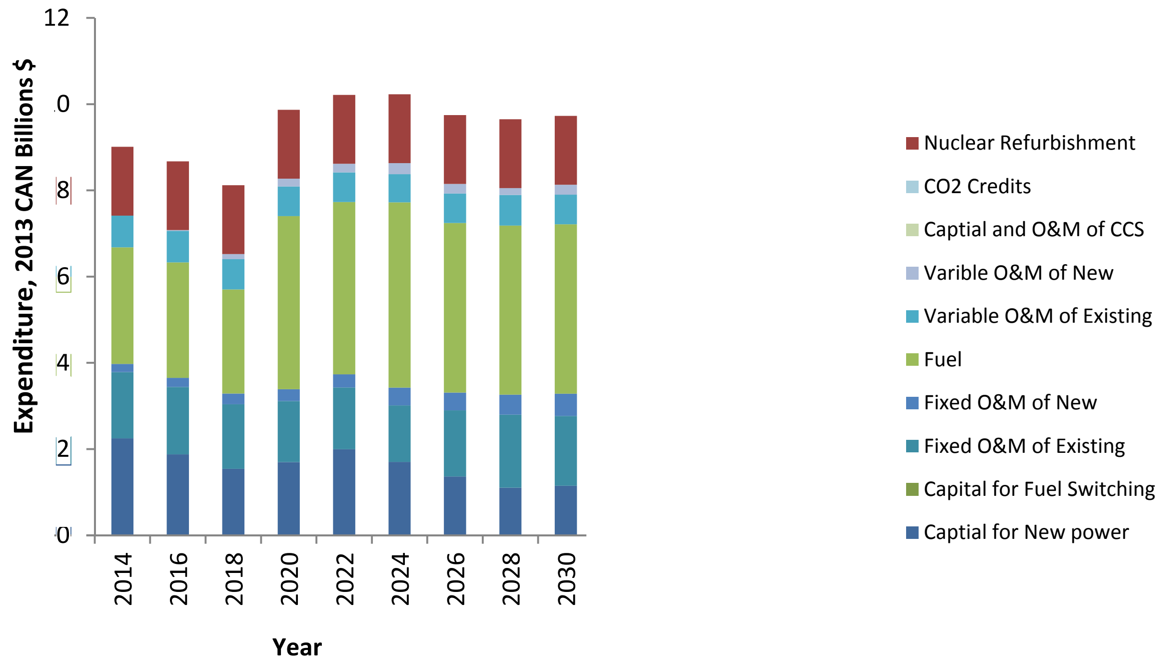


Figure 7.2 Detail Expenditure_ Base Case with Increased NG Prices.

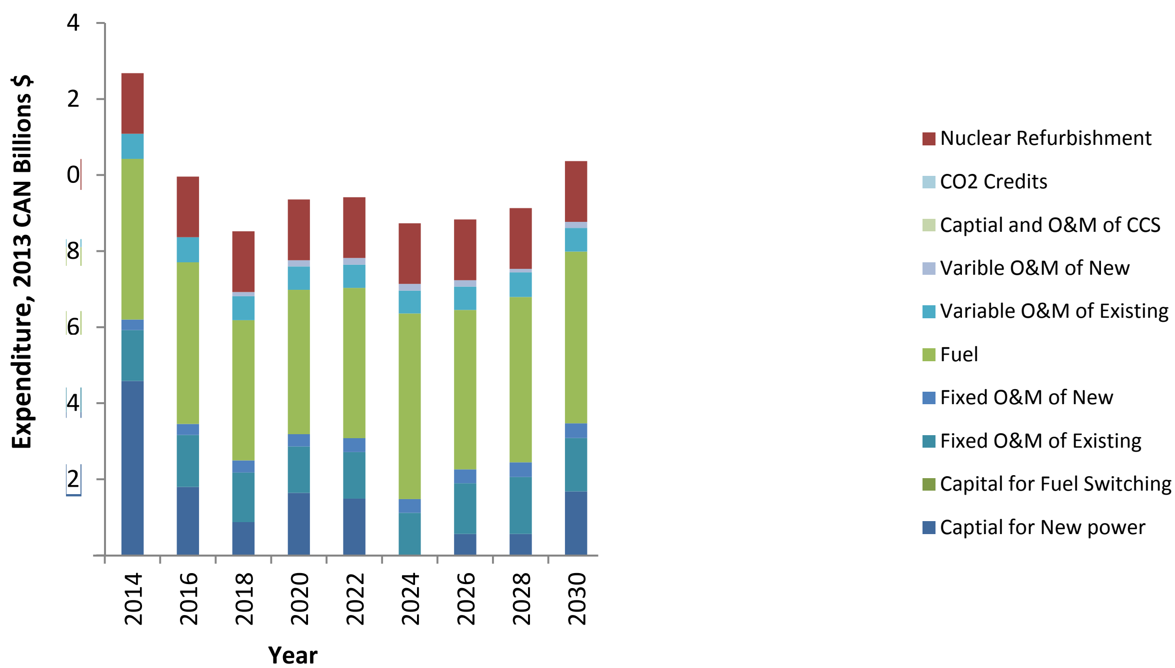


Figure 7.3 Detail Expenditure_ Base Case.

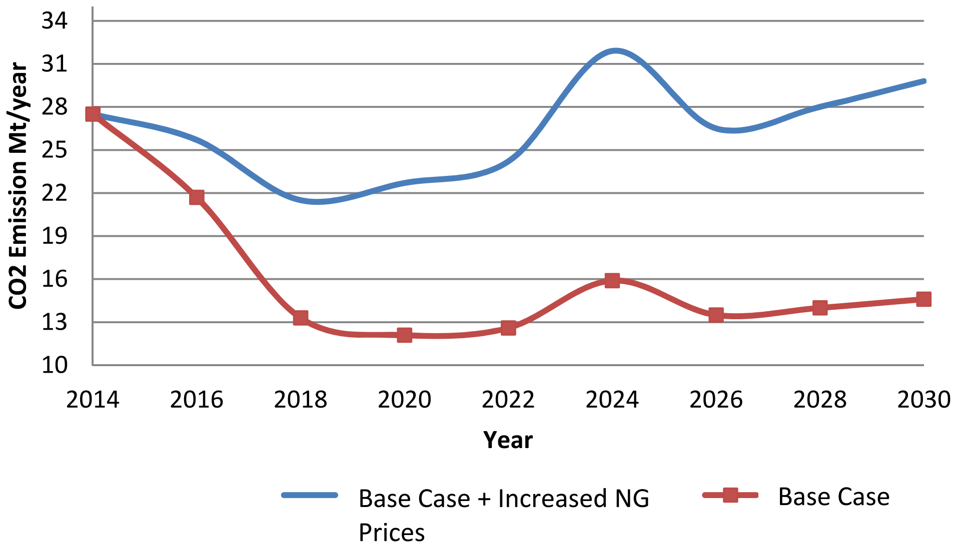


Figure 7.4 Overall CO_2 Emissions.

