

An Environmentally Conscious Robust Optimization Approach for Planning Power Generating Systems

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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.

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Abstract

Carbon dioxide is a main greenhouse gas that is responsible for global warming and climate change. The reduction in greenhouse gas emission is required to comply with the Kyoto Protocol. Looking at CO₂ emissions distribution in Canada, the electricity and heat generation sub-sectors are among the largest sources of CO₂ emissions. In this study, the focus is to reduce CO₂ emissions from electricity generation through capacity expansion planning for utility companies. In order to reduce emissions, different mitigation options are considered including structural changes and non structural changes. A drawback of existing capacity planning models is that they do not consider uncertainties in parameters such as demand and fuel prices.

Stochastic planning of power production overcomes the drawback of deterministic models by accounting for uncertainties in the parameters. Such planning accounts for demand uncertainties by using scenario sets and probability distributions. However, in past literature different scenarios were developed by either assigning arbitrary values or by assuming certain percentages above or below a deterministic demand. Using forecasting techniques, reliable demand data can be obtained and can be inputted to the scenario set. The first part of this thesis focuses on long term forecasting of electricity demand using autoregressive, simple linear, and multiple linear regression models. The resulting models using different forecasting techniques are compared through a number of statistical measures and the most accurate model was selected. Using Ontario electricity demand as a case study, the annual energy, peak load, and base load demand were forecasted, up to year 2025. In order to generate different scenarios, different ranges in economic, demographic and climatic variables were used.

The second part of this thesis proposes a robust optimization capacity expansion planning model that yields a less sensitive solution due to the variation in the above parameters. By adjusting the penalty parameters, the model can accommodate the decision maker's risk aversion and yield a solution based upon it. The proposed model is then applied to Ontario Power Generation, the largest power utility company in Ontario, Canada. Using forecasted data for the year 2025 with a 40% CO₂ reduction from the 2005 levels, the model suggested to close most of the coal power plants and to build new natural gas combined cycle turbines and nuclear power plants to meet the demand and CO₂ constraints. The model robustness was illustrated on a case study and, as expected, the model was found to be less sensitive than the deterministic model.

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Dedication

To my parents, who always support me in following my dreams.

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Nomenclature

Sets use in the capacity expansion models

Sets	Membership
F	Existing fossil fuel plants (each plant has multiple generation units)
F^c	Existing power plants with capture added; $F^c \in F$
G_h	Set of units i in plant h ($i \in G_h \quad \forall h$)
H	Fossil fuel plants with capture ($h \in F^c \cup P^c$)
I	Generation units $i \in F \cup NF \cup P^{new}$
J	Fuel type $\{coal, natural\ gas\}$
K	CO ₂ capture technologies
L	Load blocks $\{base, peak\}$
NF	Existing non-fossil fuel plants (each plant has multiple generation units)
P^{new}	New possible plants (each plant has multiple generation units)
P^c	New possible plants with capture $P^c \in P^{new}$
Q	Sequestration sites
S	Scenarios

Sets use in forecasting models

Sets	Membership
D	Days in the year $\{d=1,2,\dots 365\}$
I	Set of explanatory variables
R	Regions
T	Time index (i.e. year)

Variables use in the capacity expansion models

Variables	Description
$CO2Pi$	Capital and annual operating cost for CO ₂ sequestration pipeline
E_{ijl}	Capacity of boiler i using fuel j allocated during load block l (MW)
E_{il}	Capacity of generator i allocated during load block l (MW)
E_{ijkl}	Power required for capture system k during load block l for boiler i using fuel j (MW)
E_{ijl}^s	Capacity of boiler i using fuel j allocated during load block l under scenario s (MW)
E_{ijkl}^s	Power required for capture system k during load block l for boiler i using fuel j under scenario s (MW)
E_{il}^s	Capacity of generator i allocated during load block l under scenario s (MW)
$FCCS$	Capital and fixed operating cost for added carbon capture system to F (\$)
FNP	Capital and fixed operating cost for P^{new} (\$)
FP	Fixed operating cost for existing plants (\$)
OF	Objective function (\$)
RP	Retrofit cost (from coal-fired to natural-gas-fired) for F (\$)
u_{hs}	Selection to build pipeline from plant h to sequestration q (Binary variable)
$VCCS$	Variable operating cost for added carbon capture system to F (\$)
VNP	Variable operating cost for P^{new} (\$)
VP	Variable operating cost for existing plants (\$)
w_{iq}	Selection of sequestration site q for boiler i (Binary variable)
x_{ij}	Selection for generator i using fuel j (Binary variable)
x_i	Selection of operating non-fossil generator i (Binary variable)
y_i	Selection of building new generator i (Binary variable)
z_{ijk}	Selection for carbon capture system k for boiler i using fuel j (Binary variable)
α_i	CO ₂ produced from boiler i (tonne CO ₂ produced)
β_{iql}	Linearization variable for the multiplication of E_{il} and w_{iq}
β_{iql}^s	Linearization variable for the multiplication of E_{il} and w_{iq} under scenario s
γ_{ijkl}	Linearization variable for the multiplication of E_{ijl} and z_{ijk}
γ_{ijkl}^s	Linearization variable for the multiplication of E_{ijl} and z_{ijk} under scenario s
ϕ_{ijql}	Linearization variable for the multiplication of E_{ijl} and w_{iq}
ϕ_{ijql}^s	Linearization variable for the multiplication of E_{ijl} and w_{iq} under scenario s

Parameters use in the capacity expansion models

Parameters	Description
b_i	Capacity factor for generator i
C_i^{fixed}	Fixed operating cost of generator i (\$/MW)
C_{ij}^{fixed}	Fixed operating cost of generator i using fuel j (\$/MW)
C_i	Variable operating (without fuel) cost of generator i (\$/MWh)
C_{ij}	Variable operating (without fuel) cost of generator i using fuel j (\$/MWh)
C_{hq}^{seq}	Annual operating cost for pipeline from plant h to site q (\$)
C_k^c	Variable operating cost for carbon capture system k at generator i for a given ε_i (\$/ MWh)
C_k^{cfixed}	Fixed operating cost for carbon capture system k at generator i (\$/ MW)
$CO_2^{current}$	Current CO ₂ emission of entire fleet (tonne CO ₂)
$CO_{2\ i}$	CO ₂ produced per energy generated for generator i (tonne CO ₂ produced/MWh)
$CO_{2\ ij}$	CO ₂ produced per energy generated for generator i using fuel j (tonne CO ₂ produced/MWh)
D_l	Power Demand during load block l (MW)
D_l^s	Power Demand during load block l under scenario s (MW)
E_i^{max}	Capacity of generator i (MW)
E_{ijk}^{req}	Unit energy required for capturing unit CO ₂ in generator i using fuel j with capture system k (MWh/ tonne CO ₂ captured)
H_i	Heat Rate for generator i (GJ/MWh)
M	A large number used for linearization
P_j	Cost of fuel j (\$/ GJ)
P_j^s	Cost of fuel j under scenario s (\$/GJ)
R_{ij}	Unit amortized retrofit cost for generator i switching to / using fuel j (\$/MW)
S_i^{new}	Unit amortized capital cost for new generator i (\$/MW)
S_{hq}^{seq}	Amortized capital cost for pipeline from plant h to site q (\$)
S_k^c	Unit amortized capital cost for carbon capture system k at generator i (\$/MW)
Γ	Percentage of CO ₂ emission reduction
ε_i	percent of CO ₂ capture for generator i (tonne CO ₂ captured/tonne CO ₂ produced)
θ_l	Duration of load block l (hrs)
θ_l^s	Duration of load block l under scenario s (hrs)

Notations use in forecasting models

Notation	Description
a	Intercept of regression model
b_i	Coefficient for variable i
$Base_t$	Base load demand in year t
CDD	Annual cooling degree days
CDD_d	Cooling degree days in day d
d	Number of estimated parameters in AR models
DD_r	Annual of maximum degree days in region r
$dwelling_r$	Dwelling counts in region r
e_t	Error term in year t (i.e. $e_t = Y_t - F_t$)
$Employment_t$	Number of employments in year t
$Energy_t$	Energy demand in year t
HDD	Annual heating degree days
HDD_d	Heating degree days in day d
F_t	Observed value in time t
$MaxCDD_t$	Maximum cooling degree days value in year t
N	Number of observations
$Peak_t$	Peak load demand in year t
T_b	Base temperature for calculating degree days
T_d	Mean temperature for day d
V	Loss function
x_i	Explanatory variable i
Y_t	Forecasted value in time t
$year_t$	Value of year t (e.g. 1993)

Abbreviations

Abbreviations	Description
ACF	Autocorrelation function
AIC	Akaike's Information Criterion
AR	Autoregressive model
CCS	Carbon capture system
CDD	Cooling degree days
CO ₂	Carbon dioxide
CO ₂ eq	CO ₂ equivalent
DD	Degree days
EIA	Energy Information Administration
EVPI	Expected value of perfect information
GDP	Gross domestic products
GDPpp	Gross domestic products per capita
GHG	Greenhouse gas
HDD	Heating degree days
IECM	Integrated Environmental Control Model
IESO	Independent Electricity System Operator
IGCC	Integrated gas combined cycle
MAE	Mean absolute error
MAPE	Mean absolute percentage error
MSE	Mean squared error
MEA	Monoethanolamine
LDC	Load duration curve
NGCC	Natural gas combined cycle
OPA	Ontario Power Authority
OPG	Ontario Power Generation
PC	Pulverized coal
SS	Stochastic solution
VSS	Value of the stochastic solution
WSS	Wait and see solution

1. Introduction

Carbon dioxide is a main greenhouse gas (GHG) that is responsible for climate change. The usage of fossil fuel is the primary source that increases the concentration of carbon dioxide (CO₂) in the atmosphere (Intergovernmental Panel on Climate Change, 2007). Back in 1998, the United Nations Framework Convention on Climate Change (1998) has already developed the Kyoto Protocol to stabilize the GHG emissions in the atmosphere by having industrialized countries commit to reduce their GHG emissions. The legal binding accord was signed by 165 countries to reduce GHG emissions. Canada, for instance, committed to a GHG emission target of 6% below the 1990 levels by 2008 – 2012.

According to Environment Canada (2006), Canada emitted 758 Mt CO₂ equivalent (CO₂ eq) in 2004, an increase from 599 Mt CO₂ eq in 1990. In order to meet the Kyoto target, Canada must decrease the emission by 195 Mt CO₂ eq from the 2004 emission level. To effectively reduce GHG emissions, we should target one of the largest contributors. With emissions accounting for over 17% of Canada's total, the electricity and heat generation sub-sectors are among the largest GHG contributors. In this study, the focus is to reduce CO₂ emission from electricity generation. Using the fleet of Ontario Power Generation (OPG), the largest electric utility company in Ontario, Canada, as a case study, this thesis will develop a capacity expansion planning model to satisfy demand in 2025 while meeting CO₂ emission targets at a minimum cost.

To reduce CO₂ emissions from a fleet of power plants, Hashim *et al.* (2007) proposed the use of different CO₂ control strategies, which include employing fuel balancing and/or fuel switching, making enhanced use of alternative energy and/or advanced technologies, and employing CO₂ removal technologies. Fuel balancing is to adjust the operation of

generation stations to reduce CO₂ emissions. Fuel switching is to switch from carbon-intensive fuels (e.g. coal) to less carbon-intensive fuels (e.g. natural gas). Existing generation stations must be retrofitted in order to use another fuel. Energy produced by alternative fuel (e.g. uranium, wind, and solar) emits no CO₂, and hence will reduce CO₂ emission. Advanced fossil-fuel technologies include integrated gasification combined cycle (IGCC), supercritical and ultra-supercritical pulverized coal power plants, and natural gas combined cycle (NGCC). These generators have higher efficiency than sub critical pulverized coal power plants, and therefore, less CO₂ is produce from them per unit energy generated. The CO₂ removal technologies considered here are an end-of-pipe option, namely CO₂ scrubbing from flue gas. CO₂ is captured instead of released to the atmosphere, transported through pipelines under critical pressures, and sequestered deep into reservoirs to ensure that the temperature and pressure conditions are beyond critical values. Shafeen *et al.* (2004a, 2004b) have recently shown that CO₂ sequestration is a feasible option in Ontario, Canada.

It would be difficult to incorporate mitigation options into a fleet in a short period, except for fuel balancing. Long-term planning is important to the electric sector because the lead time of construction is long. Using optimization methods, one could determine an expansion plan with minimal cost while meeting CO₂ constraints.

Optimization is used in many practical decision problems. It can inform the decision maker which strategy to execute in order to minimize the cost or maximize the profit. Typical applications of optimization could be found in engineering, transportation, production, and many other fields. An example of an optimization problem would be minimizing the cost of capacity expansion while satisfying future demand and meeting all regulations. In the electricity sector, power generation expansion planning is very

important because the lead time of construction is long. Many models in the past addressed the issue of power generation planning, including models incorporating distributed regional demand (e.g. Nakata & Ashina , 2002), models considering multi period planning (e.g. Turvey & Anderson , 1977), and models including emission constraints (e.g. Bai & Wei ,1996, Hashim *et al.*, 2005 and 2007, Hsu & Chen, 2004, Johnson & Keith, 2004, and Sirikum & Techanitisawad, 2006).

All the models mentioned above are deterministic in nature and this represents a major drawback. Deterministic electric capacity planning models find the optimal solution (i.e. least-cost investment solution), which allows the utility to meet demand growth. Deterministic models are incapable of resolving most real world problems. In reality, model parameters are uncertain and always have a probability of occurrence. Parameters such as the fuel prices and power demand are not known with certainty. Consider the problem where it is desired to plan for power generation in order to provide reliable supply of electricity in a given country or region. The amount of electricity generated must satisfy electricity demanded. However, the electricity demand is uncertain, and this is especially true for long term expansion planning where the electricity demand ten or twenty years from now is needed as an input parameter. An expansion plan found to be optimal for one particular scenario might be very costly for another.

Stochastic programming can be used to incorporate uncertainties of the parameters in the solution. In stochastic programming, uncertainty is accounted by using a set of scenarios with known probabilities. Stochastic programming models attempt to explicitly incorporate the conflicting objectives of optimal solutions and model robustness. When the error (i.e. slack or surplus) is ‘almost’ zero for any realization of the scenario, the optimal solution is model robust. Robust programming models take a step further and incorporate

the objective of solution robustness in addition to the objectives of optimal solutions and model robustness. The optimal solution is solution robust when the cost for any realization of the scenario is 'close' to the scenario optimal. Scenario optimal is the optimal of a scenario when we know that particular scenario will occur with certainty. Robust programming models are often employed with the ability of incorporating the decision makers' risk aversion into the model (Yu & Li, 2000). The objective here is to formulate a more "robust" model that can lead to a more robust plan. Both stochastic and robust optimizations deal with uncertain and noisy information in which the parameters have a probability of occurrences.

Robust optimization models have been used in logistic problems (e.g. Yu & Li, 2000 and Leung *et al.*, 2002), financial risk management (e.g. Mulvey, 1996), and process design (e.g. Kang *et al.* 2004). The only attempt in using robust optimization for power generation planning seems to be that of Malcolm & Zenios (1994). However, power capacity planning with CO₂ constraints has never been modeled with robust optimization before. In this thesis, we will develop such a model and illustrate its use with a case study.

As mentioned above, both stochastic and robust programming require a set of scenarios with known probabilities as an input. Most scenario sets in the literature are often not assigned properly. From the articles we have studied, they are either made up from a combination of certain percentage above or below a mean value, (e.g. Killmer *et al.*, 2001, Chaton & Doucet, 2003, and Yokoyama & Ito, 2002) or made up of arbitrary values and probabilities without proper forecasting (e.g. Yu & Li, 2000, and Leung *et al.*, 2002). In order to obtain dependable results from stochastic models, the model should have a more reliable input data. If the data is not dependable, the results will not be reliable. This is why forecasting represents an important step in stochastic power system planning. Scenario sets can be

generated by forecasting different situations (e.g. economic conditions, climatic data, etc.). This thesis proposes the use of simple forecasting techniques to develop such scenario sets and should lead to an enhancement in stochastic planning models.

The proposed model is based on the capacity expansion model developed by Hashim *et al.* (2007). Hashim *et al.* (2007) developed a power system capacity expansion model under CO₂ consideration. The model is a deterministic mixed integer linear program that minimizes cost and satisfies the annual energy demand, physical constraints, and CO₂ constraints. The model described in this thesis takes into account uncertainties in the parameters, such as power demand and fuel prices. By incorporating these uncertainties, the model becomes capable of tackling the decision makers' favoured risk aversion, and the optimal solution becomes less sensitive to fluctuations of the parameters.

This thesis applies the proposed methodology on a real-life case study. With technical and economical data gathered through literature, an optimal capacity expansion plan is developed for OPG to meet the demand in 2025, while reducing CO₂ emissions by 40%.

The remainder of this thesis is organized as follows. After this introductory chapter, the deterministic formulation of the capacity expansion model will be described. In Chapter 3, different forecasting techniques are described, and a case study of forecasting Ontario electricity demand is presented. The concept of robust optimization and the robust formulation of the capacity expansion model are presented in Chapter 4. The description and solution of the case study will then be presented in Chapter 5. Chapter 5 also discusses the effects on the optimal solution when the risk aversion of the decision maker changes, and compares the robust solution with deterministic solutions. Concluding remarks are given at the end of the thesis.

2. Formulation of the power system capacity expansion model

In order to present the robust optimization formulation of the capacity expansion model, it is important to describe the deterministic formulation because the robust optimization model is built on the deterministic formulation. The power system capacity expansion problem deals with minimizing capital and operating costs of the system while satisfying customer demand and meeting physical constraints. In addition, we included CO₂ considerations in developing the optimal system. The CO₂ mitigation options considered in this work consist of structural and non-structural changes. Structural changes include 1) fuel switching, switching from carbon-intensive fuel (i.e. coal) to less carbon-intensive fuel (i.e. natural gas), 2) adding carbon capture and sequestration systems, and 3) building new power plants. The non-structural change considered includes fuel balancing by adjusting the operation of generating station to reduce CO₂ emissions.

Electric power demand is not constant over time. Figure 1a shows the hourly power demands of Ontario in 2005. Power demand is higher during the day and it changes with the season. The load duration curve (LDC) (Figure 1b) is obtained by rearranging the demands in decreasing order. The continuous curve is then approximated by step functions to facilitate the use of mathematical programming model. In Figure 1c, the LDC is decomposed into two piecewise functions corresponding to peak and base load demand. D_l and θ_l are the demand and duration of load block l (i.e. peak and base load), respectively.

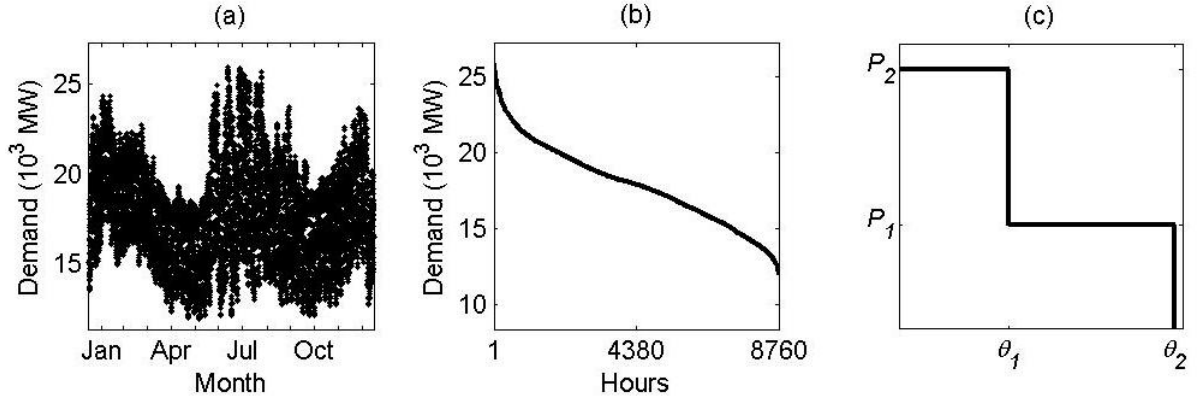


Figure 1 – Electric power demand

a) Electric power demand over a year (Independent Electricity System Operator [IESO], 2007),
b) Load duration curve, and c) Piecewise load duration curve

2.1. Deterministic power capacity expansion model

In this section we will present the deterministic model for power capacity expansion planning with CO₂ mitigation. The model is an extension to that of Hashim *et al.* (2007) in that it also incorporates the use of load duration curves.

The objective function (*OF*) is the annualized cost for operating the fleet including the operating cost of existing fleet, the retrofit cost for fuel switching, the capital and operating cost of new possible plants, and the cost for capture, transport, and storage of CO₂. Capital, retrofit, and fixed operating costs depend on the capacity of the plant (i.e. cost is independent of the energy output of the plant, \$ / MW). On the other hand, variable costs depend on the operation of the plant (i.e. cost is dependent on the energy output of the plant, \$ / MWh). Equations (1) to (8) list the different components associated with the *OF*.

Fixed operating cost for existing plants (*F* and *NF*):

$$FP = \sum_{i \in NF} C_i^{fixed} E_i^{\max} x_i + \sum_{i \in F} \sum_j C_{ij}^{fixed} E_i^{\max} x_{ij} \quad (1)$$

The fixed operating cost is a function of plant capacity.

Variable operating cost for F and NF :

$$VP = \sum_{i \in F} \sum_j \sum_l (C_{ij} + P_j H_i) \theta_l E_{ijl} + \sum_{i \in NF} \sum_l C_i \theta_l E_{il} \quad (2)$$

VP accounts for the variable operating cost for existing generators. For F , the unit variable cost is separated into two components: the variable operating cost excluding fuel and the fuel cost (i.e. the cost of fuel j that generator i is using, P_j , multiply by the heat rate for generator i , H_i). For NF , the unit variable operating cost includes the fuel cost.

