Electricity Demand Forecast Review June 2006

National Demand Forecast Model

Background

The Electricity Commission prepares national and regional level demand forecasts as required by Part F of the Electricity Governance Rules. The forecasts form part of the grid planning assumptions that underlie the grid investment test and are intended to support industry transmission planning processes.

The Commission published an initial national demand forecast in March 2005. Preparation of material underlying the 2007 Statement of Opportunities is currently underway. This paper outlines the review of the national demand forecasts undertaken as part of that work.

Process

The existing Electricity Commission models were used as the starting point for this year's review. In brief the process undertaken was to:

- review ad-hoc analysis work carried out since the last national forecasts were published;
- fully review and restate the input variables used in the modelling;
- review the performance of the existing models against the updated data sets;
- test alternative models where necessary; and
- select the preferred model.

Ad hoc analysis : comparison of Electricity Commission and Ministry of Economic Development (MED) forecasts

The large difference between the MED's Energy Outlook to 2025 electricity demand forecast and the Commission's forecast has been noted by a number of industry participants. A number of informal discussions were held between the Commission and the MED during 2005 to share information on modelling approaches and ongoing forecasting development work.

The comparison of approaches highlighted a fundamental difference in approach used by each organisation. MED forecast **total energy demand**, with electricity demand being estimated based on an assumed/forecast electricity 'market share'. Electricity Commission forecasts are based on historical **electricity demand** patterns rather than total energy.

Investigations into the relative balance of different fuel types showed that there have been significant changes over the past 30 or so years in the commercial and industrial sectors. In particular, there is a strong suggestion of substitution between fuel oil and electricity that may have increased total electricity demand growth over the 1970s and early 1980s over and above the 'underlying' rate of growth. It is not clear was whether this was an actual substitution between the energy types at an individual company level, or if it reflects a downturn in industries heavily dependent on fuel oil (in the face of high oil prices) offset by the emergence of more electricity intensive industries.

If historical demand was inflated as a result of fuel substitution, then forecast future demand may be overstated if modelling fails to take the inter-fuel movements into account (provided that the fuel substitution is not expected to continue into the future).

The following table shows the historical energy share for each fuel type for the commercial and industrial sectors:

	Elec	Gas	Coal	Fuel Oil	Diesel	LPG
1975	36.3%	12.0%	16.5%	26.9%	8.3%	0.0%
1976	36.0%	16.1%	15.2%	25.1%	7.6%	0.0%
1977	37.1%	14.9%	15.4%	24.6%	7.9%	0.0%
1978	38.7%	16.4%	14.9%	22.1%	7.8%	0.0%
1979	39.2%	16.8%	14.6%	21.7%	7.7%	0.0%
1980	41.5%	13.7%	15.1%	21.3%	8.4%	0.0%
1981	40.8%	15.3%	14.7%	20.2%	9.0%	0.0%
1982	42.8%	20.8%	14.6%	14.2%	7.6%	0.0%
1983	44.0%	21.8%	14.3%	12.1%	7.8%	0.0%
1984	45.3%	26.0%	13.6%	8.2%	6.9%	0.0%
1985	50.1%	21.1%	13.8%	7.9%	7.1%	0.0%
1986	51.3%	23.8%	13.5%	5.6%	5.9%	0.0%
1987	53.4%	22.6%	12.9%	5.2%	5.9%	0.0%
1988	54.2%	22.7%	12.8%	5.3%	5.0%	0.0%
1989	55.2%	22.0%	14.9%	3.7%	4.2%	0.0%
1990	56.3%	21.2%	14.1%	3.9%	4.4%	0.0%
1991	55.4%	19.9%	14.2%	4.7%	5.7%	0.0%
1992	58.6%	21.6%	11.5%	3.7%	4.6%	0.0%
1993	56.9%	21.6%	12.7%	3.7%	5.1%	0.0%
1994	57.7%	22.2%	13.2%	3.3%	3.6%	0.0%
1995	60.0%	20.2%	12.7%	3.1%	3.9%	0.0%
1996	62.6%	19.0%	11.7%	2.5%	4.2%	0.0%
1997	59.8%	22.2%	10.9%	3.2%	3.8%	0.0%
1998	65.9%	17.0%	10.8%	2.6%	3.7%	0.0%
1999	66.2%	18.3%	9.3%	2.6%	3.6%	0.0%
2000	62.9%	23.4%	7.9%	2.5%	3.3%	0.0%
2001	65.7%	20.1%	8.3%	2.0%	3.9%	0.0%
2002	63.7%	21.3%	9.7%	1.7%	3.6%	0.0%
2003	66.8%	18.6%	10.3%	0.9%	3.5%	0.0%
2004	65.9%	17.2%	10.0%	3.0%	3.8%	0.0%