CO_2 emission from the base case and base case with increased NG prices are ~500Mt and ~900 Mt correspondingly. The same general trend is observed in both curves in Figure 7.4. In the base case, the overall emission is reduced dramatically due to the elimination of both new and existing coal power stations.

7.3 Case Study C: Base Case with Coal

Case Study C assumes, there would be Low PHEVs penetration in Ontario from the year 2014 to 2030. Besides, all the coal power stations are in operating condition and persist on generating electricity. In addition, CO_2 emission restriction does not apply in the time frame; however CCS technology is available in Ontario.

7.3.1 New Power Generating Stations

In this case the best possible solution for the Ontario power stations to meet the load demand from the year 2014 to 2030 is determined. As indicated in Table 7.4, the model recommended a significant increase in electricity obtained through two new PC and two new NGCC generating stations with total capacity of 3,136 MW and 3,364 MW respectively. Figure 7.4 presents that Nuclear, Wind and Hydro Power stayed at about the same power generation levels which are equal to 12,947, 1,948, and 8,014 correspondingly, therefore rate of power allocated for renewable energies does not change. The reason is the more economical capital cost of coal power plants than other sources of electricity. As a result of no CO_2 limit, cheaper operating cost of a unit fuelled by coal rather than Biomass and extra retrofitting cost, there is not any fuel switching proposed. Additionally, in case of retrofitting the coal power station to whether Biomass or NG without employing CCS technology, the emission penetration would be more than coal power plants.

Table 7.4 New Power Generating Stations and their Construction Time_ Base Case with Coal

	Capacity (MW)	Year (20..)																
		14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30
PC	2119																	
NGCC	1568																	
NGCC	1568																	
PC	1245																	

Figure 7.6 displays the percentage change of power allocated in the four different years, 2014, 2021, 2026 and 2030. Power allocated from nuclear from 40% in 2014 decreased to 35% in 2030. Also natural gas and oil power plants generate more amount of the electricity from 30% in 2014 to 35% in 2016 and will keep constant rate of power percentage to 2030.

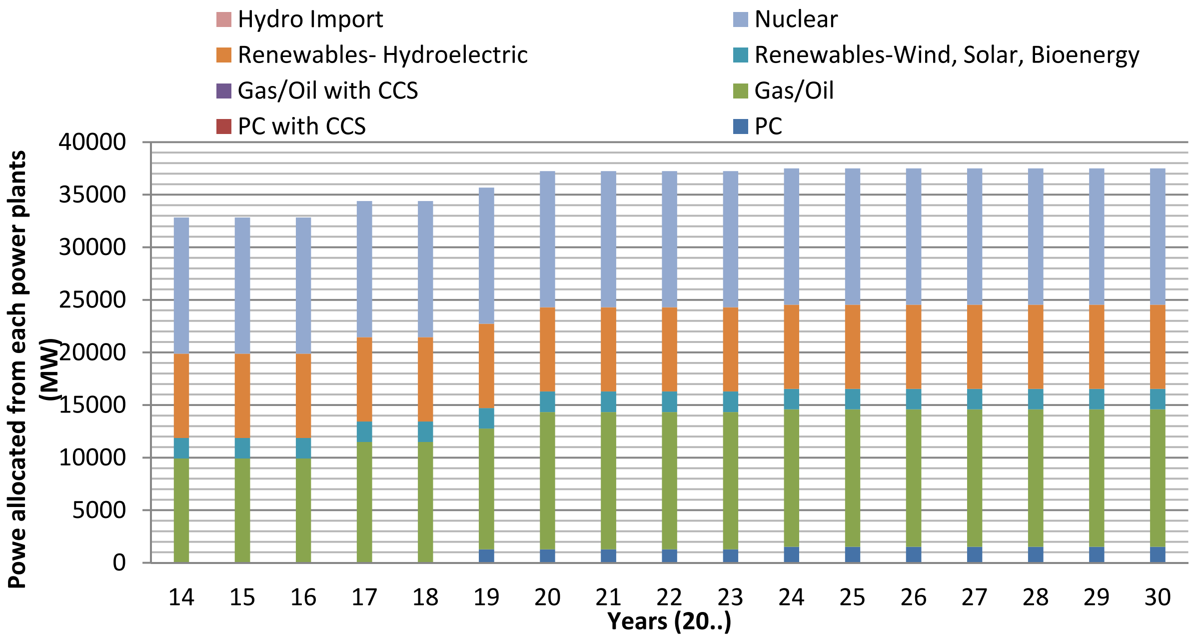


Figure 7.5 Total Allocated Capacities of each Power Plant (MW) from 2014 to 2030_Base Case with Coal.