Retrofit cost (from coal-fired to natural-gas-fired) for F :

$$RP = \sum_{i \in F} \sum_j R_{ij} E_i^{\max} x_{ij} \quad (3)$$

If an existing coal-fired plant is chosen to be retrofitted, RP will account for the capital cost for fuel switching.

Capital and fixed operating cost for P^{new} :

$$FNP = \sum_{i \in P^{new}} (S_i^{new} + C_i^{fixed}) E_i^{\max} y_i \quad (4)$$

For every new plant (i.e. $y_i = 1$), annualized capital and fixed operating costs are added to the objective function.

Variable operating cost for P^{new} :

$$VNP = \sum_{i \in P^{new}} \sum_l (C_i + P_j H_i) \theta_l E_{il} \quad (5)$$

VNP accounts for the variable operating cost and the fuel cost for generating electricity from new possible power plants. The fuel j is presubscribed to either coal or natural gas for new fossil-fuelled plants. For non-fossil plants, the term $P_j H_i$ is dropped from the equation.

Capital and fixed operating cost for added carbon capture system to F :

$$FCCS = \sum_{i \in F^c} \sum_j \sum_k (S_k^c + C_k^{fixed}) E_i^{\max} z_{ijk} \quad (6)$$

$FCCS$ accounts for the annualized capital and fixed operating costs for a carbon capture system (CCS) installed at generators $i \in F^c$.

Variable operating cost for added carbon capture system to F :

$$VCCS = \sum_{i \in F^c} \sum_j \sum_k \sum_l C_k^c E_{ijl} z_{ijk} \theta_l \quad (7)$$

C_k^c is the unit variable operating cost in \$ per MWh for a given CO₂ capture percentage, ε_i .

$VCCS$ accounts for the cost of operating the CCS for generators $i \in F^c$.

Capital and annual operating cost for CO₂ sequestration pipeline:

$$CO2Pi = \sum_{h \in F^c \cup P^c} \sum_q \left(S_{hq}^{seq} + C_{hq}^{fixed} \right) \mu_{hq} \quad (8)$$

$CO2Pi$ accounts for the capital and annual operating costs for all pipelines used for CO₂ transport in the fleet.

The summation of the above costs will yield the objective function, OF , which we want to minimize.

$$\text{Min } OF = FP + VP + RP + FNP + VNP + FCCS + VCCS + CO2Pi \quad (9)$$

The constraints of the model are described in Sections 2.1.1 to 2.1.8.

2.1.1. Demand satisfaction

$$\left[\left(\sum_{i \in NF \cup P^{new}} E_{il} + \sum_{i \in F} \sum_j E_{ijl} \right) - \sum_{i \in F^c} \sum_j \sum_k E_{ijkl} \right] \theta_l \geq D_l \quad \forall l \quad (10)$$

The energy generated in load block l , which is the capacity allocated during load block l minus the power required for the CCS multiply by θ_l , must be greater or equal to the energy demand during load block l . Energy demand, D_l , is given by:

$$D_l = (P_j - P_{j-1}) \theta_j \quad (11)$$

2.1.2. *Fuel selection and plant shut down*

$$\sum_j x_{ij} \leq 1 \quad \forall i \in F \quad (12)$$

The above constraint states that each existing fossil fuel generator is either shut down (i.e. $\sum_j x_{ij} = 0$) or operates on one fuel.

2.1.3. *Capacity constraints*

$$\sum_l E_{ijl} \leq E_i^{\max} x_{ij} \quad \forall i \in F, \forall j \quad (13)$$

$$\sum_l E_{il} \leq E_i^{\max} x_i \quad \forall i \in NF \quad (14)$$

$$\sum_l E_{il} \leq E_i^{\max} y_i \quad \forall i \in P^{new} \quad (15)$$

For existing fossil fuel generators, the total capacity allocated for fuel j must equal zero if the generator is not using fuel j , otherwise, it must not exceed the capacity of the generator. For new power plants, if y_i equals zero (i.e. no new plant i is built), the capacity allocated to all load blocks must be zero; otherwise, it must not exceed the capacity of the plant. In addition to meeting power capacity constraints, the generators should not exceed the amount of energy output governed by the capacity factor.

$$\sum_l E_{ijl} \theta_l \leq E_i^{\max} \theta_l b_i x_{ij} \quad \forall i \in F, \forall j \quad (16)$$

$$\sum_l E_{il} \theta_l \leq E_i^{\max} \theta_l b_i x_i \quad \forall i \in NF \quad (17)$$

$$\sum_l E_{il} \theta_l \leq E_i^{\max} \theta_l b_i y_i \quad \forall i \in P^{new} \quad (18)$$

Additional constraints are added to nuclear, hydro, and wind power plants. Base load hydro stations and nuclear power plants are used to meet base load demands only because they are designed to operate continuously. Wind turbines are used to meet base load demand because they are not dispatchable and therefore cannot be used to meet peak load

demands. Peak load hydro stations are constrained to meet peak load demand because they cannot be run continuously.

2.1.4. *CO₂ emission*

CO_{2ij} is the CO₂ emission factor of boiler $i \in F$ using fuel j and CO_{2i} is the emission factor of boiler $i \in P^{new}$. The amounts of CO₂ produced in existing and new fossil fuel boilers are respectively listed below:

$$\alpha_i = \sum_j \sum_l CO_{2ij} \theta_l E_{ijl} \quad \forall i \in F \quad (19)$$

$$\alpha_i = \sum_l CO_{2i} \theta_l E_{il} \quad \forall i \in P^{new} \quad (20)$$

For boilers without a capture system, the amount of CO₂ produced equals the amount of CO₂ emitted. For each new fossil fuel boiler with a capture system, the CO₂ emission is still equals α_i because α_i already excluded the CO₂ captured from the capture system. For each existing boiler with capture system, the amount of CO₂ released will be the difference between α_i and the amount captured. The annual CO₂ emission by the entire fleet must satisfy a CO₂ reduction target.

$$\sum_{i \in F} \sum_j \sum_k \sum_l (1 - \varepsilon_i z_{ijk}) \alpha_i + \sum_{i \in P^{new}} \alpha_i \leq (1 - \Gamma) CO_2^{current} \quad (21)$$

Substituting α_i from equation (19) and (20) leads to,

$$\sum_{i \in F} \sum_j \sum_k \sum_l (1 - \varepsilon_i z_{ijk}) CO_{2ij} \theta_l E_{ijl} + \sum_{i \in P^{new}} CO_{2i} \theta_l E_{il} \leq (1 - \Gamma) CO_2^{current} \quad (22)$$

2.1.5. *Capacity constraint on CCSs*

Capacity constraints on CCSs only apply to existing fossil fuel boilers. Parameters of $i \in P^c$ already incorporated the power requirement of the capture system. For existing boilers, the amount of power required for the CCS is defined as,

$$E_{ijkl} = E_{ijk}^{req} CO_{2ij} \varepsilon_i E_{ijl} z_{ijk} \quad \forall i \in F^c, \forall j, \forall k, \forall l \quad (23)$$

To ensure that E_{ijkl} does not exceed E_i^{max} when a capture system is installed and that E_{ijkl} equals to zero when a capture system is not installed, the following inequality is used.

$$\sum_l E_{ijkl} \leq z_{ijk} E_i^{max} \quad \forall i \in F^c, \forall j, \forall k \quad (24)$$

2.1.6. Selection of CCSs

Only one capture system can be installed for each existing fossil fuel boiler. Additional constraints are added to ensure that a capture system will not be added to existing natural gas plants because the CO₂ emission is not intense for natural gas plants.

$$\sum_j \sum_k z_{ijk} \leq 1 \quad \forall i \in F^c \quad (25)$$

If an existing coal-fired boiler shuts down, no capture process will be put online.

$$\sum_k z_{ijk} \leq x_{ij} \quad \forall i \in F^c, \forall j \quad (26)$$

2.1.7. Sequestration

If CCS is put online, either for F^c or P^{new} , a CO₂ sequestration site must be determined.

$$\sum_q w_{iq} = \sum_j \sum_k z_{ijk} \quad \forall i \in F^c \quad (27)$$

$$\sum_q w_{iq} = y_i \quad \forall i \in P^c \quad (28)$$

To ensure only one sequestration location is selected for each boiler, the following inequality is used.

$$\sum_q w_{iq} \leq 1 \quad \forall i \in F^c \cup P^c \quad (29)$$

It is not reasonable for multiple boilers in the same plant to sequester to different sites.

To ensure only one sequestration site is selected for each plant with multiple boilers, the following inequality is further imposed on the model:

$$w_{iq} + w_{i'q'} \leq 1 \quad \forall i \in G_h, \forall q, i' \neq i, q' \neq q, \forall h \quad (30)$$

The following three inequalities ensure that only one pipeline is build for each power plant equipped with CCSs. Equation (31) ensures that if any boiler within the plant is selected to have sequestration to site q , u_{hq} will be equal to one.

$$u_{hq} \geq w_{iq} \quad \forall i \in G_h, \forall h, \forall q \quad (31)$$

The following inequality is used to ensure that each power plant has only one pipeline.

$$\sum_q u_{hq} \leq 1 \quad \forall h \quad (32)$$

If no boiler within plant h is being sequestered to site q , no pipeline should be built.

$$u_{hq} \leq \sum_i w_{iq} \quad \forall i \in G_h, \forall h, \forall q \quad (33)$$

2.1.8. Linearization

In VCCS, the operating cost of CCSs for F^c has a continuous variable, E_{ijl} , multiplied by a binary variable, z_{ijk} , which turns the model to a nonlinear model. We can linearize the model through an exact linearization procedure similar to the way of Hashim *et al.* (2007).

The first step is to set a new variable equal to the nonlinear term. For the operating cost of CCSs on F^c , the new variable is defined as γ_{ijkl} .

$$\gamma_{ijkl} = E_{ijl} z_{ijk} \quad \forall i \in F^c, \forall j, \forall k, \forall l \quad (34)$$

To convert γ_{ijkl} to a continuous variable, the next two constraints are used. First, γ_{ijkl} is set to a non-negative variable with an upper bound of E_{ijl} .

$$0 \leq \gamma_{ijkl} \leq E_{ijl} \quad \forall i \in F^c, \forall j, \forall k, \forall l \quad (35)$$

Secondly, γ_{ijkl} must equal zero if the binary variable z_{ijk} equals zero and γ_{ijkl} must equal E_{ijl} if the binary variable z_{ijk} is one, i.e.

$$E_{ijl} - M(1 - z_{ijk}) \leq \gamma_{ijkl} \leq Mz_{ijk} \quad \forall i \in F^c, \forall j, \forall k, \forall l \quad (36)$$

where M is any large number.

Substituting γ_{ijkl} to $VCCS$ yields the following equation

$$VCCS = \sum_{i \in F^c} \sum_j \sum_k \sum_l C_k^c \gamma_{ijkl} \theta_l \quad (37)$$

The nonlinear term exists in both Equations (22) and (23) (i.e. E_{ijl} is multiplied by z_{ijk}), and they can be linearized through the substitution of the nonlinear term with γ_{ijkl} , i.e.

$$\sum_{i \in F} \sum_j \sum_k \sum_l CO_{2ij} \theta_l (E_{ijl} - \varepsilon_i \gamma_{ijkl}) + \sum_{i \in P^{new}} CO_{2i} \theta_l E_{il} \leq (1 - \Gamma) CO_2^{current} \quad (38)$$

$$E_{ijkl} = E_{ijk}^{req} CO_{2ij} \varepsilon_i \gamma_{ijkl} \quad \forall i \in F^c, \forall j, \forall k, \forall l \quad (39)$$

2.2. Summary

The deterministic formulation of the capacity expansion model is described in this chapter. The model presented is an extension of that of Hashim *et al.* (2007). Using different structural and non-structural changes, the proposed model can help in determining the optimal system configuration for a utility company in meeting consumer demands while meeting CO₂ emission targets. One drawback of the above model is that it cannot account for uncertainty. Long term capacity expansion models for power generation should account for uncertainties because parameters such as fuel prices and electricity demands are highly uncertain in nature. To overcome this drawback, the model presented in this chapter is converted to a robust optimization model in Chapter 4.

3. Forecasting electricity demand

Forecasting is an important step in planning for any industry. It determines the quantities to be produced, the amount of raw materials to be acquired, and the capacity of a plant to be expanded. In the power generation industry, reliable forecasting is evident because the loss of load expectation should be maintained within 0.1 days/year (Ontario Power Authority [OPA], 2005b). Electric utility companies simply cannot wait for the demand to emerge and then react to it. The construction of power generators requires up to five years (Canadian Energy Research Institute [CERI], 2004). Forecasting future demand using proper techniques can ensure the inputs to planning models are more accurate.

Al-Alawi & Islam (1996) identified three main categories in load forecasting problems: 1) long term forecasting (5 to 25 years ahead) is used for system and capacity planning and is usually called annual peak load demand and energy forecast, 2) medium term forecasting (few months to few years ahead) is used for maintenance schedules and is commonly called monthly load and energy forecast, and 3) short term forecasting (few hours to few weeks ahead) is used for scheduling generating capacity and day to day operations and is commonly referred as to hourly load forecast.

This thesis will focus on long term forecasting of Ontario electricity demand. In particular, this thesis will forecast Ontario annual energy demand, annual peak load demand, and base load demand. Annual energy demand and annual peak load demand models have been developed in the past using both time series and regression approaches. Al-Alawi & Islam (1996, 1997) wrote a two part tutorial on electricity demand forecasting methodologies. They suggested that demands are heavily influenced by weather, socio-economic and demographic variables. Mohamed & Bodger (2005) developed a multiple linear regression

model for forecasting electricity consumption in New Zealand. Their model forecasted electricity consumption by using factors such as Gross Domestic Product (GDP), electricity price, and population. Soliman *et al.* (2004) found that time series models of four degree are the best models compared to other multiple linear regression models in determining the peak load demand of a big utility company in Egypt. Egelioglu *et al.* (2001) developed an electricity consumption model for Northern Cyprus based on the cost of electricity, population, and number of tourists. Independent Electricity System Operators (IESO, 2005b) of Ontario developed a set of multivariate econometric equations to estimate the relationship between energy consumption, peak load demand, and other factors such as number of employments, Ontario housing stocks, population, and weather factors.

Past literature predefines the form of the forecasting model. In reality, the factors affecting electricity consumption are unknown. In this study statistical methods in determining the factors most appropriate for forecasting electricity are used in order to ensure that the factors chosen are most suitable. For the sake of simplicity of the forecasting models, this study focuses on the development of linear models only. Different forecasting techniques such as the time series approach, simple linear regression, and multiple linear regression using different independent variables are compared for forecasting Ontario electricity demand up to year 2025. The results will provide a range of values for each dependent variable and can be inputted into a stochastic model as scenario sets, for developing a capacity expansion planning strategy. The dependent variables (the variables to be forecasted) are annual energy demand, annual summer peak load demand, and base load demand. In this study we did not attempt to forecast the annual winter peak load demand because summer peak load demand has already exceeded winter peak load demand in the past few years. Also, the summer peak load demand growth rate is greater than that of the winter peak load demand.

This phenomenon exists because more consumers are using natural gas for space heating in the winter.

The steps for forecasting Ontario annual energy demand are described in Sections 3.1 to 3.3. The results of annual peak load demand and base load demand are then shown in Section 3.4.

3.1. Data analysis

Forecasting is based on the concept that data series have underlying patterns. The first thing to do in forecasting is data analysis, through plots to visualize the patterns. The plots can tell whether the data series exhibit trend, seasonality, or are stationary.

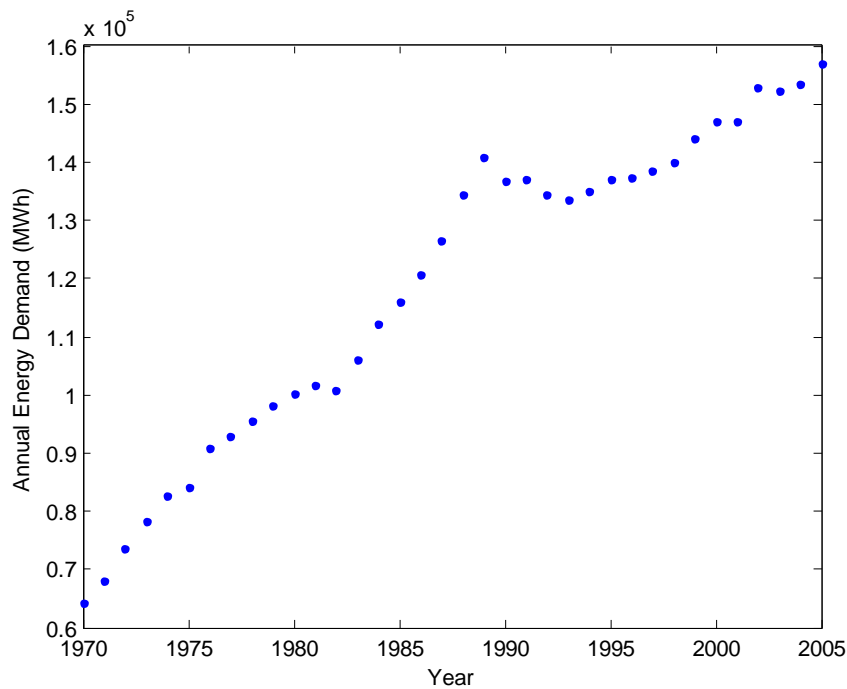


Figure 2 - Ontario's annual energy demand since 1970

Figure 2 shows the annual energy consumption of Ontario from 1970 to 2005 (Andrzej Zerek, personal communication, May 11, 2006). As expected, annual energy consumption does not have seasonality, but rather, it has a positive trend. The hump between 1988 and

1992 cannot be explained from this graph suggesting that a simple linear regression using time (i.e. year) as an explanatory variable might not yield the best model.

With all forecasting methodologies, the data series must be separated into two parts, one part for parameter estimations, or model fitting, and the other for model testing. Model testing can ensure that the developed model can produce a good prediction to the rest of the data series and is able to produce good forecasts with white noise residuals. In this study, the first 80 percent of the data was used for parameter estimations and the remaining 20 percent of the data was used for model testing.

To measure the forecasts accuracy, a number of statistics can be calculated. These measures include mean absolute error (MAE), mean squared error (MSE), and mean absolute percentage error (MAPE). The equations for these three measures are given below.

$$MAE = \frac{1}{N} \sum_{t=1}^N |e_t| \quad (40)$$

$$MSE = \frac{1}{N} \sum_{t=1}^N e_t^2 \quad (41)$$

$$MAPE = \frac{1}{N} \sum_{t=1}^N \left| \frac{e_t}{Y_t} * 100 \right| \quad (42)$$

Where N is the number of observations, e_t is the error term (i.e. $e_t = Y_t - F_t$), Y_t are the observed values, F_t are the forecasted values, and t is the time index.

To determine whether there are any remaining patterns in the residuals, Makridakis *et al.* (1998) suggested using an autocorrelation function (ACF). This is a statistical function that measures how two data series are related. In time series, the correlation is measured within the same data series at different lags and hence the name autocorrelation. ACF

shows whether the residual at time t is correlated with the residual at times $t-1$, $t-2$, and etc. If the resulting values calculated from the residuals are larger than the ACF critical value then Makridakis *et al.* (1998) suggested that some information in the series is not captured by the model.

3.2. Time series

Forecasting using time series is a well developed technique. Time series is usually used for short term load forecasting. Examples from the literature can be found in Hagan & Behr (1987), Amjady (2001), and Paarmann & Najar (1995). Soliman *et al.* (2004) suggested the use of time series analysis of order 4 to conduct long term peak load demand forecast for an Egyptian utility company.

Time series modelling explains the current demand using past data. The general form of autoregressive (AR) models is:

$$Y_t = b_1 Y_{t-1} + b_2 Y_{t-2} + b_3 Y_{t-3} \dots + b_n Y_{t-n} \quad (43)$$

In AR models, the right hand side variables are past observations of the dependent variable. Y_t is the current demand, which we wish to forecast, and depends on the demand at $t-1$, $t-2$, ... to $t-n$, where n is the order of the time series. The general notation of an AR model with order n is AR(n). For example, the model in Soliman *et al.* (2004) is an AR(4) model; the current demand depends on the past four observations.

The preferred order of the time series can be determined by using Akaike's Information Criterion (AIC) (Akaike, 1974). AIC balances the complexity of the model with the goodness of its fit to the sample data. AIC is calculated using the following formula

$$AIC = \log(V) + \frac{2d}{N} \quad (44)$$

where V is the loss function, d is the number of estimated parameters (with AR, d equals to n), and N is the number of observed values. The preferred order of the time series would be the one with the smallest AIC value.

Table 1 - AIC of different order for the annual energy demand of Ontario

Order	AIC
1	2.86
2	2.30
3	2.33
4	2.43
5	2.53
6	2.62
7	2.64
8	2.68
9	2.73
10	2.84

For Ontario annual energy demand, the AICs of orders one to ten were computed and the results are shown in Table 1. The smallest AIC value occurs at order 2, which means that an AR(2) model would be preferred over other AR models. The energy regression model using and AR(2) model was found to be

$$Energy_t = 1.684Energy_{t-1} - 0.685Energy_{t-2} \quad (45)$$

The forecasted demand and the actual energy demand are plotted in Figure 3a. Figure 3b shows the residuals, and Figure 3c shows the ACF. The vertical dashed line on the graphs separates the fitting data (on the left) and the testing data (on the right). Looking at the residuals and the ACF, there is no trend or correlation indicating that the residuals yield white noise. A statistical analysis of the above model will be discussed in Section 3.5 along with the detailed comparison to other forecasting models.