(Source : Ministry of Economic Development)

NZIER were commissioned to review the relationship between historical electricity demand and total energy use with respect to the industrial and commercial sectors.

The lack of consistent long term historical data made drawing firm conclusions difficult. It is clear that there were shifts between the various fuel types over the past 30 years, and that it is likely that there was some level of substitution between fuel oil and electricity. However, there are a number of factors driving the movements of each fuel type, and movements in one fuel type are not necessarily directly related to movements in other types.

NZIER's recommendation was to continue with the current general modelling approach, focusing on fuel use in specific industries as the Commission's modelling capability is developed over time. There was sufficient evidence to support the exclusion of the period where significant substitution occurred from the commercial and industrial sector modelling. The implications of this are significant, and the pros and cons of adopting a shorter period and covered in more detail later.

Review of input series

The input series used for the 2004 forecasts were based primarily on the original Transpower series, updated to include the most recently available year's data. Work undertaken as part of the preparation of the recently published Centralised Dataset has resulted in consistent long term metering data series becoming available for some direct connect heavy industrial customers. The Commission reviewed each of the input series used in the 2004 model against published series in order to confirm the accuracy of the input data, and updated series where newly available data allowed it.

As would be expected, in most cases there were only minor differences between the original and revised series. These generally arose from differences in the treatment of discontinuous historical series (the definition and availability of the various GDP and population series has changed over time). The main area where figures were revised was heavy industrial demand. The definition of demand for this sector was unclear across the full period covered by the original series, particularly in earlier years. An updated series was constructed using meter data from the Centralised Dataset for those grid exit points servicing heavy industrial loads.

Initial model testing (covered below) was carried out in late 2005 using newly published 2004 data from MED and Statistics New Zealand (unavailable at the time the 2004 forecasts were prepared).

MED have since published 2005 data. Final selection of the short-listed models was carried out using the updated data.

Review of Existing Models

Summary of the Commission's modelling approach

The Commission uses econometric models to forecast electricity demand. The models use the relationship between historical demand and key drivers (such and GDP and population) to forecast future demand based on forecasts of the key drivers.

Forecasts produced by the Commission are made publicly available and face potential scrutiny through consent process. The models therefore need to be intuitive and easily explained to non-experts. Alternative model types such as partial or general equilibrium models, hybrid models or neural network models have **not** been considered as part of this assessment. While such models may provide useful tools for the validation of forecasts, they are not necessarily best suited for long term forecasting. Further assessment of alternative model types will be carried out as part of the long term development of forecasting capability.

Econometric model development has been carried out in MATLAB.

Forecasts are at grid exit point. They include lines company losses but exclude consumption met by embedded generation.

Electricity demand modelling has been broken down into three main sectors:

Residential
Commercial and industrial
Heavy industrial direct connects

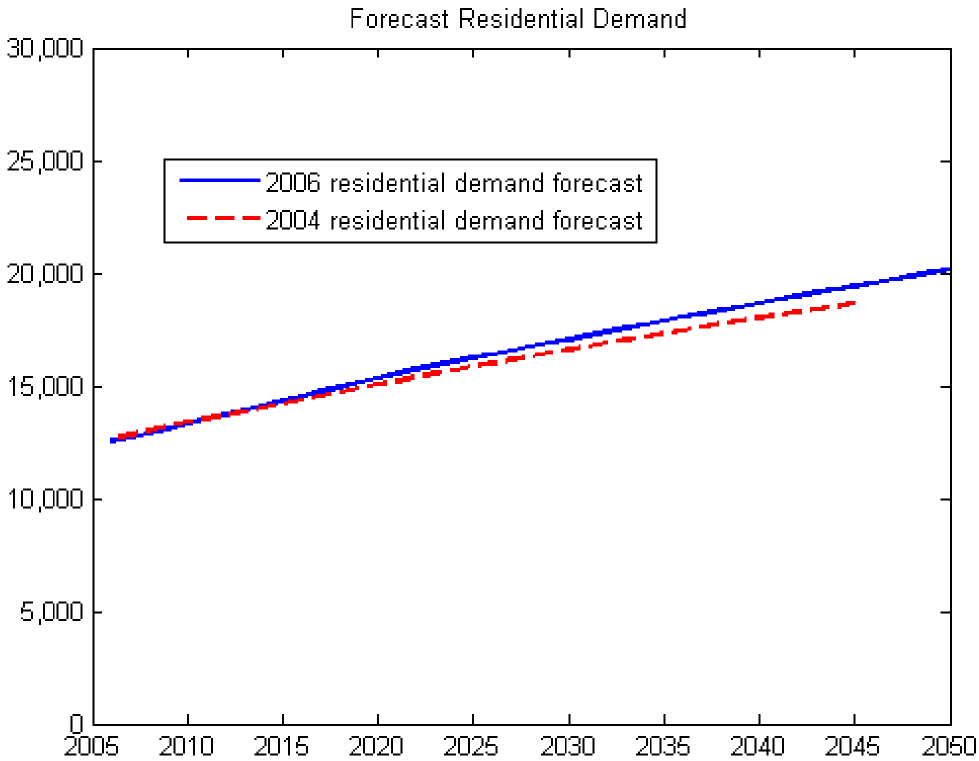
Residential Forecasts

Only minor changes were made to the input series used in the residential modelling. The temperature adjustment applied to the raw demand series in 2004 prior to the residential model being estimated was removed. The adjustment was based on a Kalman filter applied to historical demand and temperature data developed by Jonathan Lermit in 2002/2003 on behalf of EECA. While the adjustment resulted in a marginal improvement in model statistics, the adjustment had a negligible impact on the long term forecasts and added unnecessary complexity to the modelling[1].

The residential model selected as part of the 2004 demand forecasting review performed well using the updated data series as inputs. The table below compares the results obtained in 2004 and 2006.

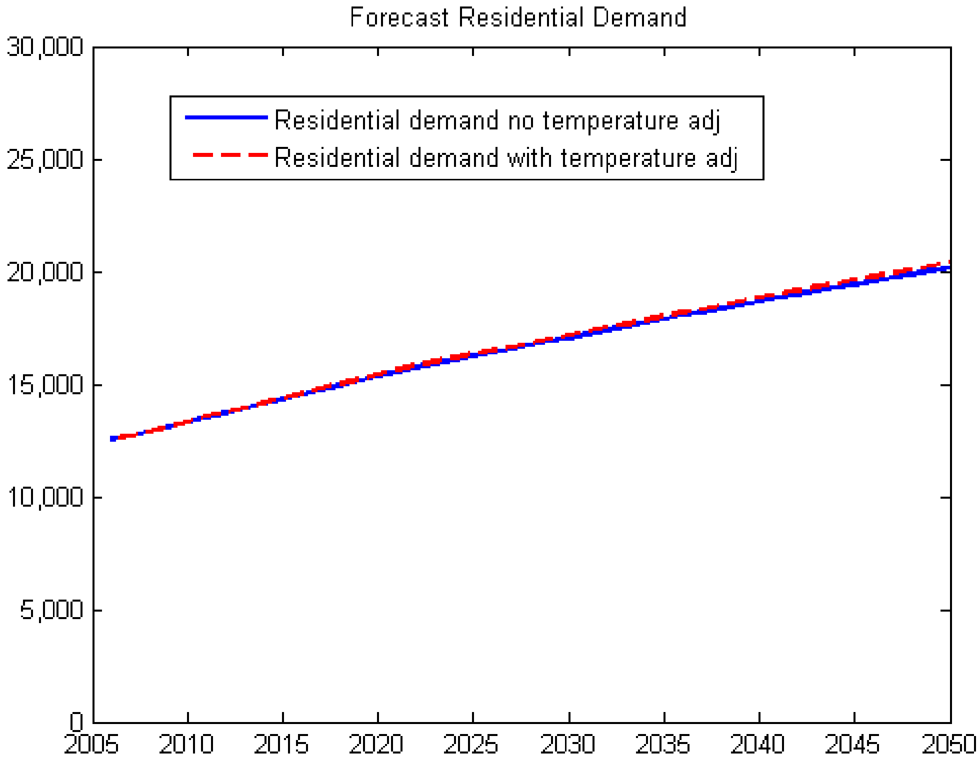
Model	2004 Residential Model Results				Updated 2006 Residential Model Results			
	Variable	coeff.	s.d.	t-stat	Variable	coeff.	s.d.	t-stat
Coefficients, standard deviations, and t-statistics	Constant log(GDP/Capita) log(HH/Capita) log(Price)	-3.441 0.310 0.864 -0.158	0.28 0.07 0.13 0.04	-12.17 4.33 6.47 -3.77	Constant log(GDP/Capita) log(HH/Capita) log(Price)	-3.446 0.310 0.898 -0.150	0.32 0.07 0.12 0.05	-10.69 4.32 7.28 -3.10
R^2	0.9793				0.9774			
Adjusted R^2	0.9770				0.9750			
Durbin-Watson	1.3354 (d_L = 1.24371 d_U=1.65046)				1.3117 (d_L = 1.27074 d_U=1.65189)			