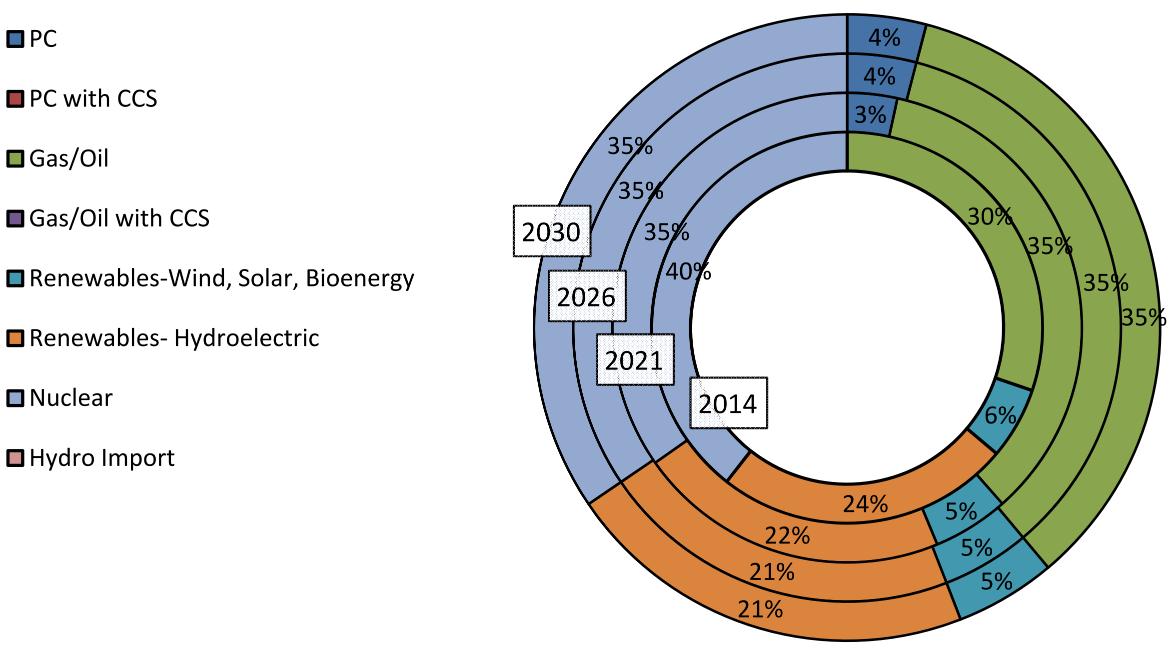


Figure 7.6 Total Power Allocated Percentage _Base Case with Coal.

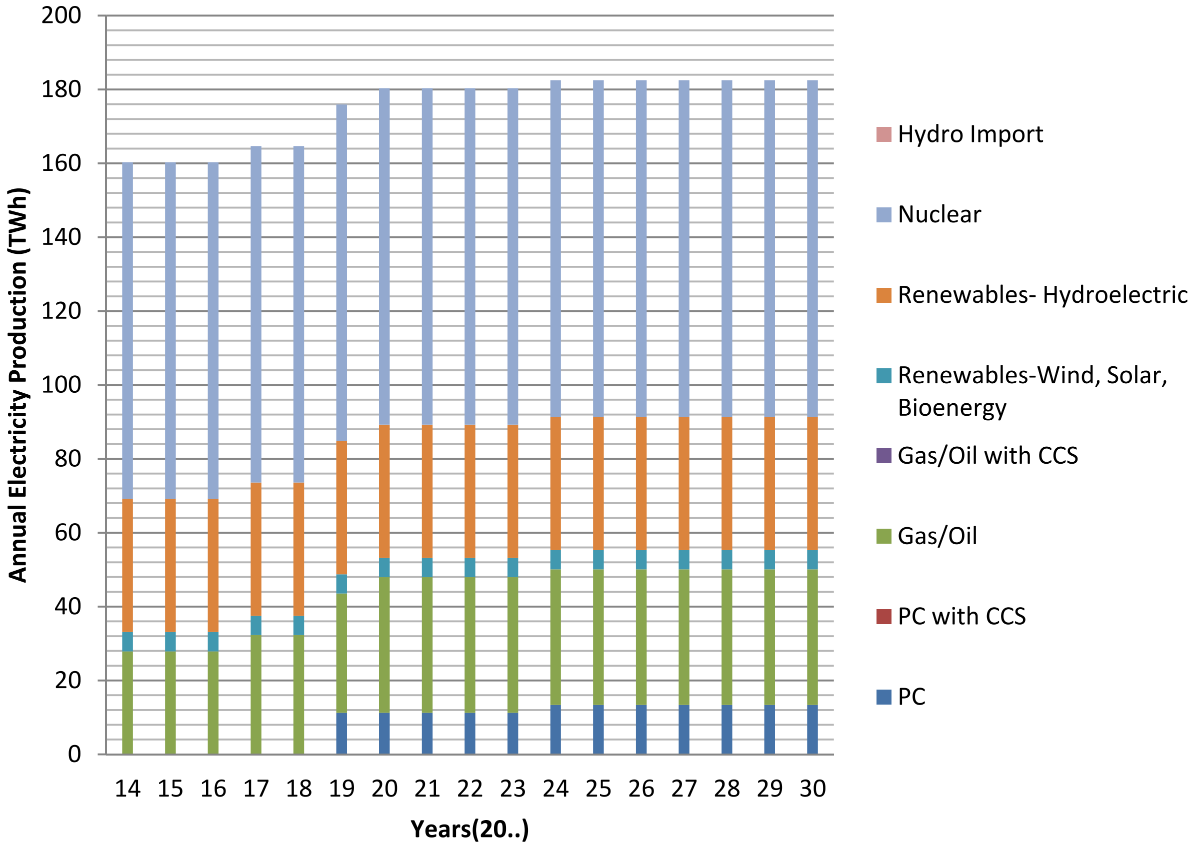


Figure 7.7 Annual Electricity Production _ Base Case with Coal.

Annual electricity generation by new power plants are established in Figure 7.7. After 2018, new power stations, PC and NG, generate a significant amount of energy. Although results present that the programming code succeed in modeling the power generation needs for the Ontario load demand by meeting the goal of finding the lowest electricity cost, the proposed solution is not feasible with the current state of the Ontario power plants and the plans of the Government of Ontario and the Companies that Produce Ontario's Electricity due to phasing out all the coal stations by the end of 2014.

7.3.2 Economic and Emission Analysis,

Figure 7.8 and Figure7.9 indicate detailed expenditure of entire electricity sector and electricity cost of the total investment from 2014 to 2030 for Base Case with Coal. The expenditure including Nuclear refurbishment, CO_2 credits, capital and O&M cost of CCS, variable O&M cost of new and existing power plants, fuel, fixed O&M of new and existing units , capital cost of fuel switching, capital cost of new power plants, are revealed based on 2013 Canadian dollars.