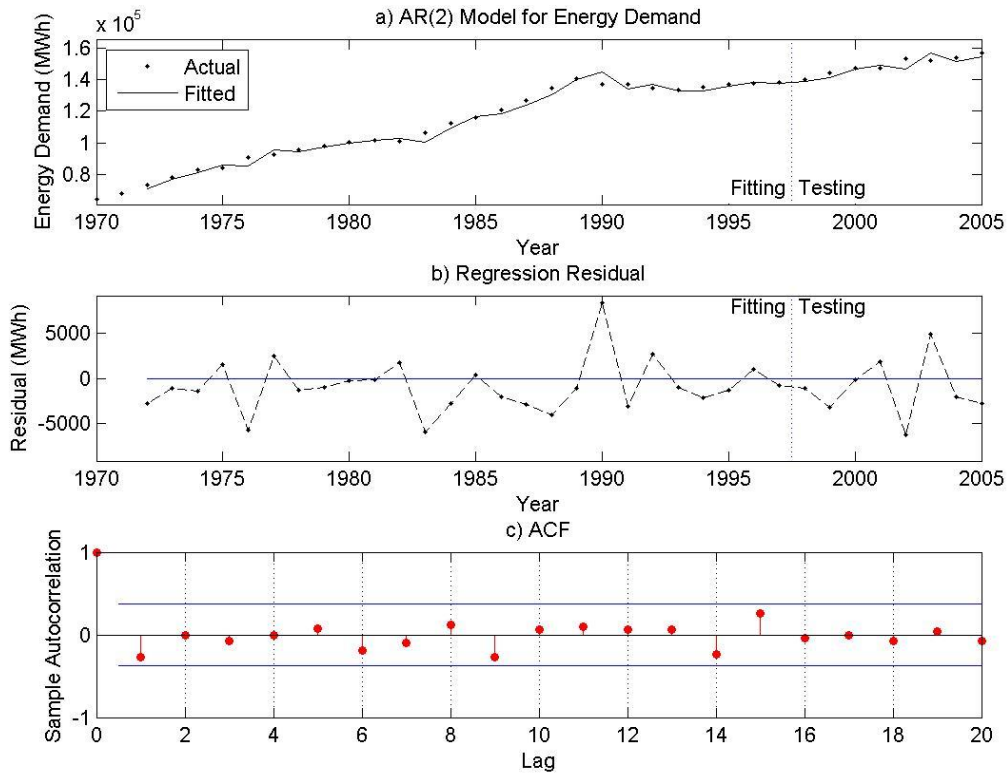


Figure 3 - AR(2) model for energy demand

3.3. Regression

Most of the time, load and energy demand depends on other variables; these variables are called explanatory variables. For short term forecasts, load and energy demand are correlated with weather, time of the day (e.g. morning, evening, and overnight), day of the week (e.g. weekdays and weekends), and holidays. For medium term forecasts, load and energy demand are correlated with weather and season. Socio-economic variables such as gross domestic products (GDP) and population of the region tend to have an impact on long term forecasts. Nonlinear relationship of the form $f(\text{GDP, population, peak load demand})$, and $f(\text{energy demand, temperature, GDP, population})$ can therefore be employed to forecast energy and load demand, respectively. Such econometric models are beneficial in understanding the system economic and are able to deal with interdependencies. However, their complexity do not necessary provide a better forecast than simple statistical

techniques. Two difficulties of such models are technical issues regarding equation specifications and the cost for the amount of data, computing, and human resources (Makridakis *et al.*, 1998). In this study, simpler regression techniques with year as the explanatory variable and with economic, demographic, and weather factors as explanatory variables are used instead of econometric models. The results of these regression models are compared with the time series model described earlier in Section 3.2.

3.3.1. *Simple linear regression*

Simple linear regression has a form of

$$Y = a + bx \quad (46)$$

where a is the intercept, b is the coefficient of the explanatory variable, and x is the explanatory variable. For simple linear regression, x represents year. Figure 2 that was discussed earlier shows a positive linear trend in energy consumption. A simple linear regression using year as an explanatory variable can, therefore, suggest how energy consumption changes as years past. In autoregression, the model relates past consumption with the demand of the current year. This simple linear regression will relate the year with energy consumption. Two regression models using year as an explanatory variable were developed: 1) using data from 1970 to 2005 and 2) using data from 1993 to 2005. The second regression model uses data since 1993 because the hump in Figure 2 diminishes in 1993 and the energy consumption seems to be linear since. The model using data since 1970 is:

$$Energy_t = -5.66 * 10^6 + 2906 year_t \quad (47)$$

and the regression model using data since 1993 is

$$Energy_t = -3.86 * 10^6 + 2004 year_t \quad (48)$$

Figure 4a and Figure 5a show the results of equation 47 and 48 respectively. Figure 4b and Figure 5b show the residual of the models. Looking at Figure 4c, the ACF plot shows

correlation with different lag indicating some information is missing from the model. Figure 5c didn't show any correlation with other lags, and therefore, the simple regression model using data from 1993 has a better fit.

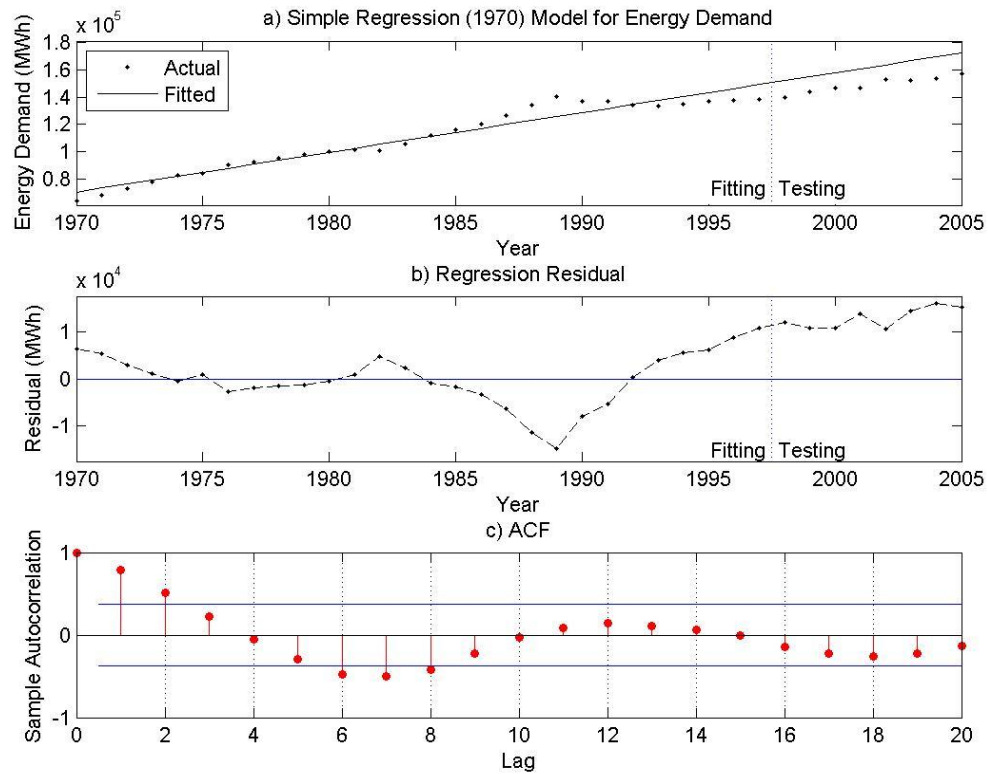


Figure 4 – Simple regression model for energy demand (from 1970)

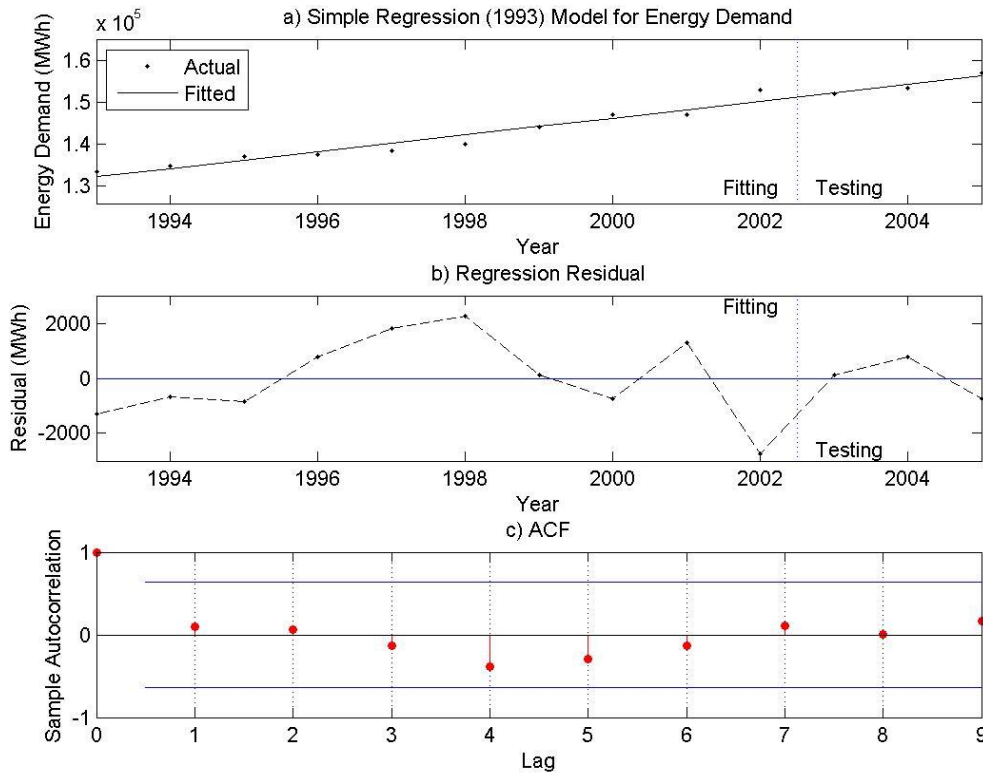


Figure 5 –Simple regression model for energy demand (from 1993)

As with the time series model, there is no underlying information provided with this type of regression. To understand the underlying effects, it is more desirable to use multiple linear regression with more representative variables.

3.3.2. *Multiple linear regression*

As mentioned before, the development of multiple linear regressions uses economic, demographic, and weather variables for long term electricity demand forecasting. The general form of a multiple linear regression model can be written as

$$Y = a + \sum_i b_i x_i \quad (49)$$

where

b_i is the coefficient for explanatory variable i

x_i is explanatory variable i

i is the set of explanatory variables

The list of potential explanatory variables are GDP, GDP per capita (GDPpp), number of employments, population, dwelling counts, heating degree days (HDD), and cooling degree days (CDD). These data are obtained from CANSIM II, Statistics Canada's key socio-economic database, and Environment Canada (2005).

Degree days (DD) measures how hot or cold the weather has been for a particular day.

HDD measures how cold the weather has been and is defined as:

$$HDD_d = \max\{0, T_b - T_d\} \quad (50)$$

where,

T_b is the base temperature, which was chosen 10°C in this study

T_d is the mean temperature of a given day

d is the number of days into the year

HDD_d is the heating degree days in day d

and CDD, measures how hot the weather has been, i.e.

$$CDD_d = \max\{0, T_d - T_b\} \quad (51)$$

where,

T_b is the base temperature, which was chosen to be 20°C in this study

CDD_d is the cooling degree days in day d

Knowing HDD_d and CDD_d can help in determining the annual HDD and CDD. The summation of HDD_d and CDD_d for the whole year will yield the annual HDD and CDD. From here onward, we will denote annual HDD and CDD as HDD and CDD , respectively. HDD and CDD are potential explanatory variables in forecasting the annual energy demand by estimating the weather in a particular year. For annual peak load demand, maximum CDD_d ($MaxCDD$), the hottest day in a year, is a potential explanatory variable.

Ontario's climate varies from one region of the province to another. To get the average DD of Ontario, we took a weighted average based on dwelling counts. DD accounts for how

much electricity is required for space heating and space cooling; dwelling counts in each region approximates the indoor area to heat or cool.

Ontario is separated in thirteen regions for calculating the weighted average DD: 4 regions in Southwestern Ontario, 3 regions in Central Ontario, 2 regions in Eastern Ontario, 2 regions in Northeastern Ontario, and 2 regions in Northwestern Ontario. The DD in each region is described by a representative city. The weighted average is:

$$DD = \sum_r \frac{dwelling_r}{Total\ dwelling} DD_r \quad (52)$$

where,

DD is the weighted average of annual or maximum degree days (HDD , CDD , or $MaxCDD$)

$dwelling_r$ is the dwelling counts in region r

$Total\ dwelling$ is the dwelling counts in Ontario

DD_r is the annual or maximum degree days (HDD , CDD , or $MaxCDD$) in region r

r is the set of regions

The regions, representative cities, and percentage of dwelling counts in each region are listed in Table 2.

Table 2 - Data for calculating the weighted average DD

Region	Representative City	Percentage (dwelling counts)
Southwestern	Windsor	4.28%
	London	8.46%
	Kitchener	6.44%
	Owen Sound	1.74%
Central	Hamilton	11.01%
	Toronto	36.96%
	Barrie	4.91%
Eastern	Peterborough	4.79%
	Ottawa	12.84%
Northeastern	Sudbury	4.91%
	Timmins	1.20%
Northwestern	Thunder Bay	1.53%
	Kenora	0.92%

The other five potential variables are economic and demographic variables. These variables should provide a strong relation with load and energy demands. To investigate the relationships between the variables, relational plots can be used. Figure 6 shows the relationship between annual energy demand and GDP. The plot shows discontinuity near 130 TWh. Two different linear relationships can be seen prior and after this point.

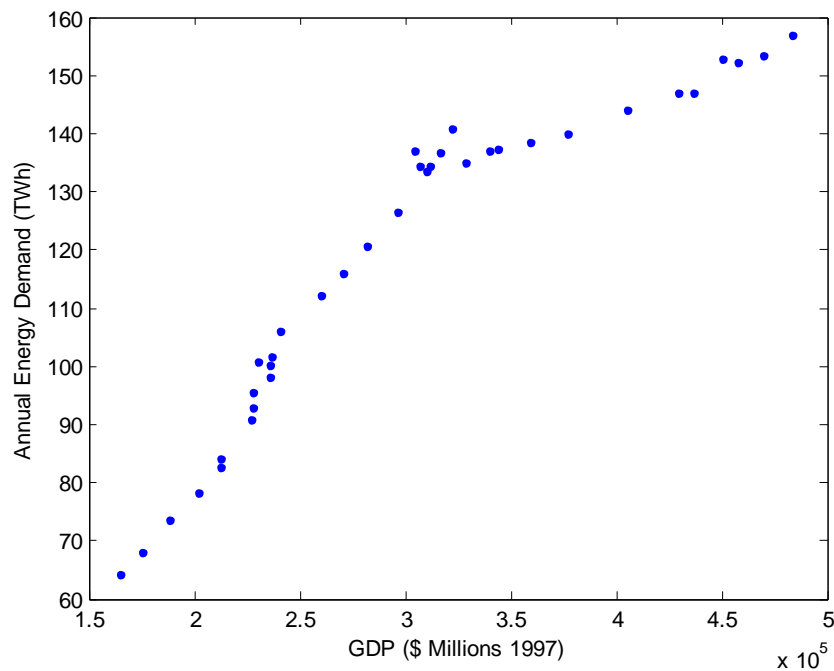


Figure 6 - Annual energy demand as a function of GDP

To examine the relationship as a time series, GDP per annual energy demand (TWh) versus year is plotted in Figure 7. The figure suggests that energy demand in Ontario has gone through three phases. In the first phase, electricity productivity decreases, meaning the electricity consumption increases faster than economic growth. In the second phase, the electricity growth and economic growth are coupled. In the last phase, electricity productivity improves. A report by ICF Consulting ([ICF], 2005) also suggests that Ontario went through different demand phases. The report suggests some reasons as to why the economy becomes more electricity efficient but very little research has been done to understand the relative importance. We decided to forecast Ontario electricity demand (i.e. annual energy demand, annual peak load demand, and annual base load demand) based on data since 1993, the beginning of the third phase, since there is not enough data to quantitatively analyze the historical trends in Ontario (ICF, 2005).

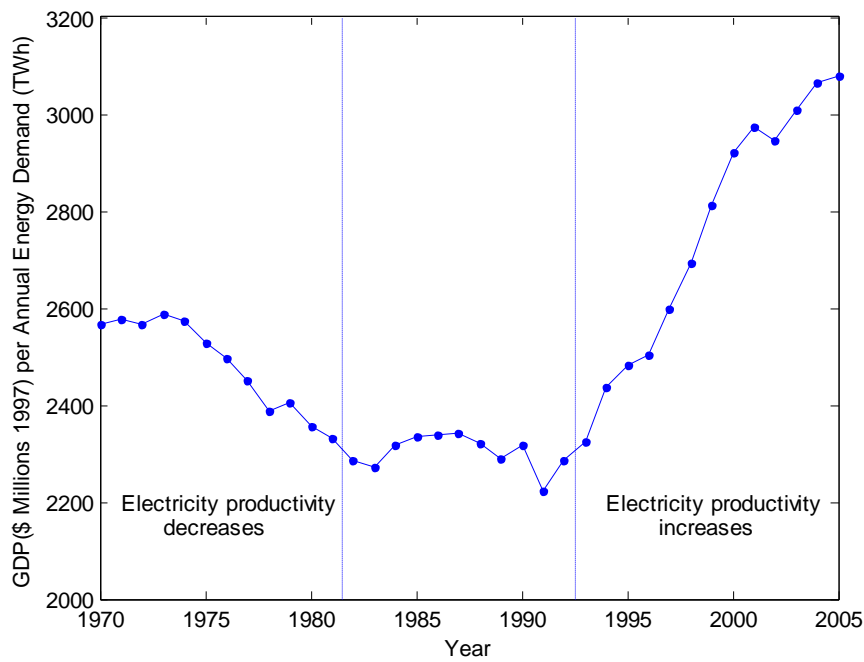


Figure 7 - GDP per annual energy demand (TWh)

Scatterplots for each combination of variables were generated and it was found that all economic and demographic variables have strong linear relations with load and energy demands. The scatterplots also showed strong linear relationships among the explanatory variables. This phenomenon is called collinearity (Miles & Shevlin, 2001 and Makridakis *et al.*, 1998). Stepwise regression to choose a subset of the variables was employed.

The procedure adds or removes the most or least statistically significant term, the one with the lowest or highest p-value, until there are none left. The p-value is recalculated on the residuals after each step. The entering p-value is set at 0.05 and the exiting p-value is set at 0.10 while formulating the regressions. The set of variables considered in stepwise regression is listed in Table 3.

Table 3 – Variables used in the stepwise regression procedure

GDP	$\ln(\text{GDP})$
GDP per capita	$\ln(\text{GDP per capita})$
Number of Employment	$\ln(\text{Number of Employment})$
Dwelling counts	$\ln(\text{Dwelling counts})$
Population	$\ln(\text{Population})$
Year	$\ln(\text{year})$
<i>HDD</i>	<i>CDD</i>
<i>MaxCDD</i> (for peak load demand)	

Defining different initial variables to be included in the first step of stepwise regression will yield different regressions. Several models were generated after experimenting with different initial variables. The resulting regression models are listed in Table 4.

Table 4 – Possible multiple linear regression models for energy demand

Dependent Variable	Explanatory Variables	Have negative coefficient?	MAE (MWh)		
			Fitting Data	Fitting + Testing Data	Testing Data
Energy	$a + b_1 * \text{Employment} + b_2 * HDD + b_3 * CDD$	No	661	755	1167
	$a + b_1 * \text{GDP}$	No	889	1034	1825
	$a + b_1 * \ln(\text{Employment})$	No	942	956	1453
	$a + b_1 * \text{Employment}$	No	855	918	1485
$\ln(\text{Energy})$	$a + b_1 * \text{Employment} + b_2 * (HDD * \text{Dwelling}) + b_3 * (CDD * \text{Dwelling})$	No	648	803	1328
	$a + b_1 * \text{Employment} + b_2 * HDD + b_3 * CDD$	No	597	819	1505
	$a + b_1 * \text{GDP}$	No	836	934	1608
	$a + b_1 * \text{Employment}$	No	813	899	1503
	$a + b_1 * \ln(\text{Employment})$	No	875	917	1469
	$a + b_1 * \ln(\text{GDP})$	No	959	1247	2432

The following approach was used in order to select the most appropriate model:

1. Remove all models with negative coefficients for any of the selected explanatory variables since it is not logical. (e.g. an increase in employment or dwelling counts will not decrease the energy demand)
2. Select models within the lowest MAE range for fitting data. To find the lowest range, plot the MAE for all models. Looking at Figure 8, a break in MAE values for the seven models is observed after the third model. After this step, the possible set of regression models that remain to be considered has decreased to three models with MAE lower than 700 MWh.

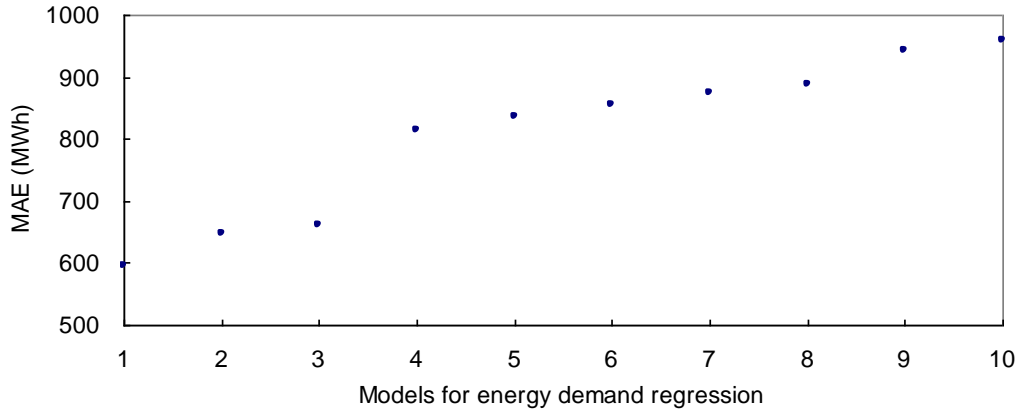


Figure 8 - MAE of possible energy demand regression models

3. From here, select the model with lowest MAE for all data (fitting and testing data).

Using the above selection approach, the final regression model for Ontario annual energy demand was chosen to be:

$$Energy_t = 47204.178 + 15.345 Employment_t + 3.877 HDD_t + 15.965 CDD_t \quad (53)$$

Energy demand in Ontario for a given year is therefore a function of number of employments, *HDD*, and *CDD* of the same year. An analysis of this model is shown in Figure 9. The residuals and ACF plot indicate that the model produces white noise residuals.