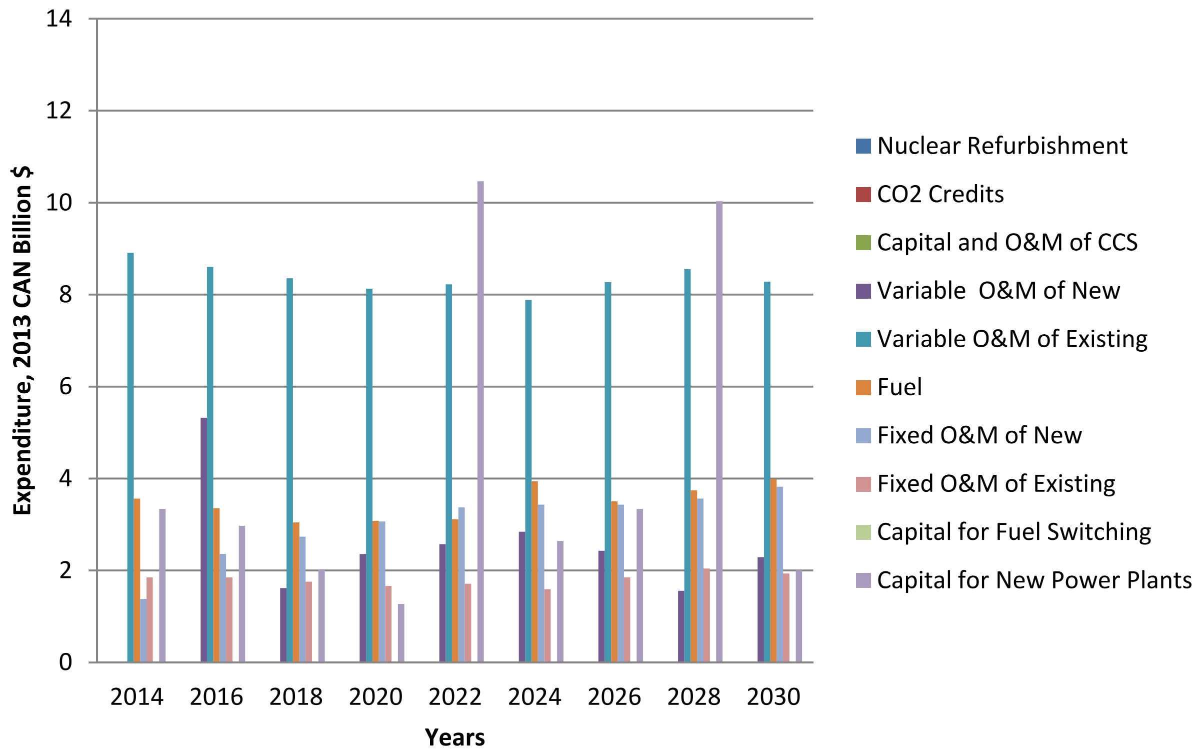


Figure 7.8 Detail Expenditure_ Base Case with Coal.

Figure 7.10 indicates the amount of CO_2 created over years, totally 869Mt, from existing and new power plants, in the case study where no PHEVs are penetrated. It is presented that the amount of CO_2 rises rapidly in between 2019 and 2024 because of new source of electricity. As a result of not considering any emission limit in Base Case with Coal, model predicted two NG and two coal power plants which cause CO_2 emission slope being steeper higher in start point of new electricity generation than the other part of the trend.

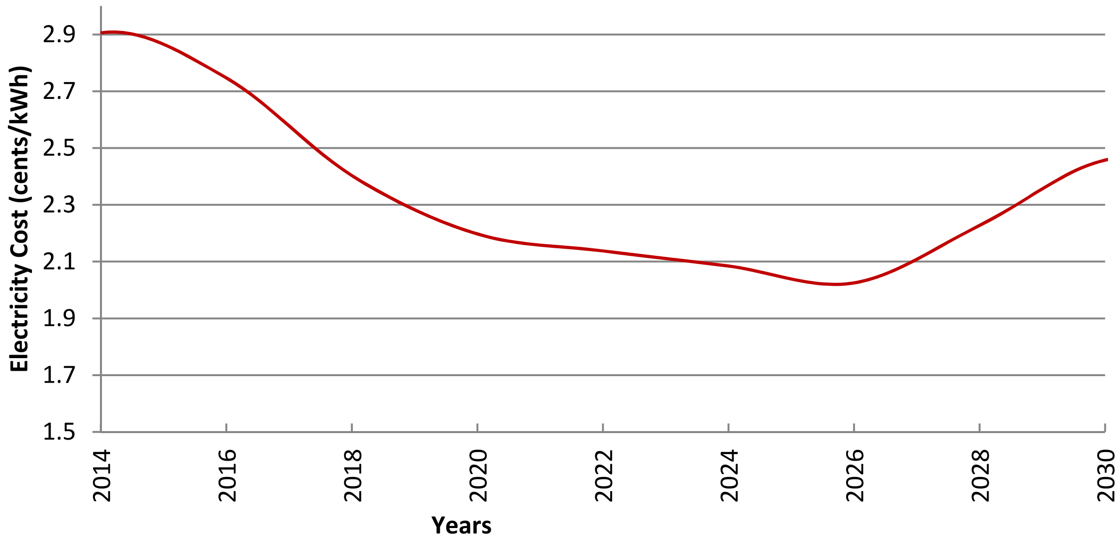


Figure 7.9 Overall Electricity Cost_Base Case with Coal.

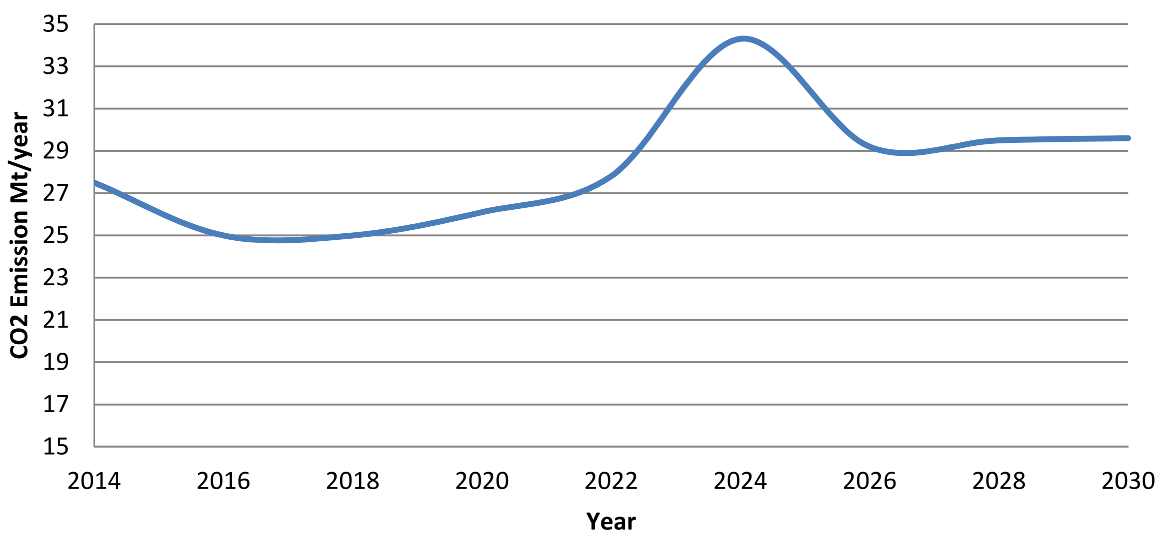


Figure 7.10 CO_2 Emissions_ Base Case with Coal.