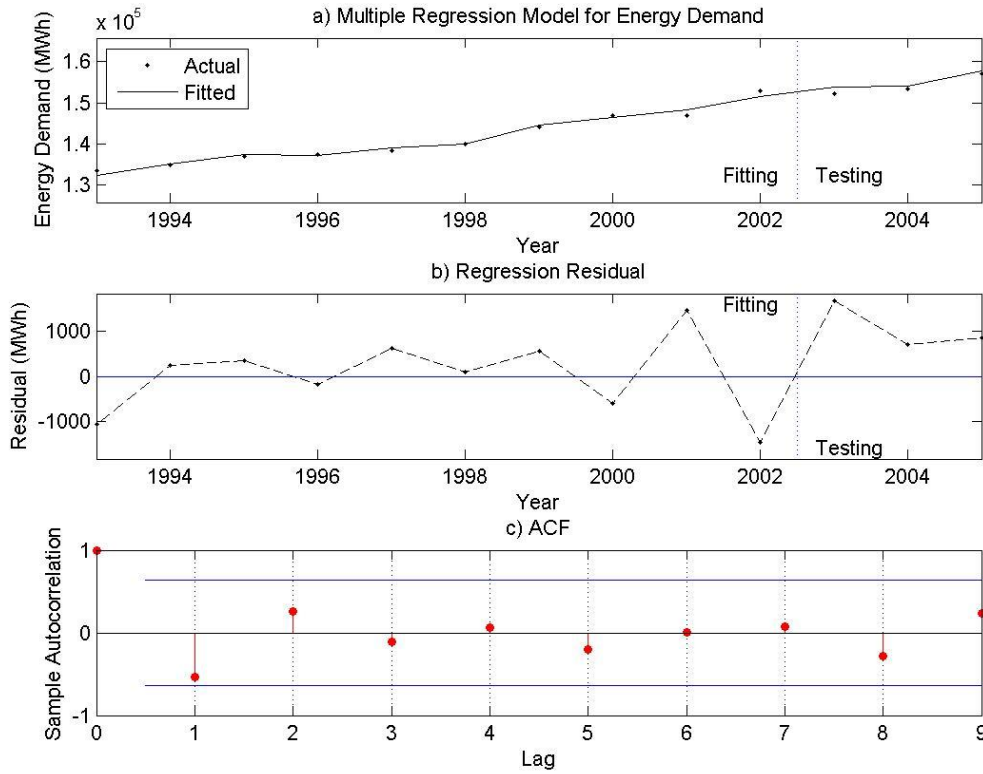


Figure 9 - Multiple regression model for energy demand

3.4. Regression models for annual peak load demand and base load demand

Regression models for annual peak load demand and base load demand were also developed using the same methodologies described in the previous section and are presented here. The MAE of all regression models will be presented and compared in the next section. After the comparison, the best regression model representing the annual energy demand, annual peak load demand, and base load demand will then be selected.

Figure 10 shows the annual peak load demand of Ontario since 1970 (Andrzej Zerek, personal communication, May 11, 2006). The figure shows a positive linear trend with no hump. From the calculation of AIC, for order one to ten, the autoregressive model should have an order of three. The formula of the AR(3) model obtained is:

$$Peak_t = 1.137 Peak_{t-1} + 0.3555 Peak_{t-2} - 0.4962 Peak_{t-3} \quad (54)$$

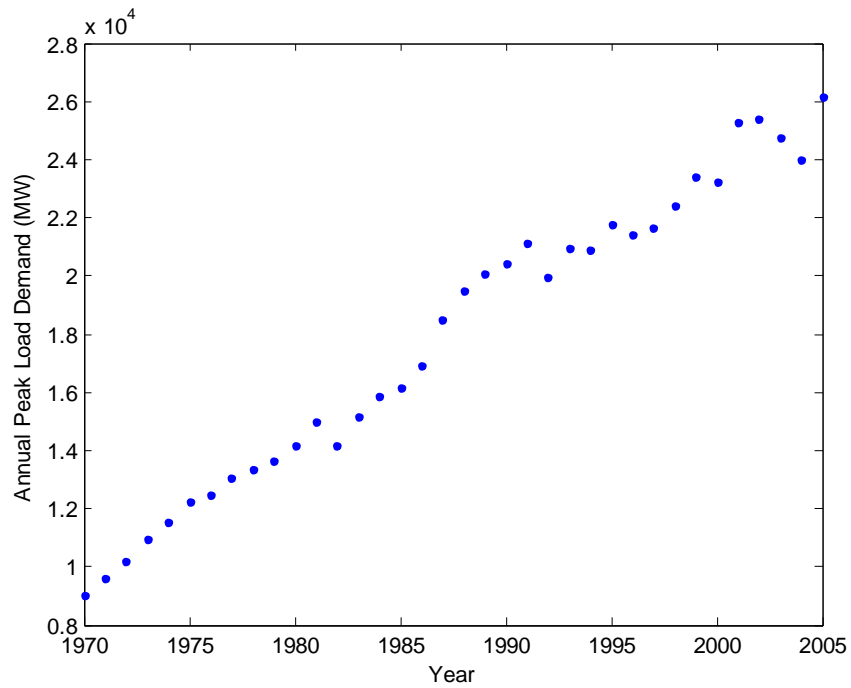


Figure 10 – Ontario’s annual peak load demand since 1970

Figure 11 shows the results, the residuals, and the ACF plot of the AR(3) model. As with the figures of Section 3.2 and 3.3, the vertical dashed line in the graphs separates the fitting data (on the left) and the testing data (on the right).

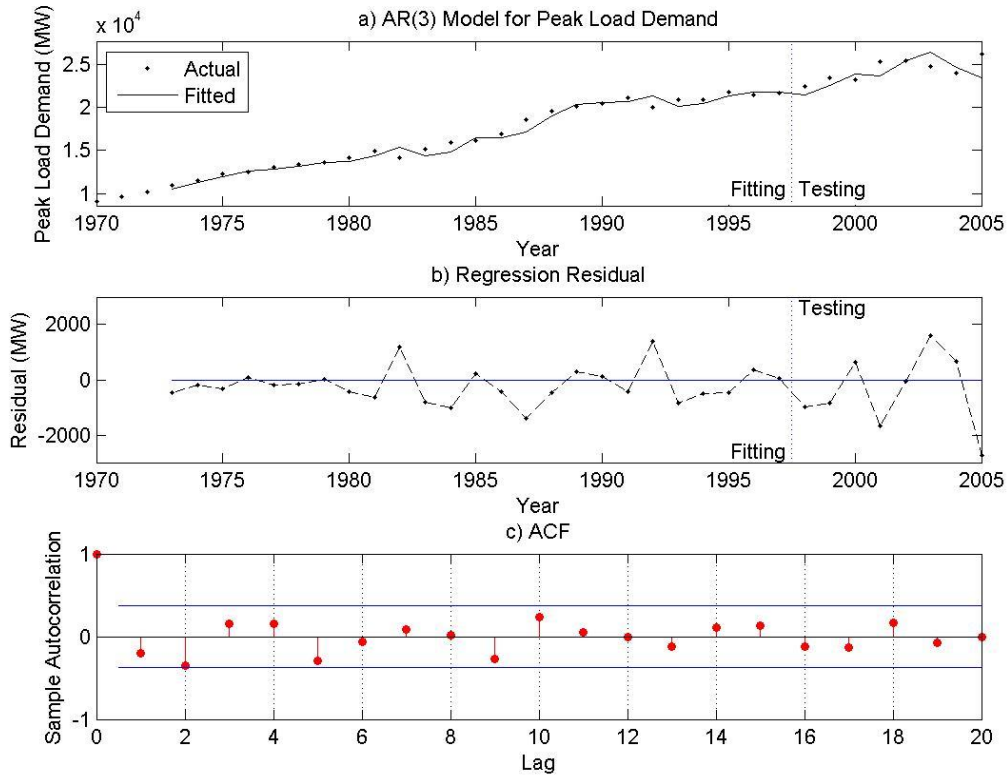


Figure 11 - AR(3) model for peak load demand

This study also developed two simple linear regression models for the annual peak load demand: using data since 1970 and using data since 1993. Figure 10 shows a linear trend since 1970 but since Ontario electricity productivity has increase since 1993 (see Figure 7), doing simple linear regression using data starting from 1993 is more accurate. The regression model using data since 1970 is

$$Peak_t = -9.73 * 10^6 + 498.8 year_t \quad (55)$$

and the regression model using data since 1993 is

$$Peak_t = -1.00 * 10^6 + 513.8 year_t \quad (56)$$

The above two models are analysed in Figure 12 and Figure 13, respectively. Looking at Figure 12c we can conclude that the simple linear regression from 1970 is not an accurate model because some lags lie outside the ACF critical value.

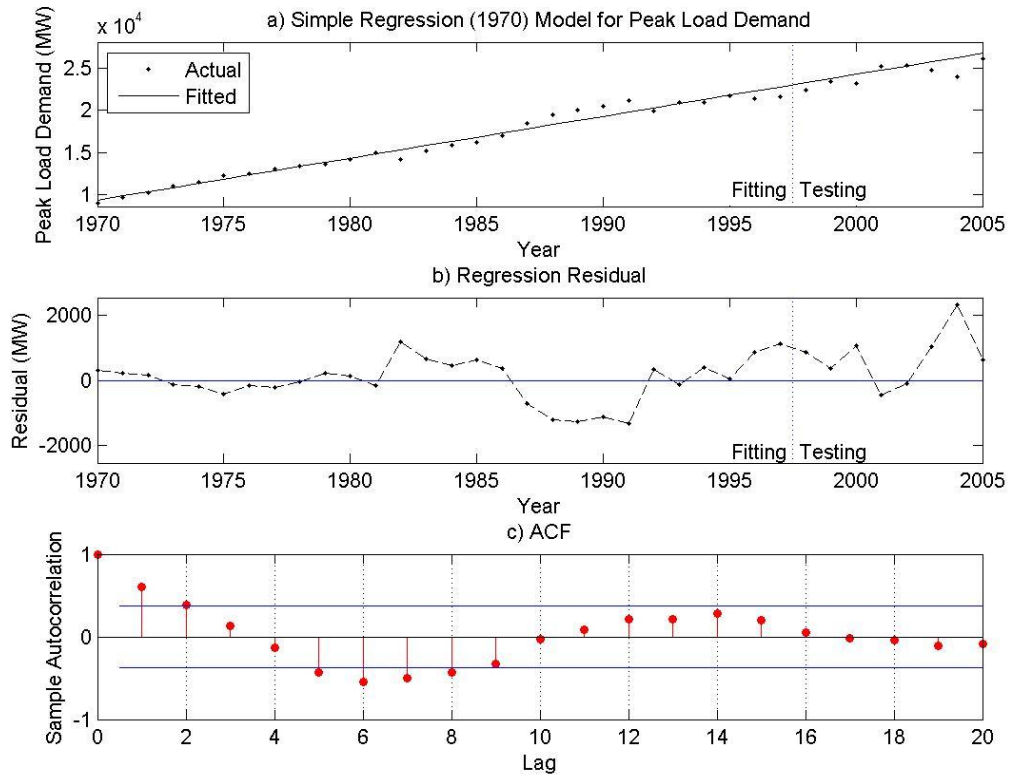


Figure 12 – Simple regression model for peak load demand (from 1970)

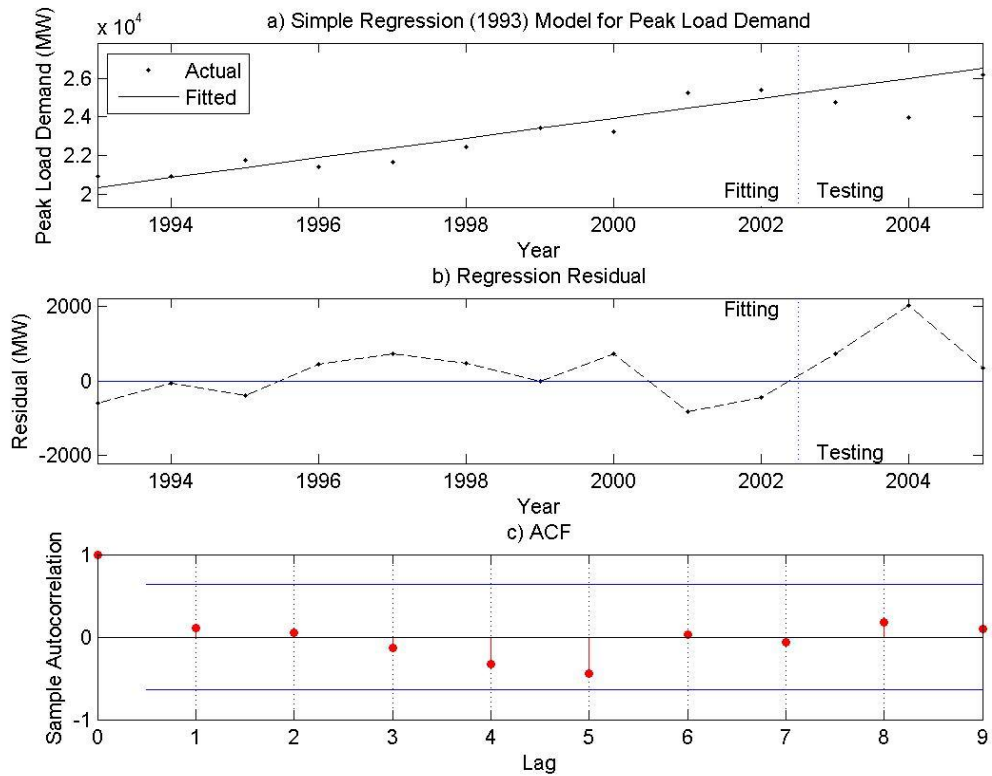


Figure 13 – Simple regression model for peak load demand (from 1993)

Using stepwise regression, different multiple linear regression models for peak load demand are developed. All possible regressions are listed in Table 5. Using the selection approach described in Section 3.3.2, the multiple linear regression model shown in Figure 14 and equation 57 was selected.

$$\ln(Peak_t) = 9.054 + 1.62 * 10^{-4} Employment_t + 1.20 * 10^{-2} MaxCDD_t \quad (57)$$

Table 5 - Possible multiple linear regression models for peak load demand

Dependent Variable	Explanatory Variables	Have negative coefficient?	MAE (MWh)		
			Fitting Data	Fitting + Testing Data	Testing Data
Peak load	$a + b_1 * Employment + b_2 * MaxCDD$	No	179	304	582
	$a + b_1 * Population + b_2 * MaxCDD$	No	206	367	686
	$a + b_1 * Employment + b_2 * GDP + b_3 * MaxCDD$	Yes	142	451	1132
	$a + b_1 * Population + b_2 * Dwelling + b_3 * MaxCDD$	Yes	157	270	531
$\ln(Peak \text{ load})$	$a + b_1 * Employment + b_2 * MaxCDD$	No	157	318	671
	$a + b_1 * Employment + b_2 * GDP + b_3 * MaxCDD$	Yes	126	468	1220
	$a + b_1 * Employment + b_2 * \ln(MaxCDD)$	No	155	334	718

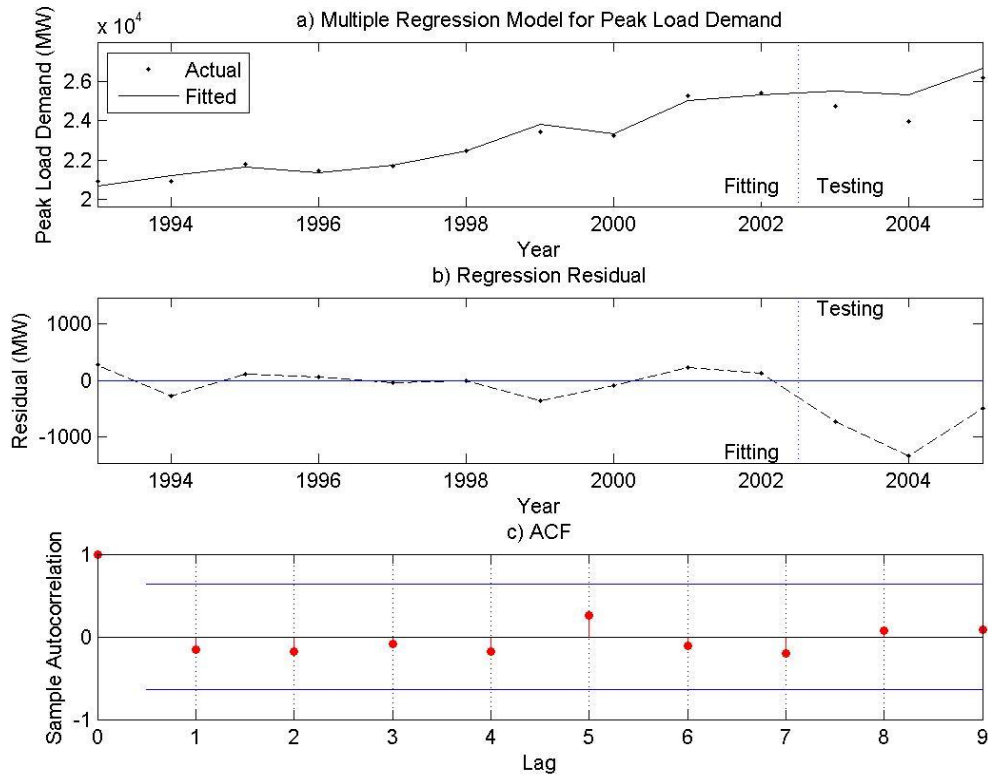


Figure 14 – Multiple regression model for peak load demand

Base load demand data from 1987 to 2004 is obtained from IESO (2005a) and is plotted in Figure 15. The time series also shows a positive trend. AR, simple linear regression, and multiple linear regression models were developed for base load demand.

AIC suggested an AR(4) be used for the time series. Simple regression using data since 1970 and 1993 and multiple linear regression were also developed.

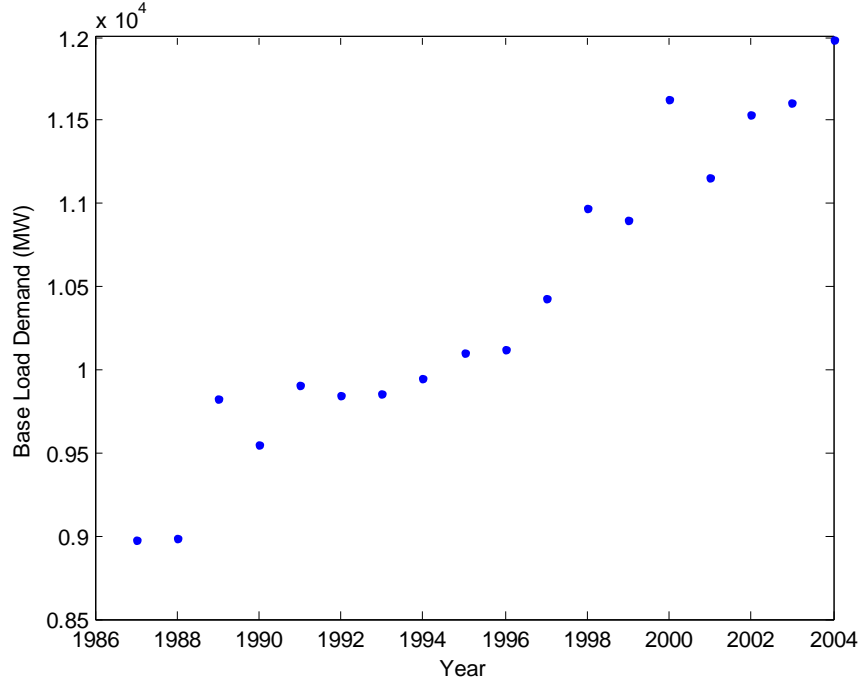


Figure 15 – Ontario's base load demand since 1987

Table 6 shows all possible multiple linear regression models generated using stepwise regression. The results are plotted in Figure 16 to Figure 19. The residuals of all four models did not exhibit any significant correlation with other lags. The formula of the AR(4) model is

$$Base_t = 0.7823Base_{t-1} + 0.7662Base_{t-2} - 0.09968Base_{t-3} - 0.4475Base_{t-4} \quad (58)$$

the regression model using data since 1970 is

$$Base_t = 3.13 * 10^5 + 162.2 year_t \quad (59)$$

the regression model using data since 1993 is

$$Base_t = -4.11 * 10^5 + 211.0 year_t \quad (60)$$

and the multiple regression model is

$$Base_t = -6.60 * 10^4 + 8.91 * 10^3 \ln(Employment_t) \quad (61)$$

Table 6 - Possible multiple linear regression models for base load demand

Dependent Variable	Explanatory Variables	Have negative coefficient?	MAE (MWh)		
			Fitting Data	Fitting + Testing Data	Testing Data
Base load	$a + b_1 * \text{Dwelling}$	No	180	231	364
	$a + b_1 * \text{Employment}$	No	132	149	230
	$a + b_1 * \text{GDP}$	No	148	136	146
	$a + b_1 * \text{GDPpp}$	No	151	154	179
	$a + b_1 * \ln(\text{Dwelling})$	No	182	217	316
	$a + b_1 * \ln(\text{Employment})$	No	133	134	179
	$a + b_1 * \ln(\text{GDP})$	No	156	140	132
	$a + b_1 * \ln(\text{GDPpp})$	No	153	163	200
$\ln(\text{Base load})$	$a + b_1 * \text{Dwelling}$	No	176	252	440
	$a + b_1 * \text{Employment}$	No	134	166	282
	$a + b_1 * \text{GDP}$	No	148	137	152
	$a + b_1 * \text{GDPpp}$	No	149	147	164
	$a + b_1 * \text{Population}$	No	163	218	374
	$a + b_1 * \ln(\text{GDPpp})$	No	151	157	187