7.4 Case Study D: Base Case with 6% Reduction in CO_2 by Year 2018

Case study D considers the impact of PHEVs high penetration rate under two conditions. The first condition is, there would not be any new nuclear power station. And the second one is CO_2 emission should reduce at 6% by the year 2018.

7.4.1 New Power Generation Stations

When high adoption rate of PHEVs, no new nuclear stations, and CO_2 emission reduction target of 6% are applied, NGCC is generating electricity with ~ 4,400 MW new installed capacities, Table 7.5. New power stations with CCS system are suggested by model to guarantee the CO_2 emission target satisfaction.

Table 7.5 New Power Generating Stations and their Construction Time_ Base Case with 6% Reduction in CO_2 by Year 2018

	Capacity (MW)	Year (20..)																
		14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30
NGCC	528																	
NGCC	730																	
NGCC	950																	
NGCC	892																	
NGCC	866																	
IGCC+CCS	700																	
IGCC+CCS	400																	
NGCC+CCS	432																	
Import	1250																	
Wind	1000																	
Wind	1000																	

7.4.2 Economic and Emission Analysis

Following figures indicate overall and detailed expenditure for base case with 6% reduction in CO_2 by year 2018.

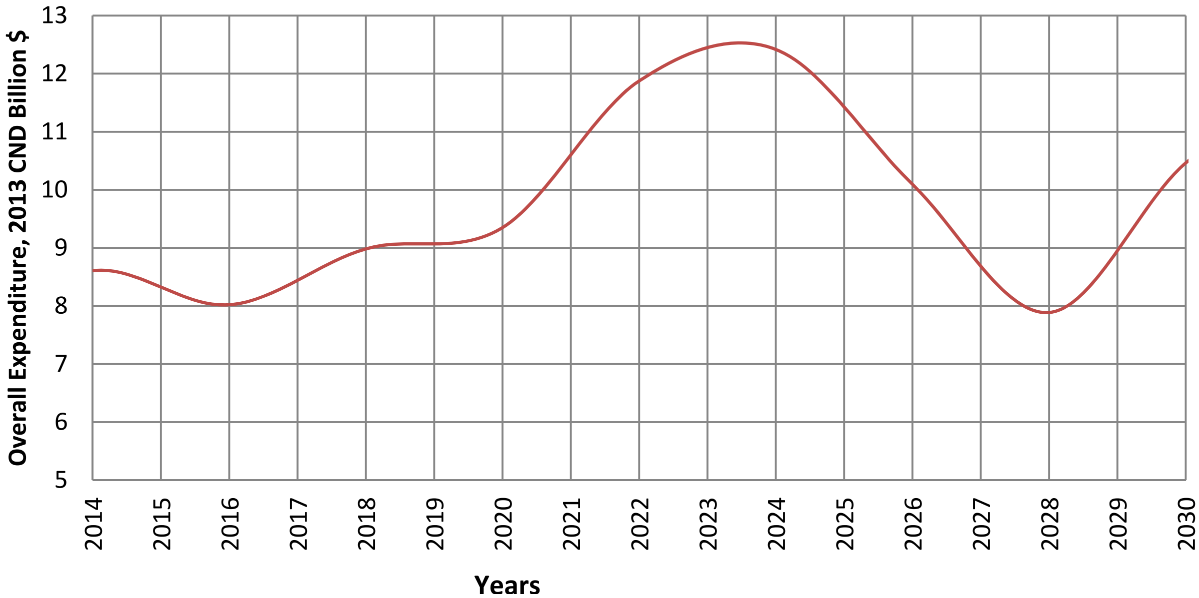


Figure 7.11 Overall Expenditure_ Base Case with 6% Reduction in CO_2 by Year 2018.

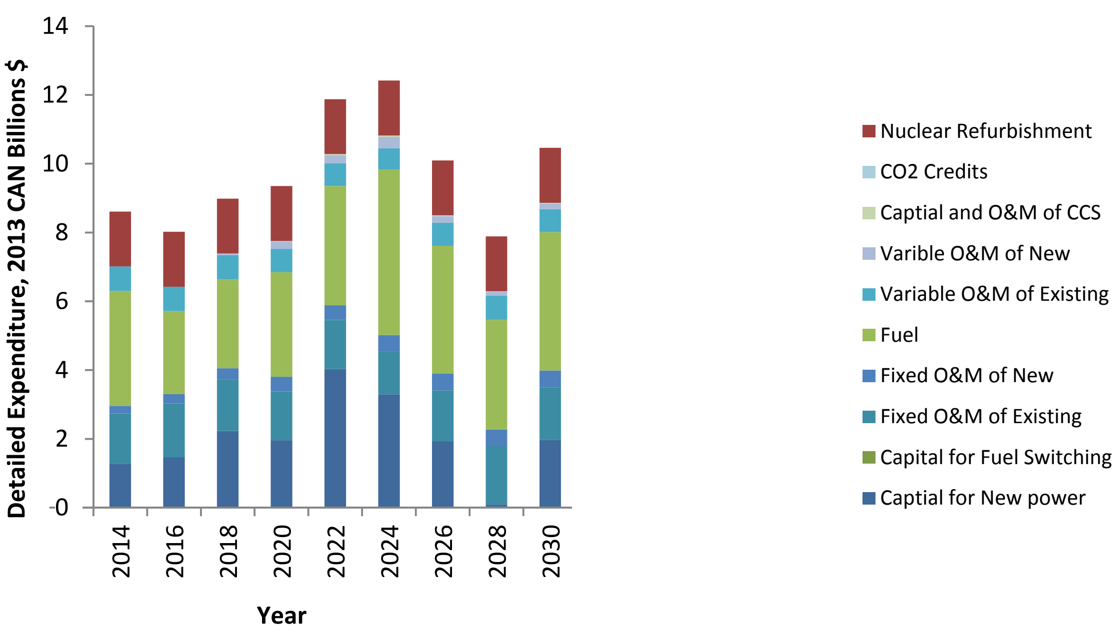


Figure 7.12 Detail Expenditure_ Base Case with 6% Reduction in CO_2 by Year 2018.