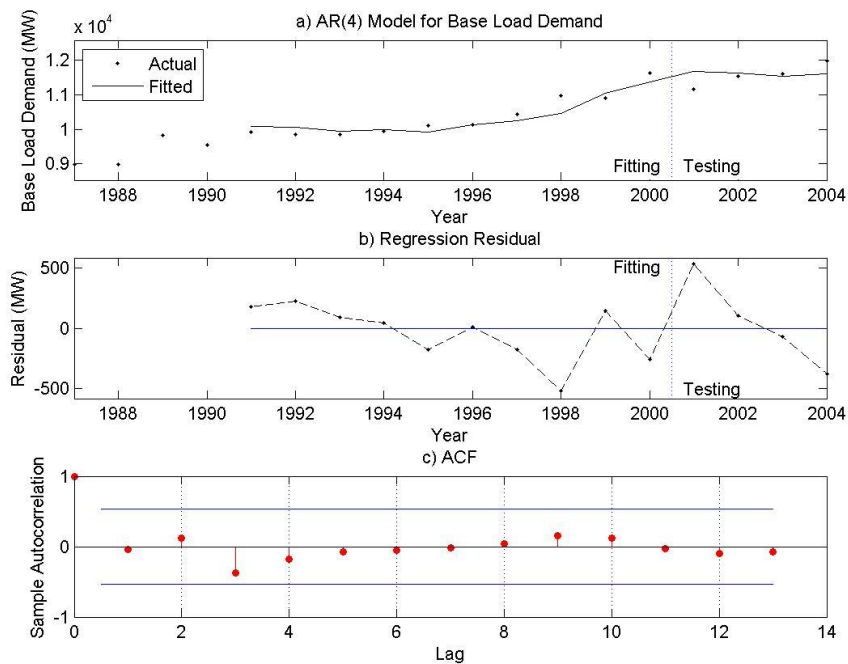


Figure 16 - AR(4) model for base load demand

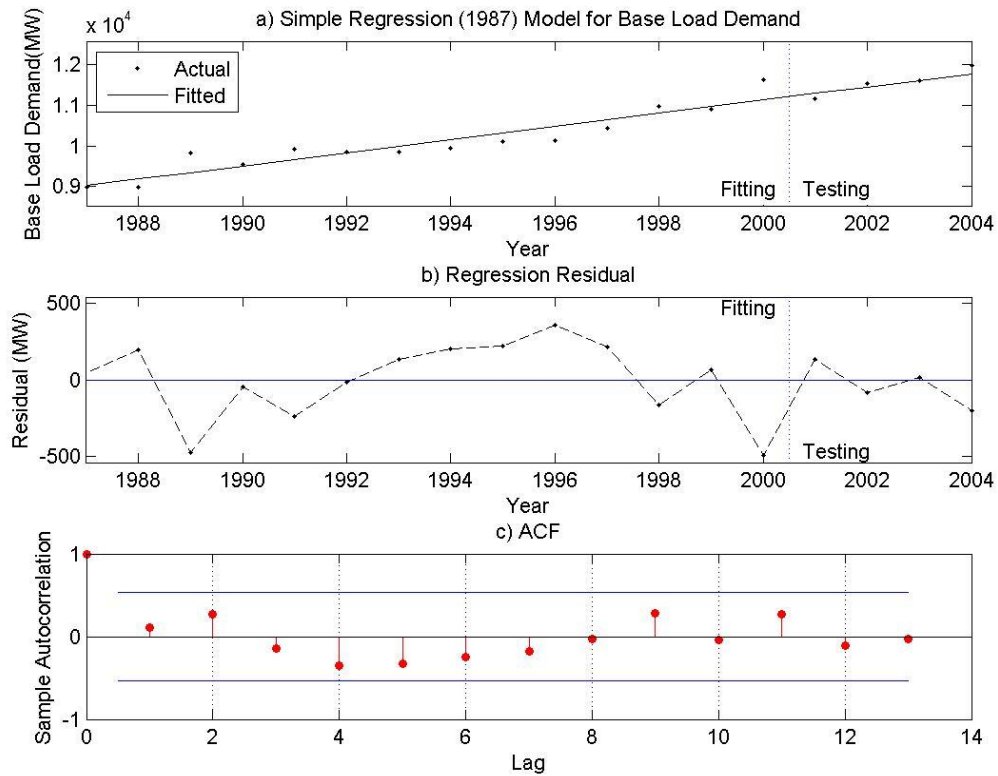


Figure 17 – Simple regression model for base load demand (from 1987)

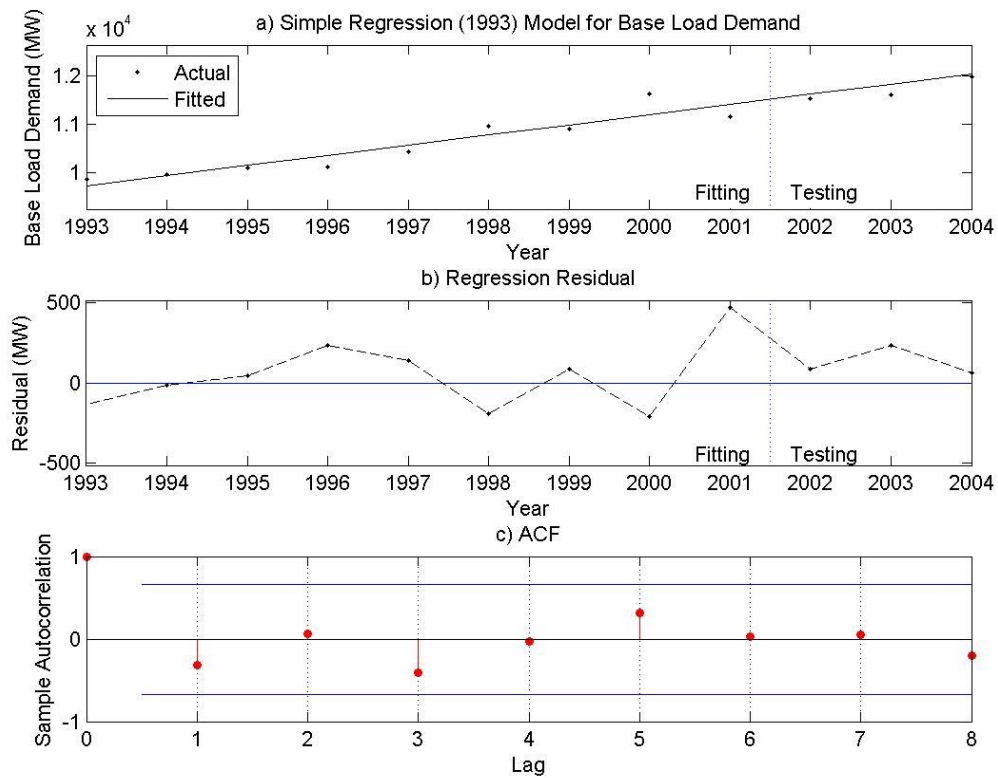


Figure 18 – Simple regression model for base load demand (from 1993)

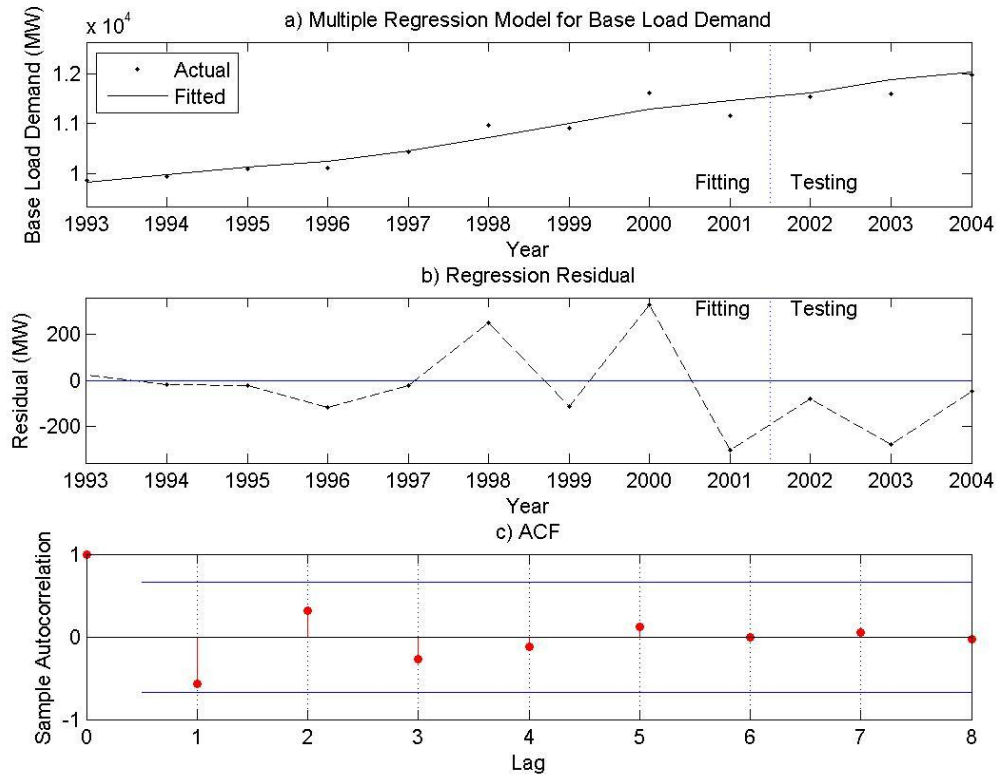


Figure 19 – Multiple regression model for base load demand

3.5. Comparisons of models

Comparisons were made among the four different regression models: AR, simple linear regression (using data since 1970 and data since 1993), and multiple linear regression. To see which model yielded the most accurate results, we looked at MAE, MSE and MAPE. The mean errors in Table 7 are calculated using the entire set of data (both fitting and testing data). Simple linear regression using data from 1970 for energy and peak load demand are not included because the ACF plots suggested that these two models have autocorrelation and hence they are not accurate models. Multiple linear regression was chosen to be the best model in all instances because the mean error values are the lowest among different forecasting methods.

Table 7- Comparisons between models

	MAE	MSE	MAPE
Energy Demand Models			
Multiple Regression	755	813810	0.52%
Regression from 1993	1096	1764470	0.76%
AR(2)	2382	9194313	2.00%
Peak Load Demand Models			
Multiple Regression	318	225697	1.34%
Regression from 1993	600	581434	2.57%
AR(3)	656	763922	3.38%
Base Load Demand Models			
Multiple Regression	134	31552	1.20%
Regression from 1987	184	53074	1.77%
Regression from 1993	159	38884	1.45%
AR(4)	207	67567	1.90%

3.6. Forecasting electricity to year 2025

Forecasting results can be inputted into a stochastic model as a set of scenarios. With employment forecasts from Ontario Ministry of Finance (2005) and different weather scenarios, different electricity demand can be forecasted. The lower bound on the forecast uses low employment growth rate with mild weather scenarios; the upper bound on the forecast uses high employment growth rate with extreme weather scenarios. The values of mild weather scenario are the minimum *HDD*, *CDD*, and *MaxCDD* from 1978 to 2005; the values of extreme weather scenario are the maximum *HDD*, *CDD*, and *MaxCDD* from 1978 to 2005. Figure 20 to Figure 22 show the forecast of annual energy, peak load, and base load demand from 2006 to 2025, respectively. The figures show the upper and lower bound, the median forecast (using median employment growth and median weather values), and IESO (2005a) forecast.

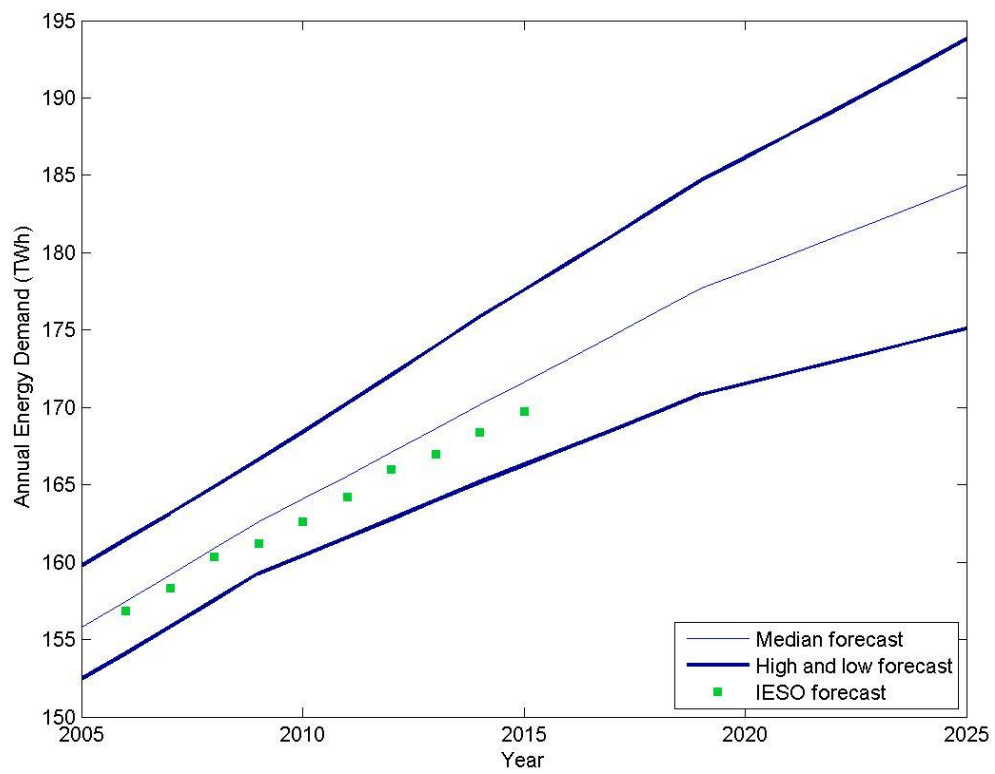


Figure 20 – Annual energy demand forecast to 2025

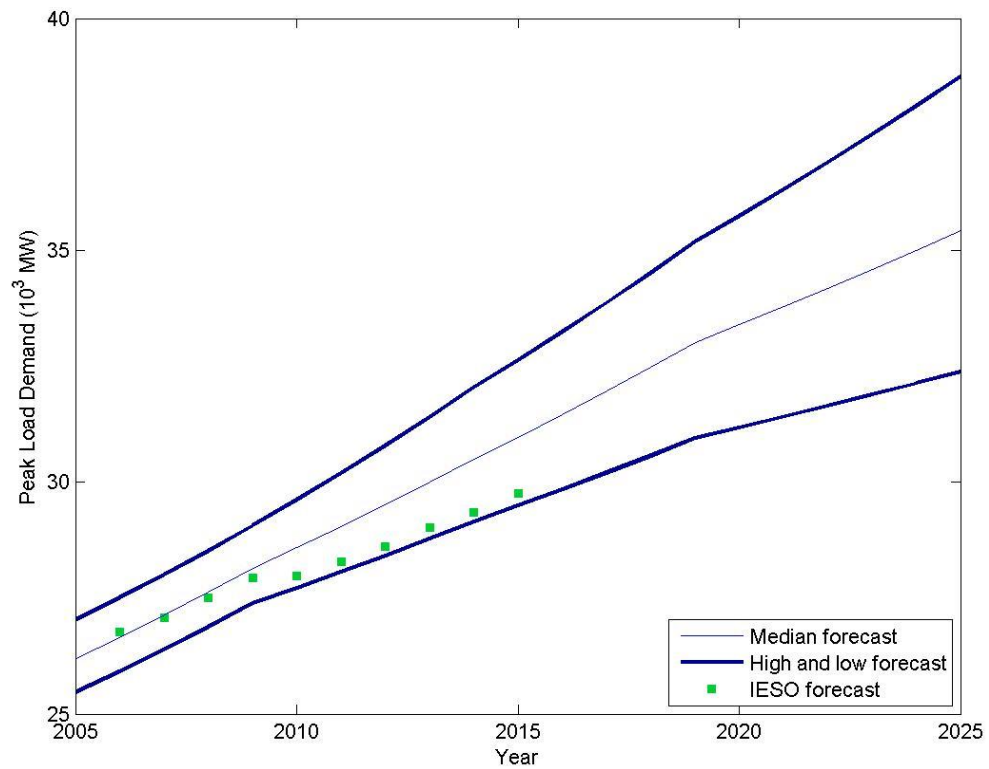


Figure 21 – Peak load demand forecast to 2025

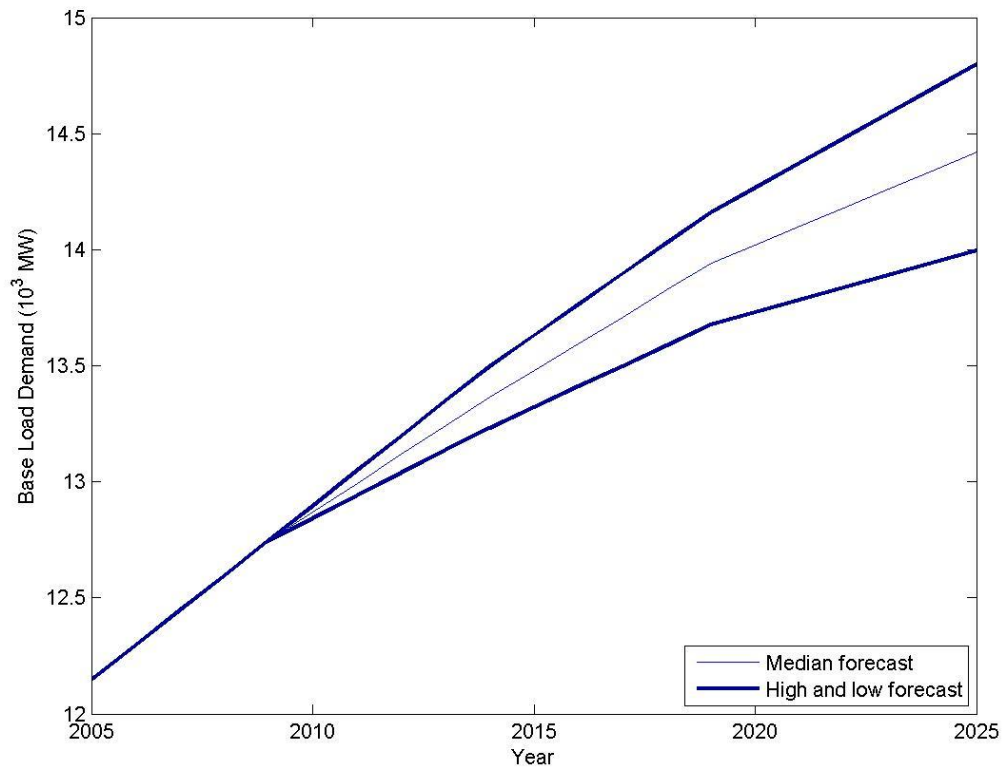


Figure 22 – Base load demand forecast to 2025

In Ontario, provincial electricity forecasts are published by IESO. IESO (2005b) uses multivariate econometric equations to estimate the relationship between different factors and electricity demands. In 2005, IESO forecasted the energy and peak load demand for years 2006 to 2015. Their forecast lies within the range of our proposed forecast. For annual peak demand, IESO forecasts lie near the lower bound of the proposed forecast after 2010. It might be because they assume large conservation efforts will take effect starting from 2010. In 2010, the Smart Meters program will be in place and will require all consumers to install a Smart Meter (PowerWise, 2006). Smart Meters will allow distribution companies to track the time and interval use of electricity. By adjusting the price of electricity during peak hours, it will encourage consumers to use less electricity during those hours.

The models presented here did not account for the conservation efforts that the Government of Ontario is persuading. In 2004, the Government of Ontario established the Conservation Bureau to develop a provincial wide electricity conservation program (Conservation Bureau, 2006). Since the program has only been in place for one year, it is unsure how electricity usage will get altered in the future.

In 2025, the annual energy demand lies within the range 175 TWh to 194 TWh; the annual growth rate ranges from 0.7% to 0.97%, and peak load demand will range from 32,300 MW to 38,800 MW, which represents a 1.21% to 1.82% annual growth. The base load demand will be between 14,000 and 14,800 MW in 2025, this represents a growth rate between 0.71% and 0.99% annually. To incorporate these results into a stochastic model, we take the values in 2025 and assume uniform distributions. Therefore, the probabilities and values of the scenario sets can be established.

3.7. Summary

Stochastic models require a scenario set. Using forecasting techniques, this study generates scenario sets to input to stochastic models instead of selecting arbitrary values as done in past literature. Comparing different forecasting techniques such as autoregressive models, simple linear regression, and multiple linear regression, it is shown that multiple linear regression most accurately describe Ontario electricity demands. Three models were developed: annual energy demand, peak load demand, and base load demand. It was found that by the year 2025, annual energy demand will range from 175 TWh to 194 TWh, peak load demand will range from 32,300 MW to 38800 MW, and base load demand will range from 14,000 MW to 14,800 MW. Using these ranges, a scenario set is generated by assuming uniform probability distributions.