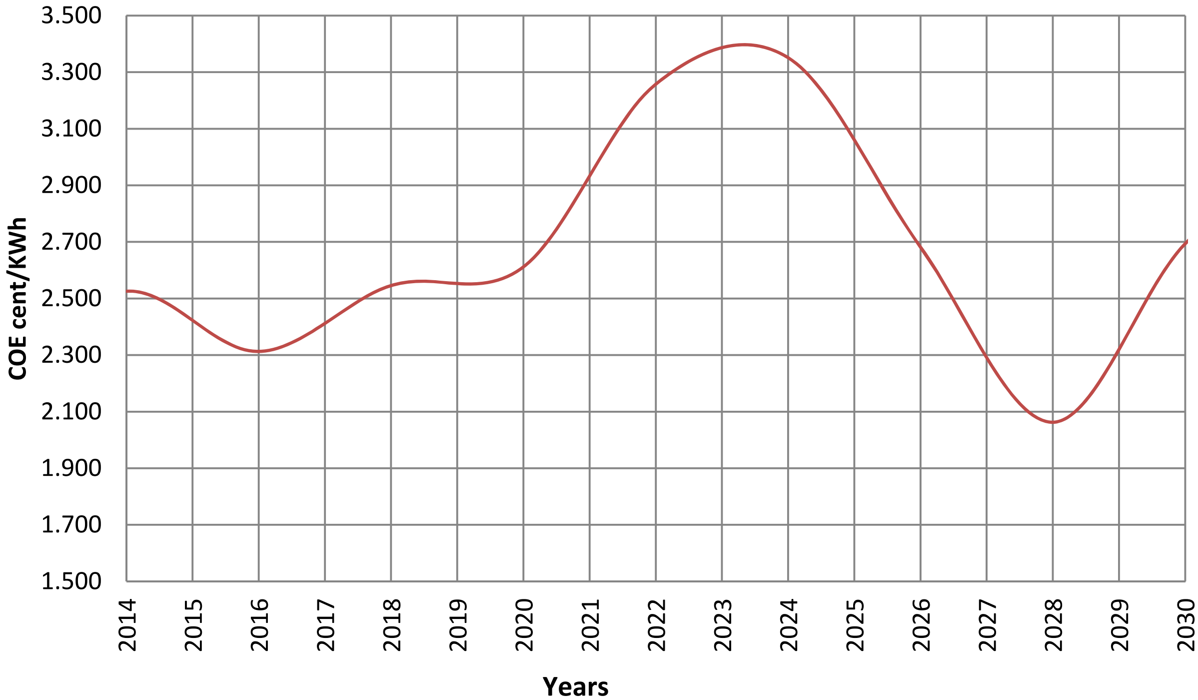


Figure 7.13 Overall Cost of Electricity_ Base Case with 6% Reduction in CO_2 by Year 2018.

Overall average cost of electricity is 2.36 c/kWh. The similarities between the previous cases and this case are not significant. As indicated in Figure 7.14 the overall CO_2 emission is stay steady after 2020. Total of ~600 Mt of CO_2 emissions is detected in the case with 6% emission reduction by the year 2018. Emission curve show a minimum points in 2018 because of the significant number of PHEVs after 2018.

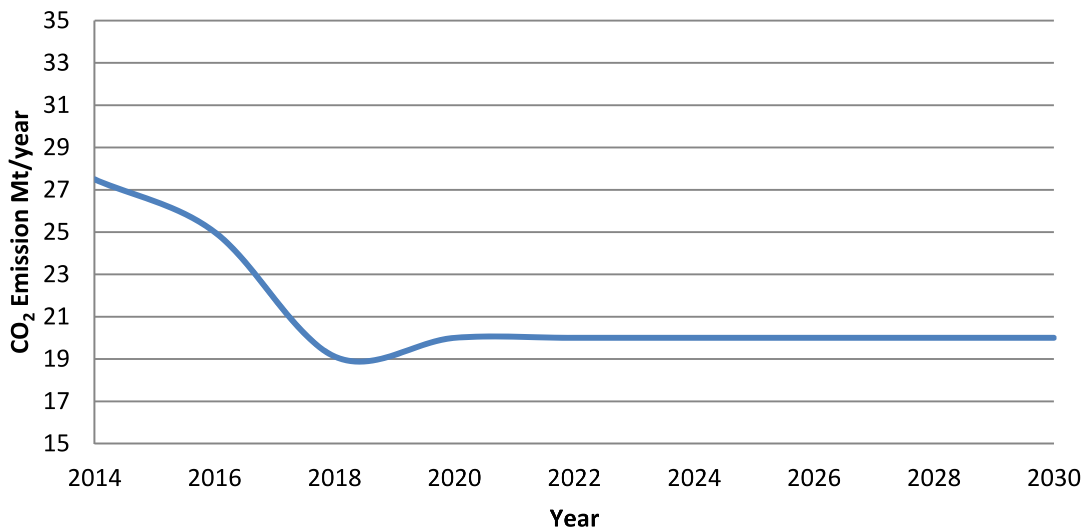


Figure 7.14 Overall CO_2 Emissions_ Base Case with 6% Reduction in CO_2 by Year 2018.

7.5 Case Study E: Base Case without Considering Current Load Deficit

Case E does not consider current load deficit in Ontario. PHEVs penetration rate is Medium. All Coal power plants have been phased out in the year 2014.

7.5.1 New Power Generating Stations

In the base case without considering current load demand, depicted in Table 7.6, new NGCC stations and wind stations are added over time, which is because of adding more PHEVs over time and all are transferring there electricity load to the grid. NGCC makes up 80% of the total new installed capacity.

Table 7.6 New Power Generating Stations and their Construction Time_ Base Case without Considering Current Load Deficit

	Capacity (MW)	Year (20..)																
		14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30
NGCC	210																	
NGCC	320																	
NGCC	375																	
Wind	500																	
NGCC	530																	
NGCC	550																	

7.5.2 Economic and Emission Analysis

As indicated in Figure 7.15, the base case without considering current load deficit has a lower average cost of electricity. Because of having cheaper capital cost of NG power plants and also almost half of the installed capacity than other case studies (due to less electricity deficit), the average cost of electricity is the lowest one among all the case studies.

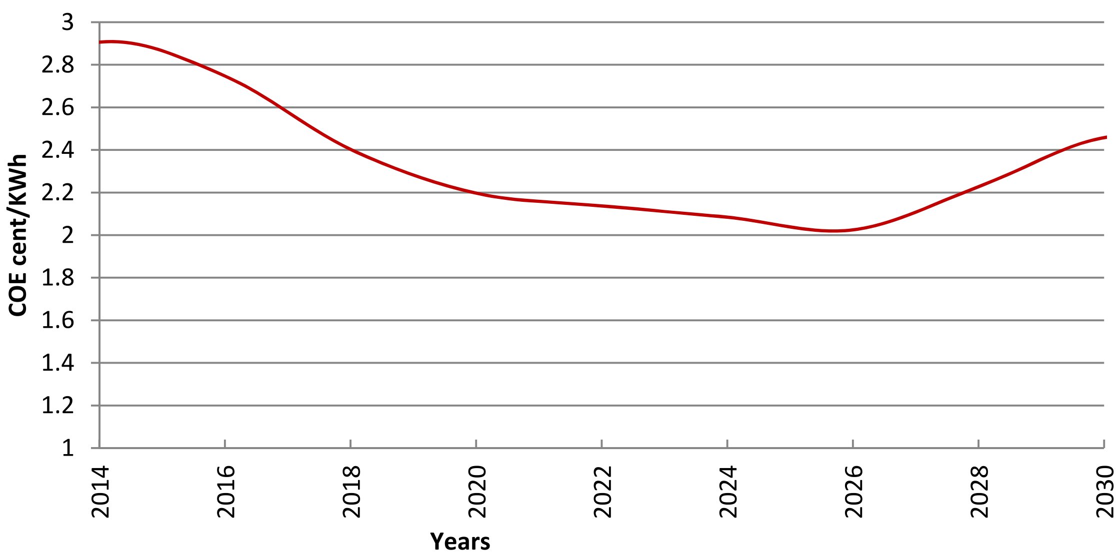


Figure 7.15 Overall Cost of Electricity_ Base Case without Considering Current Load Deficit.

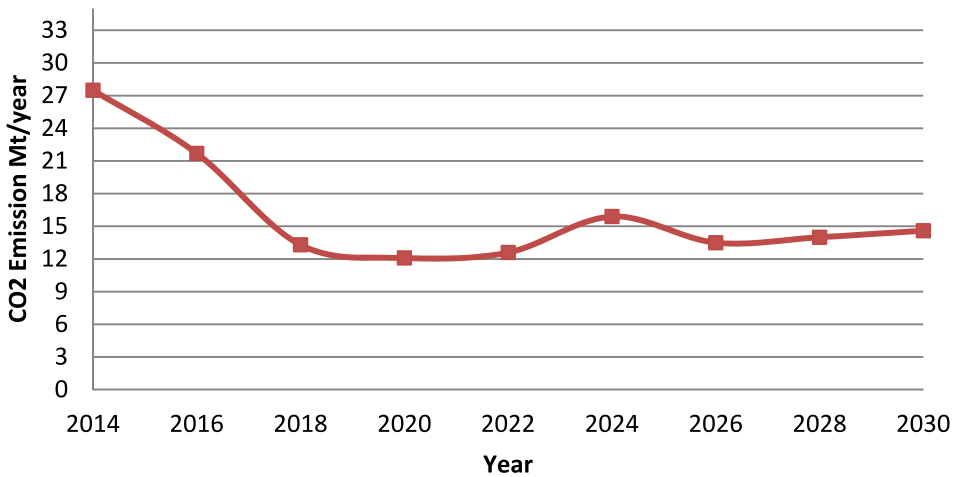


Figure 7.16 Overall CO_2 Emissions_ Base Case without Considering Current Load Deficit.

No CO_2 emission reduction constraint is applied in this case. Because of increasing number of PHEVs as a function of square time, there would be less gasoline consumption by vehicles each year compare to the previous year. Therefore, amount of CO_2 emission decreases over time, as it is shown in Figure 7.16. In the next section, all cases are compared together.

7.6 Summary

As indicated in Figure 7.17, base case without considering current load demand deficit has the lowest average cost of electricity and base case with increased natural gas prices has the highest one. Total new installed capacity in base case with 6% reduction in CO2 in year 2018 is the highest amount, 8,748 MW, and 2,400 MW as the lowest for base case without considering current load demand deficit, Table 7.7.

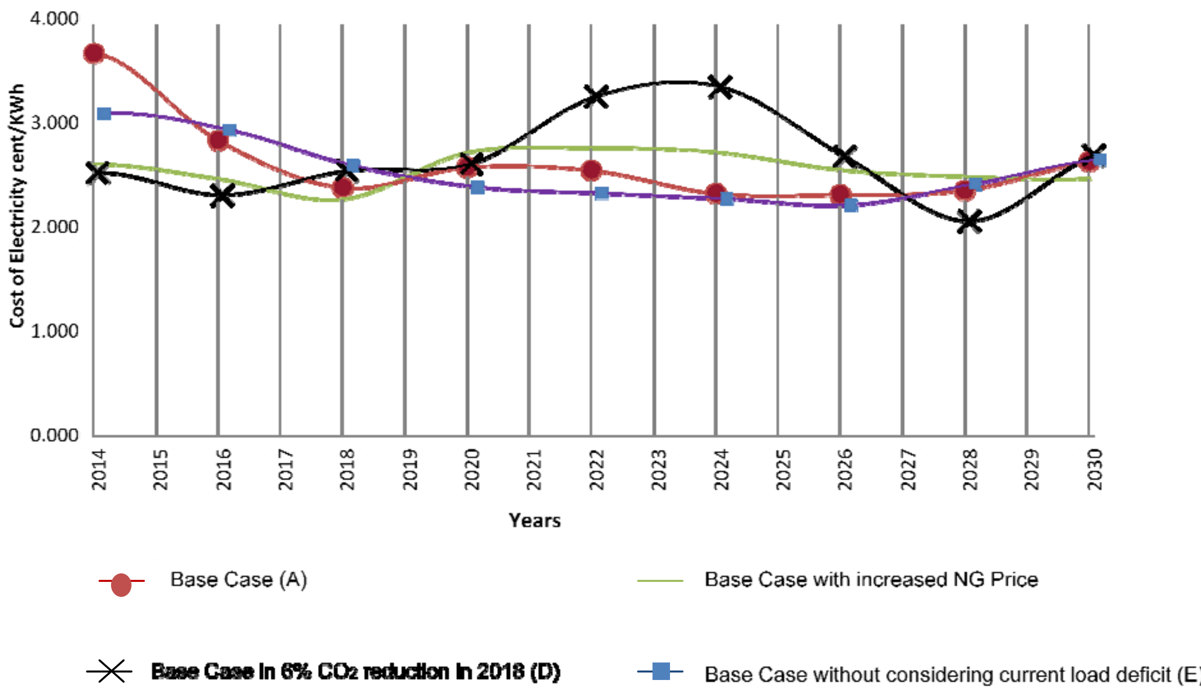


Figure 7.17 Overall Cost of Electricity Comparison.