4. Robust optimization

Capacity expansion models have two distinct components: structural and control (Mulvey *et al.*, 1995 and Malcolm & Zenios, 1994). The structural component is fixed and free of noise from the inputs while the control component is subjected to noisy input data. Two types of decision variables are usually used in this type of models: design and control variables. Design variables, part of the structural component, determine the structure and the size of the process. These variables are fixed and can not be adjusted once a specific realization of the data is observed. Control variables, part of the control component, state the mode and level of production. These variables can be adjusted after observing the values of the uncertain parameters. The optimal value of a control variable depends on the observation of the uncertain parameters and the optimal value of the design variables. In the models within this section, the design and the control variables are denoted by $x \in R^{n_1}$ and $y \in R^{n_2}$, respectively. To illustrate, let's consider the following deterministic model [P1]:

$$[P1] \quad \text{Minimize} \quad c^T x + d^T y \quad (62)$$

$$\text{subject to} \quad Ax = b \quad (63)$$

$$Bx + Cy = e \quad (64)$$

$$y \geq 0 \quad (65)$$

$$x \in \{0,1\}^{n_1}, y \in R^{n_2}$$

Equation (63) is the structural constraint, meaning that the coefficients are fixed and free of noise. Equation (64) is the control constraint, meaning that the coefficients are subject to noise.

A scenario set, $s = \{1, 2, \dots, S\}$, is introduced to define the robust optimization problem. For each scenario, $s \in S$, the coefficients in the control constraints will become $\{d_s, B_s, C_s, e_s\}$ with a probability of p_s , where $\sum_{s \in S} p_s = 1$.

Robust optimization uses the concept of multiple criteria decision-making to balance the trade-off between solution robustness and model robustness. The optimal solution is solution robust if it remains close to the optimal solution of any scenario realization. The optimal solution is model robust if the violation of constraints is close to zero for any realization of the scenario. It is unlikely that [P1] can yield a solution that is both solution and model robust for all scenarios and a trade off must be considered. Mulvey *et al.* (1995) developed the following general modeling framework of robust optimization to measure such a trade-off between solution robustness and model robustness.

A set of control variables $\{y_s, s = 1, 2, \dots, S\}$ and a set of error vectors $\{z_s, s = 1, 2, \dots, S\}$, to measure the infeasibility of the control constraints in scenario s , are introduced with a variable for any realization of s . The robust optimization model version of model [P1] is then formulated as:

$$[\text{RO1}] \quad \text{Minimize} \quad \sigma(x, y_1, y_2, \dots, y_S) + \omega \rho(z_1, z_2, \dots, z_S) \quad (66)$$

$$\text{subject to} \quad Ax = b \quad (67)$$

$$B_s x + C_s y + z_s = e_s \quad \forall s = 1, 2, \dots, S \quad (68)$$

$$y \geq 0 \quad (69)$$

$$x \in \{0, 1\}^{n_1}, y \in R^{n_2}$$

When considering multiple scenarios in robust optimization, the objective function, $\xi = c^T x + d^T y$, will become a random variable taking the value $\xi_s = c^T x + d_s^T y_s$, with a probability p_s . In stochastic programming, $\sigma(\cdot)$ takes the mean value of ξ_s (i.e.

$\sigma(\cdot) = \sum_{s \in S} p_s \xi_s$). A distinguishing feature of robust optimization from stochastic programming is that higher moments of the distribution of ξ_s can be introduced to measure the trade-off between the mean difference between the cost of implementing the plan in scenario s and the optimal cost for scenario s had we known that particular scenario will occur with certainty. To account for solution robustness, $\sigma(\cdot)$ should be the expected cost (i.e. $\sum_{s \in S} p_s \xi_s$) plus a solution robustness measures (λ) multiplied a solution robustness term, i.e.

$$\sigma(x, y_1, y_2, \dots, y_S) = \sum_{s \in S} p_s \xi_s + \lambda \sum_{s \in S} p_s (\xi_s - \xi_s^*)^2 \quad (70)$$

ξ_s^* is the optimal cost for scenario s had we known that scenario s was going to be true. As λ increases, equation (70) puts a higher emphasis on finding a solution that is close to the optimal for individual scenarios. However, the construction changes the linear model into a non-linear model due to the quadratic form in the formulation. Therefore, an alternative approach to account for the deviation and which can be easily transformed to a linear form is often used.

$$\sigma(x, y_1, y_2, \dots, y_S) = \sum_{s \in S} p_s \xi_s + \lambda \sum_{s \in S} p_s |\xi_s - \xi_s^*| \quad (71)$$

Equation (68) allows violation in the control constraints by adding error variables, z_s , because the problem will likely be infeasible according to [P1] under some scenarios. However, the violation is penalized in the second term of the objective function, $\rho(z_1, z_2, \dots, z_S)$, the model robustness term. As the model robustness measure, ω , increases, the model is forced to produce a solution that satisfy “most” of the constraints by ensuring the errors to be as close to zero as possible for all scenarios. Changing the value of λ and ω will vary the trade-off between solution robustness, measured by $\sigma(\cdot)$, and model robustness,

measured by $\rho(\cdot)$. Following the formulation proposed by Yu & Li (2000), we will take the following forms for $\rho(\cdot)$:

$$\rho(z_1, z_2, \dots, z_S) = \sum_{s \in S} p_s |z_s| \quad (72)$$

Equation (68) can be omitted from the model by replacing z_s with:

$$z_s = -(B_s x + C_s y_s) + e_s \quad (73)$$

Therefore, $|z_s|$ can be written as,

$$|z_s| = |B_s x + C_s y_s - e_s| \quad (74)$$

The robust formulation will then be

$$[\text{RO2}] \quad \text{Minimize} \quad \sum_{s \in S} p_s \xi_s + \lambda \sum_{s \in S} p_s |\xi_s - \xi_s^*| + \omega \sum_{s \in S} p_s |B_s x + C_s y_s - e_s| \quad (75)$$

$$\text{subject to} \quad Ax = b \quad (76)$$

$$y \geq 0 \quad (77)$$

$$x \in \{0,1\}^{n_1}, y \in R^{n_2}$$

The above model can be linearized as using the theorem (Theorem 1) initiated by Li (1996).

Theorem 1.

The following equation can be used to linearize minimize $Z = /f(x) - g/$, subject to $x \in F$

(F is a feasible set):

$$\text{Minimize} \quad ZZ = f(x) - g + 2\delta \quad (78)$$

$$\text{subject to} \quad g - f(x) - \delta \leq 0 \quad (79)$$

$$\delta \geq 0 \quad (80)$$

$$x \in F$$

This theorem can be verified as follows:

For $f(x) - g \geq 0$, δ is forced as $\delta = 0$ at the optimal solution, which results in $ZZ = Z$.

For $f(x) - g < 0$, δ is forced as $\delta = g - f(x)$ at the optimal solution, which results in $ZZ = g - f(x) = Z$.

The theorem is then proved.

The linearized form of [RO2] will then be as follows:

$$\begin{aligned} \text{[L-RO]} \quad & \text{Minimize} \quad \sum_{s \in S} p_s \xi_s + \lambda \sum_{s \in S} p_s (\xi_s - \xi_s^* + 2\delta) \\ & + \sum_{s \in S} p_s (\omega^+ (B_s x + C_s y_s - e_s + \alpha) + \omega^- \alpha) \end{aligned} \quad (81)$$

$$\text{subject to} \quad Ax = b \quad (82)$$

$$\xi_s^* - \xi_s - \delta \leq 0 \quad \forall s = 1, 2, \dots, S \quad (83)$$

$$e_s - B_s x - C_s y_s - \alpha \leq 0 \quad \forall s = 1, 2, \dots, S \quad (84)$$

$$y, \delta, \alpha \geq 0 \quad (85)$$

$$x \in \{0,1\}^{n_1}, y \in R^{n_2}$$

In addition to being a linear system, Yu & Li (2000) proved that the above approach is more computationally efficient than other conventional methods for solving robust optimization problems. [L-RO] allows also the penalty of infeasibility (i.e. ω) be different for positive and negative deviations (i.e. ω^+ and ω^-), meaning different weight can be put in penalizing positive and negation violations of the control constraints.

4.1. Robust power system capacity expansion model

Following the concept described above, the binary variables in the deterministic model described in Section 2.1 are looked at as design variables; they define the structure of the fleet, and that optimal value is independent of any realization of the uncertain parameters. The continuous variables in the deterministic model represent control variables; they could be adjusted once the uncertain parameters are observed, and the optimal value is dependent on both the realization of uncertain parameters and the value of the design variables. The uncertain parameters include demand of each load block and the fuel price of coal and natural gas. The objective function for the robust optimization becomes then:

$$\begin{aligned}
\text{Minimize} \quad & \sum_s p_s \xi_s + \lambda \sum_s p_s (\xi_s - \xi_s^* + 2\delta_s) \\
& + \sum_s p_s \left(\omega_l^+ \left(\left(\sum_{i \in NF \cup P^{new}} E_{il}^s + \sum_{i \in F} \sum_j E_{ijl}^s \right) - \sum_{i \in F^c} \sum_j \sum_k E_{ijkl}^s \right) \theta_l^s - D_l^s + \alpha_s \right) \\
& + \omega_l^- \alpha_s \quad (86)
\end{aligned}$$

where,

$$\xi_s = FP + VP^s + RP + FNP + VNP^s + FCCS + VCCS^s + CO2Pi \quad (87)$$

$$VP^s = \sum_{i \in F} \sum_j \sum_l (C_{ij} + P_j^s H_i) \theta_l^s E_{ijl}^s + \sum_{i \in NF} \sum_l C_i \theta_l^s E_{il}^s \quad (88)$$

$$VNP^s = \sum_{i \in P^{new}} \sum_l (C_i + P_j^s H_i) \theta_l^s E_{il}^s \quad (89)$$

$$VCCS^s = \sum_{i \in F^c} \sum_j \sum_k \sum_l C_k^c \gamma_{ijkl}^s \theta_l^s \quad (90)$$

ξ_s^* is the optimal cost for scenario s assuming scenario s occurred with certainty

In equation (10), the inequality shows that the energy produced in load block l must be greater than or equal to D_l , which means equation (86) shouldn't be penalizing overproduction. ω_l^+ should then be set to 0 and the optimization problem becomes:

$$\text{Minimize} \quad \sum_{s \in S} p_s \xi_s + \lambda \sum_{s \in S} p_s (\xi_s - \xi_s^* + 2\delta_s) + \sum_{s \in S} p_s (\omega_l^- \alpha_s) \quad (91)$$

subject to: (12), (25) – (33) and:

$$\xi_s^* - \xi_s - \delta_s \leq 0 \quad \forall s \quad (92)$$

$$D_l^s - \left(\left(\sum_{i \in NF \cup P^{new}} E_{il}^s + \sum_{i \in F} \sum_j E_{ijl}^s \right) - \sum_{i \in F^c} \sum_j \sum_k E_{ijkl}^s \right) \theta_l^s - \alpha_s \leq 0 \quad \forall s \quad (93)$$

$$\sum_l E_{ijl}^s \leq E_i^{\max} x_{ij} \quad \forall i \in F, \forall j, \forall s \quad (94)$$

$$\sum_l E_{il}^s \leq E_i^{\max} \quad \forall i \in NF, \forall s \quad (95)$$

$$\sum_l E_{il}^s \leq E_i^{\max} y_i \quad \forall i \in P^{new}, \forall s \quad (96)$$

$$\sum_l E_{ijl}^s \theta_l^s \leq E_i^{\max} \theta_l^s b_i x_{ij} \quad \forall i \in F, \forall j, \forall s \quad (97)$$

$$\sum_l E_{il}^s \theta_l^s \leq E_i^{\max} \theta_l^s b_i x_i \quad \forall i \in NF, \forall s \quad (98)$$

$$\sum_l E_{il}^s \theta_l^s \leq E_i^{\max} \theta_l^s b_i y_i \quad \forall i \in P^{new}, \forall s \quad (99)$$

$$\sum_{i \in F} \sum_j \sum_k \sum_l CO_2 \theta_l^s (E_{ijl}^s - \varepsilon_i \gamma_{ijkl}^s) + \sum_{i \in P^{new}} CO_2 \theta_l^s E_{il}^s \leq (1 - \Gamma) CO_2^{current} \quad \forall s \quad (100)$$

$$E_{ijkl}^s = E_{ijk}^{req} CO_2 \varepsilon_i \gamma_{ijkl}^s \quad \forall i \in F^c, \forall j, \forall k, \forall l, \forall s \quad (101)$$

$$\sum_l E_{ijkl}^s \leq z_{ijk} E_i^{\max} \quad \forall i \in F^c, \forall j, \forall k, \forall s \quad (102)$$

$$0 \leq \gamma_{ijkl}^s \leq E_{ijl}^s \quad \forall i \in F^c, \forall j, \forall k, \forall l, \forall s \quad (103)$$

$$E_{ijl}^s - M(1 - z_{ijk}) \leq \gamma_{ijkl}^s \leq M z_{ijk} \quad \forall i \in F^c, \forall j, \forall k, \forall l, \forall s \quad (104)$$

where,

$$D_l^s = (P_j^s - P_{j-1}^s) \theta_l^s \quad \forall l, \forall s \quad (105)$$

Equations (12) and (25) to (33) remain the same for the robust optimization model.

Equations (92) and (93) are constraints for transforming the absolute terms in the objective

function (solution robustness term and model robustness term, respectively) to linear functions. Equations (94) – (105) are altered from the deterministic model to incorporate different scenarios into the constraints. This robust optimization model will be illustrated in a case study as given below.

4.2. Summary

The concept of robust optimization is described in this chapter. Also, the deterministic model described in Chapter 2 is formulated as a robust optimization model in this chapter. The model described in this chapter accounts for uncertainty in fuel prices and electricity demand. Using the same methodology, one can incorporate uncertainties in different parameters. A case study is shown in the next chapter using the robust optimization model. The next chapter will also show that the optimal solution yield by the robust optimization model is less sensitive to the uncertainties given in a scenario set.

5. Case study

5.1. Problem description

OPG is the largest generation company in Ontario, Canada, owning around 70% of generation capacity and generates around 70% of the province's electricity (IESO, 2007). OPG has a total capacity of 21,920 MW with the characteristic of fossil-fuel generators listed in Table 8, the operating costs are listed in Table 9, and the characteristics and costs of non-fossil generators are listed in Table 10. All costs are in 2005 CDN dollars. The variable operating cost for fossil fuel generators does not include fuel cost. According to Energy Information Administration [EIA], (2005), the coal and natural gas prices in 2005 are \$2.35/ GJ and \$8.55/ GJ, respectively. The amortized factor is 0.10608, based on an economic life time of 30 years with an interest rate of return of 10%.

OPG currently operates 4 coal power plants and 1 natural gas (NG) power plant, emitting 30.2 million tonnes of CO₂ in 2005 (OPG,2007). In this case study, OPG's current fleet is optimized under stochastic demand and forecasted fuel prices for the year 2025 with CO₂ emission constrained to 60% of current emission levels.

Table 8 - Characteristics of existing fossil-fuel plants (Hashim *et al.*, 2007)

Plant Name	Plant Description	# of units	Unit Capacity MW	Fuel	Heat Rate ¹ GJ/MWh	Capacity Factor ²	CO ₂ Emission	
							tonne/MWh	
							Coal	NG
L	Lambton	4	487	Coal	10.07	0.75	0.94	0.56
NN	Nanticoke	8	477.5	Coal	10.18	0.75	0.93	0.56
A	Atikokan	1	211	Coal	10.61	0.75	1.02	0.61
LN	Lennox	4	525	Natural Gas	10.80	0.75	0.65	0.65
TB	Thunder Bay	2	153	Coal	10.61	0.75	1.02	0.61

1. DSS Management Consultants ([DSS], 2005)

2. Assumed to have a capacity factor of 75%

Table 9 - Cost of existing fossil-fuel plants

Plant	Var. Oper. Cost		Fixed Oper. Cost	
	\$/MWh		\$/kW	
	Coal ¹	NG ²	Coal ¹	NG ²
L	2.45	0.00	37	16
NN	2.25	0.00	33	16
A	5.11	0.00	75	21
LN	-	0.00	-	-
TB	5.11	0.00	75	21

1. DDS (2005)

2. Assumed to be same as new NG power plants (see Table 14)

Table 10 - Capacity of existing non-fossil plants

Plant Name	Plant Description	Total Capacity ¹	Capacity Factor ⁴	Var. Oper. Cost ⁶	Fixed Oper. Cost ⁶
		MW		\$/MWh	\$/kW
N	Nuclear	6645 ²	0.84	28.38	0.00
HB	Base Hydro	3138 ³	0.66	4.17	0.00
HP	Peak hydro	3745	0.42	10.38	0.00
W	Wind Turbines	7	0.3 ⁵	0 ⁵	47 ⁵

1. IESO (2007)

2. Including Pickering A, Pickering B, and Darlington nuclear plants

3. Base load hydro stations: Adam Beck, Decew and R.H. Saunders stations (Ontario Ministry of Energy, 2006)

4. Average capacity factor in 2005 (IESO, 2007)

5. Ontario Power Authority [OPA], (2005a, pp. 198)

6. Hashim *et al.* (2007)

7. OPG (2006)

To create the baseline emission level, this study optimized the current fleet based on the demand of year 2005. The electricity demands in 2005 are 156,971 GWh, 26,160 MW, and 12,145 MW for annual energy demand, peak load demand, and base load demand, respectively (IESO, 2006). In 2005, OPG generated around 70% of the electricity demand (IESO, 2007). This study also assumes that OPG holds enough generation capacity to

fulfill 70% of the base and peak load demands. Therefore, OPG's electricity demands in 2005 are assumed to be 109,880 GWh, 18,312 MW, and 8,501 MW for annual energy demand, peak load demand, and base load demand, respectively. Using a piecewise linear function, this thesis separates the LDC into two blocks, peak and base demand. The duration of peak load is calculated by first calculating the energy demand in each load block. To convert the base load power demand to the base load energy demand, the power demand was multiplied by 8760 hrs; yielding a value of 74,471 GWh. Subtracting the annual energy demand from the base load energy demand yields a peak load energy demand of 35,408 GWh. The duration for peak load is 3609 hrs, which is calculated by dividing the peak load energy demand with the incremental peak load power demand, 9097.2 MW.

The linearized planning model is written in the GAMS programming language and solved with the CPLEX solver. The fleet configuration for the baseline is optimized with the model explained in Section 2.1 and the result is shown in Table 11. The cost for operating the system generated by the model is \$2,826 million and the CO₂ emission is 28.5 million tonnes. The CO₂ emission provided by the model is 5.6% less than the actual emission published by OPG. The small difference between the two values validates the model.

Table 11 - Fleet configuration for year 2005

Plant Name	# of units in service	Fuel	Capacity in service MW	Capacity allocated to base load MW	Capacity allocated to peak load MW
L	4	Coal	1948	0	1948
NN	8	Coal	3820	833	2987
A	1	Coal	211	0	211
LN	3	Natural Gas	1575	0	1369
TB	2	Coal	306	0	306
N			6,645	5580	0
HB			3,138	2,086	0
HP			3,745	0	2,990
W			7	2.1	0

Assuming a 40% CO₂ reduction by 2025, the emission level needs to be less than or equal to 17.1 million tonnes. The optimal solution must meet both the CO₂ constraint and the electricity demand in 2025. Chapter 3 forecasted Ontario electricity demand to 2025 using socio-economic and weather factors. The electricity demand is forecasted under three different scenarios. Assuming that OPG will continually supply 70% of the electricity demand in Ontario, the annual electricity, peak load, and base load that OPG should meet in different scenarios are listed in Table 12. EIA (2005) forecasted fuel prices in 2025 under three different scenarios. Table 13 shows the natural gas and coal prices under different scenarios. Since no probabilities are given by EIA (2005), this study assumes probabilities for the different scenarios are uniformly distributed. Furthermore, the uncertainties in the demand and fuel prices are assumed to be independent, while coal and natural gas prices are assumed to be correlated. The result of this assumption is 9 different planning scenarios, each with an equal probability of occurrence.

Table 12 – OPG’s electricity demand in year 2025

Scenario	Annual Energy Demand (TWh)	Power Demand (MW)		Energy Demand in each load block (GWh)		Load block duration (hrs)	
		Peak	Base	Peak	Base	Peak	Base
Low	122.6	22,663	9,798	36,744	85,828	2,856	8,760
Medium	129.0	24,794	10,094	40,608	88,425	2,762	8,760
High	135.7	27,127	10,359	44,928	90,745	2,679	8,760

Table 13 - Fuel prices in year 2025 (EIA, 2005)

Scenario	Natural Gas	Coal
Low	\$4.96	\$1.67
Medium	\$6.10	\$2.20
High	\$7.36	\$3.02

To reduce the CO₂ emission and to meet the increasing demand, few alternatives are considered. To meet the increasing demand, different technologies of new possible power plants are considered: pulverized coal (PC), IGCC, NGCC, nuclear and wind power plants. The economic and technical data for each new possible fossil fuel plant are calculated with the Integrated Environmental Control Model (IECM, 2007). IECM is a modeling program that calculates costs and gives performance analyses of emission control equipment for coal and natural gas power plants. The results from the program are listed in Table 14. Each fossil fuel plant has a different boiler size and each plant can have up to 10 boilers. For plant PN3, the maximum number of boilers is 15 units instead of 10 units because the optimizer tends to choose to build more than 10 NGCC boilers with a capacity of 760 MW. For new fossil plants with capture, different capture technologies are used. The CO₂ recovery technique used for PC and NGCC plants is chemical absorption with monoethanolamine (MEA). Seloxol-based CO₂ capture was chosen for IGCC+CCS. For all technologies, the amount of CO₂ captured is 90 percent of the amount produced. The location of new possible plants with CCSs is assumed to be located at the Nanticoke

area. Aside from fossil fuel plants, the model also allows for up to 6 nuclear plants to be built to meet the base load demand and for up to 10 wind power plants to be built to meet the demand.