Almost half of electricity generated by new fleet is from nuclear power stations. However case studies are different, there are many similarities between them. For example, after optimization of the model, large amount of electricity are generated from nuclear stations in base case and base case with increased NG prices. At the same time, 49% of new power plants are NGCC in base case, in which utilizing coal power plants are not allowed, and 47% percent of new units are coal generating stations in base case with coal.

Table 7.7 New Power Generating, COE Comparison

	Total New Installed Cap (MW)	COE ¢/kwh	New Power (MW)	Installed Cap in 2030 Compared to 2013				
				Coal	**NGCC**	**Wind**	**Hydro**	**Nuclear**
Base case **no CO_2 constraints, no Coal** **Medium PHEVs Penetration**	7270	2.27	NGCC: 2890 Wind:2000 Nuclear: 1080	2%↓	4%↑	4%↑	0	3%↓
Base case with increased NG prices **no CO_2 constraints** **Medium PHEVs Penetration**	7270	2.34	Coal:1660 NGCC: 1370 Wind:2000 Nuclear:12010	2%↑	0	4%↑	3%↓	3%↓
Base case with Coal **no CO_2 constraints** **Low PHEVs Penetration**	6500	2.20	Coal: 2792 NGCC:3136	7%↑	4%↑	1%↓	4%↑	6%↓
Base case with 6% reduction in CO_2 in year 2018; no Nuclear **High PHEVs Penetration**	8748	2.36	IGCC: 1100 NGCC: 4398 Wind: 2000	1%↑	6%↑	4%↑	4%↑	7%↓
Base case without considering current load deficit; **no CO_2 constraints, no Coal** **Medium PHEVs Penetration**	2400	2.19	NGCC: 1985 Wind: 500	2%↓	5%↑	1%↑	1%↓	3%↓

7.7 Conclusions

Among all the case studies, highest new capacity (~8,748 MW) is installed for base case with 6% reduction in CO_2 in year 2018 which considers high adoption rate for PHEVs, and not utilizing any new nuclear power plants, with the carbon dioxide emissions restriction. The next highest ones are base case and base case with increased NG price with ~7,270MW, which considers NG price increases to be double in 2020 with the medium PHEVs adoption rate. One of the main reasons of having more installed capacity in base case with 6% reduction in CO_2 in year 2018, is high PHEVs penetration which leads to more electricity consumption. Therefore, more electricity needs to be generated to satisfy load demand over years.

As a result of highest amount of installed capacity in the case of the base case with 6% reduction in CO_2 in year 2018, the total expenditure and average cost of electricity of this case (148 CND billion, and 2.36 c/kWh) are more than three other cases.

Results show that by phasing out coal power stations in the base case the total amount of the CO_2 emissions is the lowest amount among the different case studies. The total CO_2 emissions for base case is the lowest one (~500 tonnes), almost half of the base case with coal (~900 tonnes), which is the highest one.

Chapter 8: Conclusions and Recommendations

Number of PHEVs is forecasted through consideration of three scenarios of penetration levels, and the maximum number of PHEVs would be 890,362 vehicles at the end of 2030 in Ontario. There are different factors effecting on PHEVs penetration, such as socio-economic factors including age, gender, location, insurance, vehicle model, etc. By considering socio economic factors, PHEVs adoptions will increase substantially in the future, comprising a fraction of approximately 30%-38% (dependent on the considered scenario) of the total conventional vehicles sold. In addition by accomplishing zonal analysis the total emissions per season will drop by roughly 40% to 50% of the quantity they would emit when no PHEVs are penetrated. Moreover, four different scenarios of the charging pattern are developed. Additional peak load demands in December 2030 from PHEVs charging in different scenarios are 1,051.3 MW, 788.5 MW, 525.7 MW, and 0 MW. Also, additional base load demands in December, 2030 from PHEVs charging are 0 MW, 20.9 MW, 41.7 MW, and 83.5 MW. After PHEVs penetration, peak load demands and base load demands in December 2030 would be increased by ~13% and 4% compared to the 2013 demand. Consequently, supply is less than the peak load demand. The additional electricity demand on the Ontario electricity grid from charging PHEVs is incorporated for electricity production planning purposes. Therefore, we need more power plants if PHEVs are widely adopted.

Finally, the Ontario energy planning is optimized to minimize the value of the cost of the electricity over sixteen years (2014-2030). The mathematical objective function consists of the fuel costs, fixed and variable operating and maintenance costs, the capital costs for a new power plant, and the retrofit costs of existing power plants (associated with fuel switching from coal to natural gas for coal-fired stations). The mathematical model of objective function and related constraints are applied in the GAMS software. Because of having mixed integer model, the programming code set to be solved through CPLEX solver. Five different case studies are performed with different penetration rate, type of new power plants, and CO_2 emission constraints. Among all the case studies, the one requiring the most new capacity, (~8,748 MW), is Case D, assuming the base case with 6% reduction in CO_2 in year 2018 and high PHEV penetration. The next highest one is Case B, assume the base case, doubled NG prices, medium PHEV and no CO_2 emissions reduction target with an increase of 34.78% in the total installed capacity in 2030. Furthermore, optimization results indicate that by not utilizing coal power stations the CO_2 emissions are the lowest; ~500 tonnes compared to ~900 tonnes when coal is permitted.

For the future work, different type of PHEVs could be considered based on percentage of people with specific driving distance. For this purpose, different scenarios could be defined. The similar procedure as chapter three could be developed. Moreover, the computational time of the model could be improved by modifying the model development to utilize less memory. Other work could be decentralizing and integrating the zonal PHEVs penetration, develop optimization model to address optimal planning of the Ontario zonal power generating sector, some part of the work has been accomplished in chapter six of this thesis. Furthermore, multi objective functions could be considered for operating and maintenance cost of various power plants, such as considering fuel (NG) cost fluctuations.

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=0&SHOWALL=0&SUB=0&Temporal=2006&THEME=76&VID=0&VNAMEE=&VNAMEF=&D1=0&D2=0&D3=0&D4=0&D5=0&D6=0#FN2> .

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