Table 14 - Economic and technical data for new possible plants

Plant Name	Plant Description	Max. # of units	Unit Capacity	Heat Rate	Capacity Factor	Capital Cost	Var. Oper. Cost	Fixed Oper. Cost	CO₂ Emission
			MW	GJ/MWh		\$/kW	\$/MWh	\$/kW	tonne/MWh
New fossil plants without capture¹									
PP1	PC	10	458	9.60	0.75	1,777	2.87	57	0.88
PP2	PC	10	527	9.59	0.75	1,725	2.86	53	0.87
PI1	IGCC	10	275	11.17	0.75	2,377	1.24	98	0.99
PI2	IGCC	10	552	11.11	0.75	2,217	1.24	73	0.98
PI3	IGCC	10	830	11.09	0.75	2,140	1.24	63	0.98
PN1	NGCC	10	253	7.18	0.75	753	0.00	21	0.37
PN2	NGCC	10	507	7.18	0.75	749	0.00	16	0.37
PN3	NGCC	15	760	7.18	0.75	746	0.00	14	0.37
New fossil plants with capture¹									
PC1	PC+CCS	10	337	13.02	0.75	3,074	7.35	96	0.12
PC2	PC+CCS	10	459	13.01	0.75	2,900	6.08	83	0.12
PC3	PC+CCS	10	492	13.01	0.75	2,851	5.82	80	0.12
IC1	IGCC+CCS	10	466	13.27	0.75	3,328	5.81	112	0.09
IC2	ICGG+CCS	10	701	13.23	0.75	3,264	5.65	74	0.09
NC1	NGCC+CCS	10	432	8.41	0.75	1,221	1.89	29	0.04
NC2	NGCC+CCS	10	648	8.41	0.75	1,241	1.87	27	0.04
New non-fossil plants									
Nuc	Nuclear	6	1346		0.9 ²	3,094 ²	15.56 ²	-	
NW	Wind	10	10		0.3 ³	1,913 ³	0.00 ³	47 ³	

1. Calculated with IECM (2007)

2. CERI (2005)

3. OPA (2005a)

To meet the CO₂ emission constraints, less CO₂ must be emitted. Other than closing the existing fossil boilers, the model can choose to retrofit the existing coal power plants to NGCC or add CCSs. For existing boilers, chemical absorption with MEA is the capture

technology used in the model. The percent of CO₂ captured is 90 percent. The retrofit and CCS costs for the existing fossil fuel plants are listed in Table 15.

Table 15 - Capture system cost of existing fossil-fuel plants

Plant	Retrofit Cost¹	Electricity Required for Carbon Capture²	Capital Cost³	Fixed Oper. Cost³	Var. Oper. Cost³
	\$/kW	MWh/tonne CO₂	\$/kW	\$/kW	\$/MWh
L	599	0.317	654	18	6.05
NN	599	0.317	654	18	6.05
A	602	0.317	683	22	6.07
TB	602	0	762	26	6.08

1. Assumed retrofit costs 80% of new NGCC of the same size

2. Hashim *et al.* (2007)

3. Calculated with IECM

The captured CO₂ is assumed to be transported by pipelines to Lake Erie or Lake Huron. The two lakes are saline aquifers located within Ontario and have been shown to be good locations for CO₂ storage (Shafeen *et al.*, 2004). Based on Shafeen *et al.* (2004) findings, Hashim *et al.* (2007) conducted an economic evaluation on CO₂ sequestration for different plants in Ontario. The results of the economic evaluation are used in this study and are shown in Table 16.

Table 16 - Costs associate with carbon transportation and storage (Hashim *et al.*, 2007)

Plant	Capital Cost of Pipeline		Fixed Oper. Cost	
	\$M		\$M/year	
	Erie	Huron	Erie	Huron
Existing plants				
L	351	617	27	47
NN	331	717	25	53
A	1,884	1,489	141	112
TB	121	949	121	72
New plants with capture				
PC1	325	711	24	53
PC2	339	725	25	54
PC3	347	733	26	55
IC1	335	721	25	54
IC2	337	723	25	54
NC1	302	688	23	52
NC2	311	697	23	52

5.2. Robust solutions

For robust models, the values of λ and ω will change the solution. As λ increases, the model puts a higher emphasis on minimizing the deviation of the scenario cost from the scenario optimal cost. As ω increases, the model puts a higher emphasis on minimizing the violation of the constraints for all scenarios. To assist with the selection, the model was run by varying λ and ω . The expected generation shortage, expected cost deviation, and expected cost for different pairs of λ and ω are shown in Figure 23.

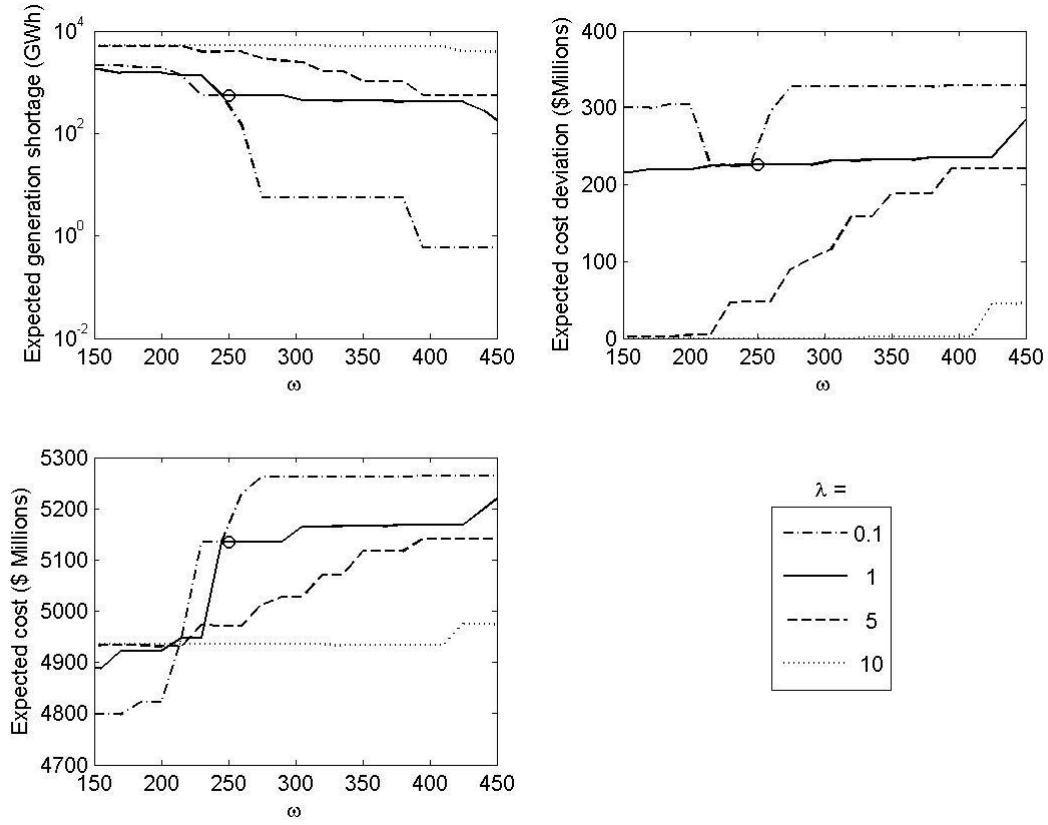


Figure 23 - Results from varying λ and ω (o denotes robust solution described in text)

For a given λ , the expected shortage decreases as ω increases. With a smaller λ , the expected shortage decreases faster because the conflict between objectives is reduced and is easier to reduce the error with less emphasis on solution robustness. For a given ω , the expected cost deviation decreases as λ increases. With a larger λ , the solution is closer to scenario optimal. However, the solution is kept close to scenario optimal by increasing the amount of shortage. The expected cost increases as ω increases. With a small ω , the model decides to generate less electricity since shortage is not being penalized much. As λ increases, the expected cost decreases. With more emphasis on solution robustness, the model tries to minimize deviation from scenario optimal, and hence, lowering the expected cost.

From Figure 23, the decision maker can identify unattainable goals and select the best value of λ and ω according to their needs. For example, suppose it is desired to get a plan that can meet 99.5% of the expected energy demand, which means that the expected shortage should be less than 645 GWh, with an expected cost less than \$ 5150 millions and an expected cost deviation less than \$ 230 millions. To meet all three criteria, the following combinations can be used: $\lambda = 0.1$ and $230 \leq \omega \leq 245$, $\lambda = 1$ and $245 \leq \omega \leq 2290$, or $\lambda = 5$ and $395 \leq \omega \leq 455$. From the plots it can also be seen that it is impossible to meet 99.9% of the expected energy demand with an expected cost less than \$ 5150 millions.

The robust model is solved with $\lambda = 1$ and $\omega = 250$, shown as 'o' on Figure 23, and the optimal fleet configuration is shown in Table 17. Except for 7 boilers in NN and 4 boilers in LN, all the existing fossil fuel boilers are shut down. To meet the demand, the model chose to build 13 NGCC with a total capacity of 9,880 MW and 2 nuclear plants with a total capacity of 2,692 MW. To reduce 40% CO₂ emission, no CCS is required, and therefore, no sequestration is required. The model chose to build new NGCC boilers instead of retrofitting existing boilers because the cost for retrofitting existing boilers is not low enough to offset the high heat rates of existing boilers. With close to 12,000 MW of power generation capacity using natural gas, the infrastructure for transporting natural gas might not be able to accommodate the needs of the power plants. In future works, the amount of fuel used should also be considered when developing the optimal strategy.

Table 17 – Optimal fleet configuration for year 2025

Plant Name	Plant Description	# of units in service	Fuel	Capacity in service MW
NN	Nanticoke	7	Coal	3,342.5
LN	Lennox	4	NG	2,100
N	Existing Nuclear			6,645
HB	Hydro Base			3,138
HP	Hydro Peak			3,745
W	Existing Wind			7
PN3	New NGCC (760 MW)	13	NG	9,880
Nuc	New Nuclear	2		2,692

When we know which scenario will occur with certainty, we can implement the optimal plan. However, if we plan for a specific scenario and another scenario is realized, the chosen plan will be sub-optimal. To evaluate whether the plan of the robust model is less sensitive to different scenarios within the set, the result of the robust model is compared to two different scenario optimal plans. The two scenarios compared are the ‘baseline’ case, with the medium scenario for both the demand and the fuel prices, and the extreme case, with the high scenario for both demand and fuel prices. The extreme case represents a very risk-averse strategy. The optimal plans for each scenario were evaluated. The resulting outcomes were ranked according to value of the cost deviation or the generation shortage.

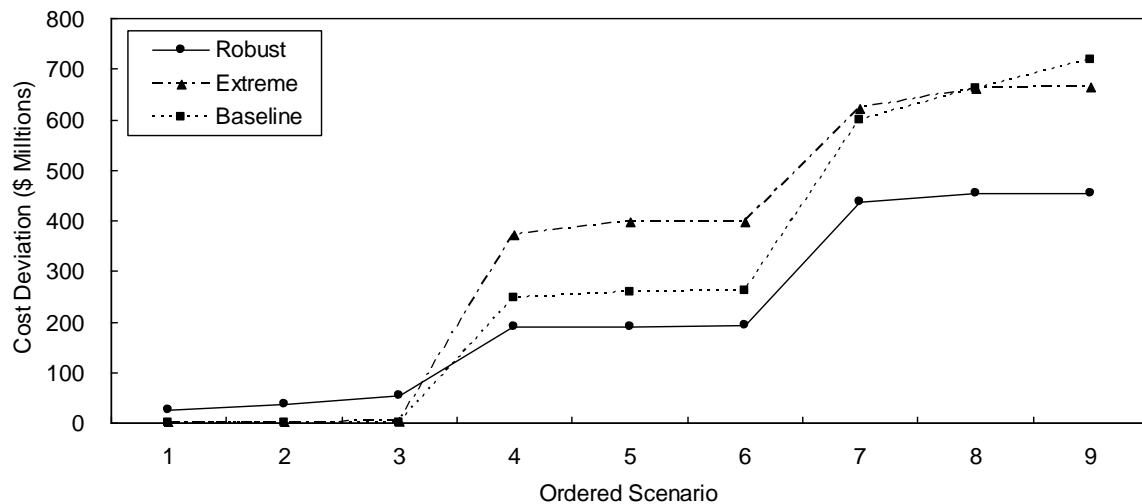


Figure 24 - Cost deviation comparison

Figure 24 shows that the extreme and baseline plans are more sensitive in most scenarios than the robust plan. The cost deviations are mostly affected by different demands rather than by different fuel prices. Other than the scenarios similar to the design scenario, the scenario optimal plans deviate more from the optimal solution for that particular scenario compared to the robust plan.

Figure 25 shows the generation shortage for the three plans. There is no shortage for the extreme case because it is designed based on the scenario with the highest demand. All three plans have enough capacity to meet the demand in the low and medium demand scenarios. For high demand scenarios, the robust plan has 1,659 GWh shortage compared to 6,242 GWh for the baseline plan.

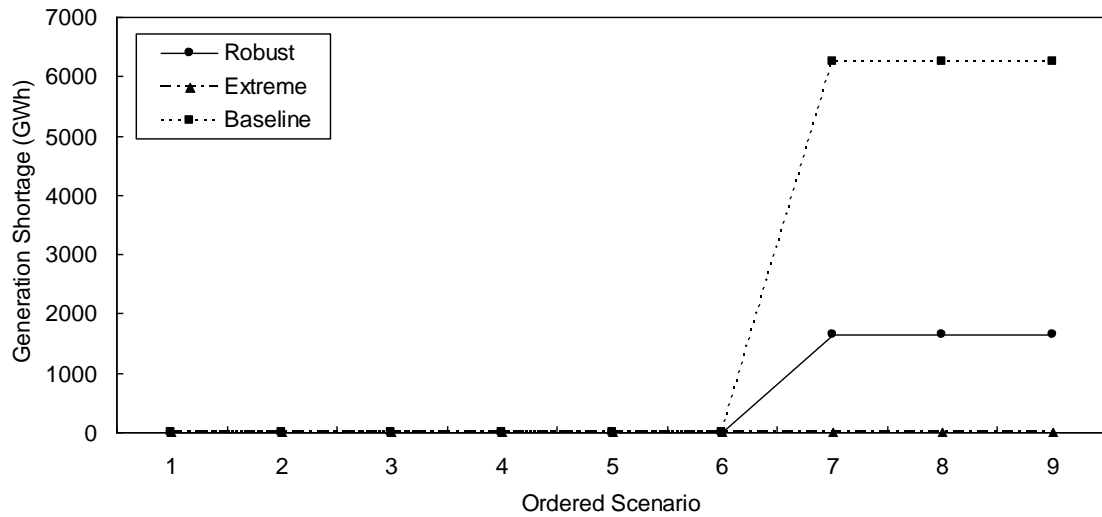


Figure 25 - Generation shortage comparison

As expected, the objective function value from the robust model is lower than implementing either the baseline or the extreme plan (Table 18). The robust plan is the optimal plan (i.e. the plan with the lowest OF value) based on the set of scenarios. The expected cost deviation for the robust plan is also the lowest among the three plans. For the expected cost, the robust plan has a higher value than the baseline plan; however, the baseline plan has a much higher expected shortage. The expected shortage of the extreme plan is zero, at a cost of higher expected cost than the two other plans.

Table 18 - Overall costs for different plans

	Robust	Extreme	Baseline
OF			
(\$ millions)	5,499	5,627	5,626
Expected cost			
(\$ millions)	5,135	5,281	4,801
Expected cost deviation			
(\$ millions)	226	346	305
Expected shortage			
(GWh)	553	0	2,081

To quantify the importance of randomness when solving stochastic problems, two values can be used: Value of the Stochastic Solution (VSS) and Expected Value of Perfect Information (EVPI).

VSS is the difference between the objective function of the expected value solution (EEV) and the stochastic solution (SS) (Birge & Loveaux, 1997 and Manandhar *et al.*, 2003).

VSS is defined by

$$VSS = EEV - SS \quad (106)$$

where,

SS	objective function value of the stochastic model considering all the possible scenarios
EEV	objective function value of the stochastic problem by using optimal design variables from deterministic model

VSS is the cost of ignoring uncertainty (Birge & Loveaux, 1997), which is also the benefit of knowing the value and the probability of distribution of the uncertain parameters (Manandhar *et al.*, 2003).

EVPI is the difference between the expected value of the SS and the Wait and See Solution (WSS). In the literature, the SS is from a stochastic model without a risk parameter. Since the model in Section 4.1 involves risk parameters, EVPI is calculated as the difference between the expected total cost of the stochastic model and WSS. EVPI is defined by

$$EVPI = Ex(SS) - WSS \quad (107)$$

where,

$Ex(SS)$	expected total cost of the robust solution considering all the possible scenarios
WSS	mean expected values for solving all the deterministic objective function within the scenario set

$$WSS = \sum_s p_s \xi_s^*$$

EVPI is the loss of profit due to the presence of uncertainty (Birge & Loveaux, 1997), which is also the measurement of the maximum amount a decision maker would pay in return for a complete and accurate information about the future (Manandhar *et al.*, 2003).

VSS of the model is \$127 million and \$ 128 million based on the baseline and the extreme plan, respectively; in other words, by considering the uncertain parameters, the robust plan saves \$127-128 millions. EVPI of the model is \$200 million; in other words, if it were possible to know the demand and prices perfectly and expand the capacity that can accommodate all fluctuations, the capacity expansion plan can save \$200 millions.

5.3. Summary

This chapter presents a case study focusing on long term capacity expansion plan of OPG given a CO₂ reduction target. Different alternatives are considered to meet demand in year 2025 and the CO₂ reduction target including structural and nonstructural changes. With fuel balancing and building new power plants with less CO₂ emission, OPG can reduce its CO₂ emission by 40% without installing CCS. In order to reduce the CO₂ emissions, it is required to close all coal plants except for the Nanticoke plant. To meet the demand in 2025, the model suggests that 13 NGCC power plants (total of 9,882 MW) and 2 nuclear power plants (total of 2,690 MW) be installed. The amount of fuel available is not constrained in the model and hence the model chose to have close to 12,000 MW of power generating capacity fuelled by natural gas. In future work, the amount of fuel available should be constrained. Comparison between deterministic models and robust models were made in this chapter and it can be seen that the optimal strategy from robust models are less sensitive to the scenario sets than the optimal strategies from deterministic models.

6. Concluding remarks

Power capacity expansion models frequently encounter uncertainty in parameters, which have a probability of occurrence. When parameters are uncertain, it is impossible to satisfy demand in all scenarios without a high cost. With the use of robust optimization, trade-offs between suffering shortage and the cost of operating the fleet can be identified. This thesis presented a robust optimization model for power capacity expansion problems with CO₂ consideration and is formulated as a mixed integer linear program. The model is then applied to a case-study using Ontario Power Generation's fleet to satisfy demand in 2025 and reduce CO₂ emission by 40%. The uncertain parameters are demand and fuel prices. Assuming a scenario set with associated probability, the optimal plan yield is less sensitive to the changes in the input parameters. That is, the optimal plan is more solution and model robust than deterministic plans.

The scenario set used are also generated in this thesis. In past literature, all scenario sets are selected arbitrary. This thesis uses forecasting techniques to generate scenario sets. Different types of regression methods are discussed and compared, such as, autoregressive models, simple linear regression, and multiple linear regression. After comparison, multiple linear regression yields the most accurate model for describing Ontario electricity demands. Three models were developed: annual energy demand, peak load demand, and base load demand. It was found that by the year 2025, annual energy demand will range from 175 TWh to 194 TWh, peak load demand will range from 32,300 MW to 38,800 MW, and base load demand will range from 14,000 MW to 14,800 MW. The scenario set is then used in the proposed robust optimization model with uniform distribution.

With the proposed robust optimization model, the optimal fleet configuration of OPG in year 2025 with CO₂ consideration should be as follow:

1. Close all coal power plants except for 7 boilers at Nanticoke. (3,342.5 MW)
2. In addition of the Lennox plant, build 13 760 MW NGCC power plants. (11,980 MW)
3. In addition to the existing nuclear plants, build 2 new nuclear plants. (9,337 MW)
4. Operates all existing power plants using renewable energy. (6,890 MW)
5. No CCS is required to reduce CO₂ emissions by 40%.

It might not be reasonable to have 11,980 MW of power generating capacity fuelled by natural gas because the availability of a fuel is constrained by the infrastructure of transporting that fuel. In future work, the amount of fuel available should be constrained.

Robust optimization can also incorporate decision maker's risk aversion. To help the decision makers with their preference, this thesis generates a series of solution by varying the value of model and solution robustness measures. This series of solution provides an idea as to how the model and solution robustness is related to the expected cost. By determining their preferences on model robustness, solution robustness, and expected costs, the decision makers can choose an optimal solution reflecting their risk aversion by choosing the value of the measures that meets their needs. The series of solution can also notify the decision makers which preferences are non-feasible.

To quantify the importance of considering randomness in the robust model, we determined the value of stochastic solution (VSS) and the expected value of perfect information (EPVI). By calculating the VSS, it can be shown that it will costs the decision makers \$127 and 128 million if they ignore the uncertainty and develop the capacity expansion plan using baseline and extreme scenarios, respectively. By calculating the EPVI, it can be shown

that the capacity expansion plan can save \$200 million if all the demand and prices are known with certainty, meaning the decision makers should pay up to this amount for more complete and accurate information about the future.

The proposed methodology offers an alternative to developing a power capacity expansion model with CO₂ consideration. Using this methodology, the decision makers can generating solutions that takes into account for uncertainty and are consistent with their preferences.

References

- Akaike, H. (1974). A new look at the statistical model identification. *IEEE Transactions on Automatic Control*, Vol. 19(6), pp. 716–723.
- Al-Alawi, S.M. & Islam, S.M. (1996). Principles of electricity demand forecasting. I. Methodologies. *Power Engineering Journal*, Vol. 10 (3), pp. 139-143.
- Al-Alawi, S.M. & Islam, S.M. (1997). Principles of electricity demand forecasting. II. Applications. *Power Engineering Journal*, Vol. 11 (2), pp. 91-95.
- Amjady, N. (2001). Short-term hourly load forecasting using time-series modeling with peak load estimation capability. *IEEE Transactions on Power Systems*, Vol. 16(4), pp. 798-805.
- Bai, H. & Wei, J.H. (1996). The CO₂ mitigation options for the electric sector: A case study of Taiwan. *Energy Policy*, Vol. 24 (3), pp. 221-228.
- Birge, J.R. & Louveaux, F. (1997). *Introduction to Stochastic Programming*. New York: Springer-Verlag, pp. 4-36.
- Canadian Energy Research Institute (CERI). (2004). *Levelised Unit Electricity Cost Comparison of Alternate Technologies for Baseload Generation in Ontario*. Retrieved on January, 2006 from www.ceri.ca/Publications/LUECReport.pdf.
- Canadian Energy Research Institute (CERI). (2005). *Electricity generation technologies: Performance and cost characteristics*. Retrieved Feb 13, 2006, from http://www.powerauthority.on.ca/Storage/15/1107_Part_4.3_CERI_Report_to_OPA_August_24_2005_D.pdf
- Chaton, C. & Doucet, J.A. (2003). Uncertainty and investment in electricity generation with an application to the case of Hydro-Quebec. *Annals of Operations Research*, Vol. 120, pp. 59-80.
- Chui, F., Elkamel, A., Croiset, E., & Douglas, P. (2006). Long term electricity demand forecasting for power system planning using economic, demographic, and climatic variables. *Energy Conversion and Management*, under review.
- Conservation Bureau (2006). *Conservation Bureau Mandate*. Retrieved on September 2006, from <http://www.conservationbureau.on.ca/Page.asp?PageID=376&ContentID=1491>
- DSS Management Consultants Inc. (2005). *Cost Benefit Analysis: Replacing Ontario's Coal-Fired Electricity Generation*. Retrieved January 26, 2006, from <http://www.energy.gov.on.ca/index.cfm?fuseaction=electricity.reports>

- Egelioglu, F., Mohamad, , & Guven, H. (2001). Economic variables and electricity consumption in Northern Cyprus. *Energy*, Vol. 26, pp. 355-362.
- Energy Information Administration (EIA). (2005). *Annual Energy Outlook 2006*. DOE/EIA-0383(2006). United States: National Energy Information Center.
- Environment Canada. (2005). *Canadian Climate Data*. Retrieved on May 2006, from http://www.climate.weatheroffice.ec.gc.ca/climateData/canada_e.html.
- Environment Canada (2006). *Canada's greenhouse gas inventory: Report summary*. Retrieved March 12, 2007, from http://www.ec.gc.ca/pdb/ghg/inventory_e.cfm
- Hagan, M.T. & Behr, S.M. (1987). The time series approach to short term load forecasting. *IEEE Transaction on Power System*, Vol.PWRS-2 (3), pp, 785-791.
- Hashim, H. (2006). *An optimal fleet-wide CO₂ mitigation strategy for a network of power plants*. Unpublished Ph.D., University of Waterloo.
- Hashim, H., Douglas, P., Elkamel, A., & Croiset, E. (2005). Optimization model for energy planning with CO₂ emission considerations. *Industrial & Engineering Chemistry Research*, Vol. 44, pp. 879-890.
- Hsu, C.C. & Chen, C.Y. (2004). Investigating strategies to reduce CO₂ emission from the power sector of Taiwan. *International Journal of Electrical Power & Energy Systems*, Vol. 26(7), pp. 487-492
- ICF Consulting. (2005). *Electricity Demand in Ontario – A Retrospective Analysis*. Retrieved on July, 2006, from powerauthority.on.ca/Storage/26/2122_OPA_Report_FactorAnalysis_Nov8_Rev.pdf
- Integrated Environmental Control Model. (2007). Retrieved on September 2006 from <http://www.iecm-online.com/>
- Independent Electricity System Operators (IESO). (2005a). *10-year outlook: Ontario Demand Forecast: From January 2006 to December 2015*. Retrieved on March 2006 from http://www.ieso.ca/imoweb/pubs/marketReports/10Year_ODF_2005jul.pdf
- Independent Electricity System Operators (IESO). (2005b). *Methodology to Perform Long Term Assessments*. Retrieved on March 2006 from http://www.ieso.ca/imoweb/pubs/marketReports/Methodology_RTAA_2005jun.pdf
- Independent Electricity System Operator (IESO). (2007). *Monthly generator disclosure report*. Retrieved Feb 06, 2007, from <http://www.ieso.ca/imoweb/marketdata/genDisclosure.asp>
- Intergovernmental Panel on Climate Change. (2007). Climate change 2007: The physical science basis: Summary for policymakers. In *Fourth assessment report of the*

- Intergovernmental Panel on Climate Change* (Vol. 1). Retrieved March 12, 2007, from <http://www.ipcc.ch/>
- Johnson, T.L. & Keith, D.W. (2004). Fossil electricity and CO₂ sequestration: how natural gas prices, initial conditions and retrofits determine the cost of controlling CO₂ emissions. *Energy Policy*, Vol. 32, pp. 367-382.
- Kang, J.S., Suh, M.H., & T.Y. Lee. (2004). Robust economic optimization of process design under uncertainty. *Engineering Optimization*, 36 (1), 51–75.
- Killmer, K.A., Anandalingam, G., & Malcolm, S.A. (2001). Siting noxious facilities under uncertainty. *European Journal of Operational Research*, Vol. 133, pp.596-607.
- Leung, S.C.H., Wu, Y., & Lai, K.K. (2002). A robust optimization model for a cross-border logistics problem with fleet composition in an uncertain environment. *Mathematical and Computer Modelling*, Vol. 36, pp. 1221-1234.
- Li, H. L. An efficient method for solving linear goal programming problems. *Journal of Optimization Theory and Applications*, Vol. 90(2), pp. 465-469.
- Makridakis, S., Wheelwright, S.C., & Hyndman R.J. (1998). *Forecasting: Methods and Applications 3rd ed.* John Wiley & Sons, Inc. United States.
- Malcolm, S. A., & Zenios, S. A. Robust optimization for power systems capacity expansion under uncertainty. *Journal of the Operational Research Society*, Vol. 45(9), pp. 1040-1049.
- Manandhar, S., Tarim, A., & Walsh, T. (2003). Scenario-Based Stochastic Constraint Programming. *International Joint Conferences on Artificial Intelligence, Acapulco, Mexico, August 9-15, 2003*, paper 214.
- Miles, J., & Shevlin, M. (2001). *Applying Regression and Correlation: A Guide for Students and Researchers*. SAGE Publications Ltd. Great Britain
- Ministry of Finance (2005). *Toward 2025: Assessing Ontario's Long-Term Outlook*. Retrieved on March, 2006. from http://www.fin.gov.on.ca/english/economy/ltr/2005/05_ltr.html.
- Mohamed, Z. & Bodger, P. (2005). Forecasting electricity consumption in New Zealand using economic and demographic variables. *Energy*, Vol. 30, pp. 1833-1843
- Mulvey, J.M. (1996). Solving robust optimization models in finance. *IEEE/IAFE Conference on Computational Intelligence for Financial Engineering, Proceedings*, pp. 1-13
- Mulvey, J. M., Vanderbei, R. J., & Zenios, S. A. Robust optimization of large-scale systems. *Operations research*, Vol. 43(2), pp. 264-281.

- Nakata, T. & Ashina, S. (2002). Optimization for the operation of electric power generation taking account of distributed regional demand in Japan. *Proceedings of the 25th IAEE International Conference* (CD-ROM), pp. 1-10
- Ontario Ministry of Energy. (2006). *Ontario Government Ensures a Competitive Ontario Through Price Stability*. Retrieved Feb 04, 2007, http://www.energy.gov.on.ca/index.cfm?fuseaction=english.news&back=yes&news_id=120&background_id=92
- Ontario Power Authority (OPA). (2005a). Available Resources and their Impacts. In *System Mix Advice Report* (Vol. 2, Part 7). Retrieved on February, 2007, from, <http://www.powerauthority.on.ca/>
- Ontario Power Authority (OPA). (2005b). Character of the Ontario Electricity System. In *Supply Mix Advice and Recommendations report* (Vol. 3, Part 3). Retrieved on September, 2006 from <http://www.powerauthority.on.ca/>
- Ontario Power Generation (OPG). (2006). *2005 Annual Report*. Retrieved June 13, 2006, from http://www.opg.com/investor/fin_reports/index.asp
- Ontario Power Generation (OPG). (2007). *Sustainable Development: 2005 Report*. Retrieved Feb 06, 2007, from http://www.opg.com/pdf/SED_05report.pdf
- Paarmann, L.D. & Najjar, M.D. (1995). Adaptive online load forecasting via time series modeling. *Electric Power System Research*, Vol. 32, pp. 219–225.
- PowerWise. (2006). *FAQs on Smart Meters*. Retrieved on September 2006, from http://www.powerwise.ca/gov_meters.shtml
- Shafeen, A., Croiset, E., Douglas, P.L., & Chatzis, I. (2004a). CO₂ sequestration in Ontario, Canada. Part I: storage evaluation of potential reservoirs. *Energy Conversion Management.*, Vol. 45, pp. 2645-2659
- Shafeen, A., Croiset, E., Douglas, P.L., & Chatzis, I. (2004b). CO₂ sequestration in Ontario, Canada. Part II: cost estimation. *Energy Conversion Management.*, Vol. 45, pp.3207-3217
- Sirikum, J. & Techanitisawad, A. (2006). Power generation expansion planning with emission control: a nonlinear model and a GA-based heuristic approach. *International Journal of Energy Research*, Vol 30, pp. 81-99.
- Soliman, S.A., Alammari, R.A., El-Hawary, M.E., & Temraz, H.K. (2004). Long-term electric peak load forecasting for power system planning: A comparative study. *The Arabian Journal for Science and Engineering*, Vol 29 (1B), pp. 85-94.

- Turvey, R. & Anderson, D. (1977). Chapter 8: Electricity development in Turkey: a case study using linear programming. *In Electricity Economics: Essays and Case Studies*. Johns Hopkins University Press, Baltimore and London.
- Yokoyama, R. & Ito, K. (2002). Optimal design of energy supply systems based on relative robustness criterion. *Energy Conversion and Management*, Vol. 43, pp.499-514.
- United Nations Framework Convention on Climate Change. (1998). *Kyoto Protocol to the United Nations Framework Convention on Climate Change*. Retrieved November 2005 from, <http://www.unfccc.de/resource/docs/convkp/kpeng.pdf>.
- Yu, C.S. & Li, H.L. (2000). A robust optimization model for stochastic logistic problems. *International Journal of Production Economics*, Vol. 64, pp. 385-397.
- Zerek, Andrzej. (2006). "Historical Energy & Peak Data." Emailed to Flora Chui on May 11, 2006.

Appendix A. Historical electricity demand

Table A.1 – Historical electricity demand

Year	Annual Energy Demand (TWh)	Peak Load Demand (MW)	Base Load Demand (MW)
1970	64,287	9,026	-
1971	68,134	9,613	-
1972	73,496	10,184	-
1973	78,163	10,965	-
1974	82,696	11,510	-
1975	84,222	12,248	-
1976	90,852	12,497	-
1977	92,854	13,041	-
1978	95,423	13,357	-
1979	98,126	13,616	-
1980	100,172	14,189	-
1981	101,658	14,975	-
1982	100,835	14,143	-
1983	106,071	15,168	-
1984	112,293	15,869	-
1985	116,047	16,181	-
1986	120,575	16,946	-
1987	126,454	18,522	8,976
1988	134,394	19,520	8,989
1989	140,771	20,086	9,826

Table A.1 – Historical electricity demand (con't)

Year	Annual Energy Demand (TWh)	Peak Load Demand (MW)	Base Load Demand (MW)
1990	136,743	20,453	9,554
1991	136,971	21,150	9,911
1992	134,375	19,976	9,850
1993	133,486	20,937	9,859
1994	134,874	20,923	9,952
1995	137,037	21,770	10,100
1996	137,416	21,428	10,123
1997	138,371	21,667	10,430
1998	139,931	22,443	10,971
1999	144,095	23,435	10,903
2000	146,945	23,222	11,624
2001	146,911	25,269	11,157
2002	152,959	25,414	11,537
2003	152,110	24,753	11,604
2004	153,437	23,976	11,983
2005	156,971	26,160	-

Appendix B. Historical socio-economical and weather data

Table B.1 – Historical socio-economical and weather demand

Year	GDP (\$ Million 1997)	GDPpp (\$)	Employment (Thousands)	Dwelling Counts (Thousands)	Population (Thousands)	HDD	CDD	MaxCDD
1970	164,987	-	-	2,273	7,549	-	-	-
1971	175,517	-	-	2,346	7,768	-	-	-
1972	188,539	-	-	2,438	7,947	-	-	-
1973	202,173	-	-	2,531	8,058	-	-	-
1974	212,827	-	-	2,631	8,189	-	-	-
1975	212,784	-	-	2,709	8,304	-	-	-
1976	226,951	-	3,741	2,784	8,402	2,295	64	4.19
1977	227,528	-	3,804	2,854	8,496	2,048	83	6.34
1978	227,953	-	3,924	2,921	8,583	2,663	105	7.52
1979	235,881	-	4,093	2,990	8,653	2,454	98	5.43
1980	235,947	-	4,165	3,038	8,731	2,466	92	6.04
1981	237,013	26,903	4,292	3,079	8,804	2,299	86	6.10
1982	230,610	25,847	4,199	3,112	8,910	2,384	60	6.31
1983	240,958	26,646	4,249	3,166	9,029	2,252	187	7.69
1984	260,070	28,358	4,410	3,219	9,157	2,289	109	5.63
1985	270,904	29,133	4,570	3,272	9,283	2,355	75	5.40
1986	281,956	29,871	4,729	3,349	9,423	2,218	83	6.60
1987	296,072	30,700	4,896	3,451	9,617	1,996	172	7.84
1988	311,990	31,697	5,083	3,553	9,821	2,221	216	8.96
1989	322,499	31,905	5,199	3,666	10,072	2,571	126	6.51

Table B.1 – Historical socio-economical and weather demand (con't)

Year	GDP (\$ Million 1997)	GDPpp (\$)	Employment (Thousands)	Dwelling Counts (Thousands)	Population (Thousands)	HDD	CDD	MaxCDD
1990	316,929	30,779	5,194	3,755	10,269	1,958	102	7.23
1991	304,468	29,200	5,017	3,830	10,410	2,112	175	7.75
1992	307,233	29,067	4,933	3,915	10,547	2,234	31	4.38
1993	310,170	29,015	4,938	3,977	10,675	1,995	107	6.73
1994	328,500	30,366	5,014	4,044	10,799	2,391	107	7.84
1995	340,081	31,055	5,100	4,095	10,931	2,335	180	8.45
1996	343,826	31,020	5,167	4,144	11,065	2,381	94	6.42
1997	359,353	32,008	5,291	4,195	11,209	2,374	86	6.06
1998	376,716	33,144	5,453	4,241	11,348	1,692	162	6.65
1999	405,034	35,202	5,637	4,300	11,486	1,965	209	9.03
2000	429,105	36,723	5,817	4,364	11,660	2,161	94	4.85
2001	436,762	36,709	5,926	4,435	11,866	1,880	184	9.33
2002	450,636	37,236	6,031	4,511	12,070	2,035	242	8.76
2003	457,649	37,329	6,213	4,602	12,236	2,356	131	6.93
2004	470,026	37,884	6,317	4,690	12,385	2,220	88	4.95
2005	483,253	38,534	6,398	4,779	12,522	2,161	255	8.18

Source: Ontario Ministry of Fiance (2005) and Environment Canada (2005)

Appendix C. Socio-economical and weather data for forecasting demand

Table C.1 - High Scenario

Year	GDP (\$ Millions 1997)	Population (Thousands)	Dwelling Counts (Thousands)	Employment (Thousands)	GDPpp (\$ 1997)	HDD	CDD	MaxCDD
2005	483,253	12,522	4,779	6,398	38,534	2,663	255	9.33
2006	497,267	12,713	4,854	6,507	39,151	2,663	255	9.33
2007	511,688	12,874	4,929	6,617	39,777	2,663	255	9.33
2008	526,527	13,036	5,004	6,730	40,413	2,663	255	9.33
2009	541,796	13,197	5,079	6,844	41,060	2,663	255	9.33
2010	558,050	13,358	5,158	6,960	41,799	2,663	255	9.33
2011	574,792	13,519	5,236	7,079	42,551	2,663	255	9.33
2012	592,035	13,679	5,314	7,199	43,317	2,663	255	9.33
2013	609,797	13,838	5,392	7,321	44,097	2,663	255	9.33
2014	628,090	13,997	5,471	7,446	44,891	2,663	255	9.33
2015	644,421	14,154	5,548	7,558	45,564	2,663	255	9.33
2016	661,176	14,311	5,626	7,671	46,248	2,663	255	9.33
2017	678,366	14,467	5,704	7,786	46,941	2,663	255	9.33
2018	696,004	14,621	5,782	7,903	47,646	2,663	255	9.33
2019	714,100	14,774	5,859	8,021	48,360	2,663	255	9.33
2020	730,524	14,926	5,935	8,118	48,989	2,663	255	9.33
2021	747,326	15,076	6,011	8,215	49,626	2,663	255	9.33
2022	764,515	15,225	6,088	8,314	50,271	2,663	255	9.33
2023	782,099	15,371	6,164	8,413	50,924	2,663	255	9.33
2024	800,087	15,515	6,240	8,514	51,586	2,663	255	9.33
2025	818,489	15,656	6,316	8,616	52,257	2,663	255	9.33

Source: Ontario Ministry of Fiance (2005) and Environment Canada (2005)

Table C.2 - Medium Scenario

Year	GDP (\$ Millions 1997)	Population (Thousands)	Dwelling Counts (Thousands)	Employment (Thousands)	GDPpp (\$ 1997)	HDD	CDD	MaxCDD
2005	483,253	12,522	4,779	6,398	38,534	2,243	107	6.69
2006	497,267	12,713	4,854	6,507	39,151	2,243	107	6.69
2007	511,688	12,874	4,929	6,617	39,777	2,243	107	6.69
2008	526,527	13,036	5,004	6,730	40,413	2,243	107	6.69
2009	541,796	13,197	5,079	6,844	41,060	2,243	107	6.69
2010	558,050	13,358	5,158	6,940	41,799	2,243	107	6.69
2011	574,792	13,519	5,236	7,037	42,551	2,243	107	6.69
2012	592,035	13,679	5,314	7,136	43,317	2,243	107	6.69
2013	609,797	13,838	5,392	7,235	44,097	2,243	107	6.69
2014	628,090	13,997	5,471	7,337	44,891	2,243	107	6.69
2015	644,421	14,154	5,548	7,432	45,564	2,243	107	6.69
2016	661,176	14,311	5,626	7,529	46,248	2,243	107	6.69
2017	678,366	14,467	5,704	7,627	46,941	2,243	107	6.69
2018	696,004	14,621	5,782	7,726	47,646	2,243	107	6.69
2019	714,100	14,774	5,859	7,826	48,360	2,243	107	6.69
2020	730,524	14,926	5,935	7,897	48,989	2,243	107	6.69
2021	747,326	15,076	6,011	7,968	49,626	2,243	107	6.69
2022	764,515	15,225	6,088	8,039	50,271	2,243	107	6.69
2023	782,099	15,371	6,164	8,112	50,924	2,243	107	6.69
2024	800,087	15,515	6,240	8,185	51,586	2,243	107	6.69
2025	818,489	15,656	6,316	8,258	52,257	2,243	107	6.69

Source: Ontario Ministry of Fiance (2005) and Environment Canada (2005)

Table C.3 - Low Scenario

Year	GDP (\$ Millions 1997)	Population (Thousands)	Dwelling Counts (Thousands)	Employment (Thousands)	GDPpp (\$ 1997)	HDD	CDD	MaxCDD
2005	483,253	12,522	4,779	6,398	38,534	1,692	31	4.38
2006	497,267	12,713	4,854	6,507	39,151	1,692	31	4.38
2007	511,688	12,874	4,929	6,617	39,777	1,692	31	4.38
2008	526,527	13,036	5,004	6,730	40,413	1,692	31	4.38
2009	541,796	13,197	5,079	6,844	41,060	1,692	31	4.38
2010	558,050	13,358	5,158	6,919	41,799	1,692	31	4.38
2011	574,792	13,519	5,236	6,995	42,551	1,692	31	4.38
2012	592,035	13,679	5,314	7,072	43,317	1,692	31	4.38
2013	609,797	13,838	5,392	7,150	44,097	1,692	31	4.38
2014	628,090	13,997	5,471	7,229	44,891	1,692	31	4.38
2015	644,421	14,154	5,548	7,301	45,564	1,692	31	4.38
2016	661,176	14,311	5,626	7,374	46,248	1,692	31	4.38
2017	678,366	14,467	5,704	7,448	46,941	1,692	31	4.38
2018	696,004	14,621	5,782	7,522	47,646	1,692	31	4.38
2019	714,100	14,774	5,859	7,598	48,360	1,692	31	4.38
2020	730,524	14,926	5,935	7,643	48,989	1,692	31	4.38
2021	747,326	15,076	6,011	7,689	49,626	1,692	31	4.38
2022	764,515	15,225	6,088	7,735	50,271	1,692	31	4.38
2023	782,099	15,371	6,164	7,782	50,924	1,692	31	4.38
2024	800,087	15,515	6,240	7,828	51,586	1,692	31	4.38
2025	818,489	15,656	6,316	7,875	52,257	1,692	31	4.38

Source: Ontario Ministry of Fiance (2005) and Environment Canada (2005)

Appendix D. IESO forecasting results

Table D.1 – IESO forecasting results

Year	Annual Energy Demand (TWh)	Peak Load Demand (MW)
2,006	156,840	26,764
2,007	158,346	27,075
2,008	160,348	27,498
2,009	161,231	27,930
2,010	162,626	27,987
2,011	164,211	28,293
2,012	165,974	28,613
2,013	167,005	29,029
2,014	168,405	29,346
2,015	169,734	29,759

Source: IESO (2005a)