The following graph shows forecast residential demand based on the 2006 modelling compared to the results obtained in 2004.

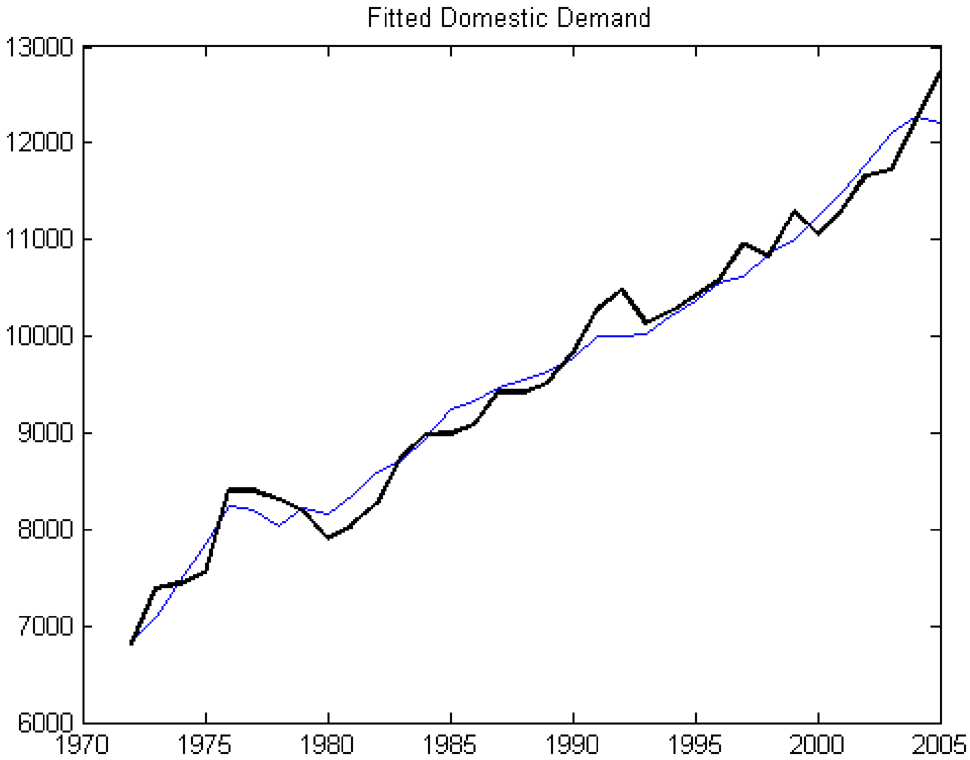


The sensitivity of the forecasts to the exclusion of the temperature adjustment is shown in the following graph.

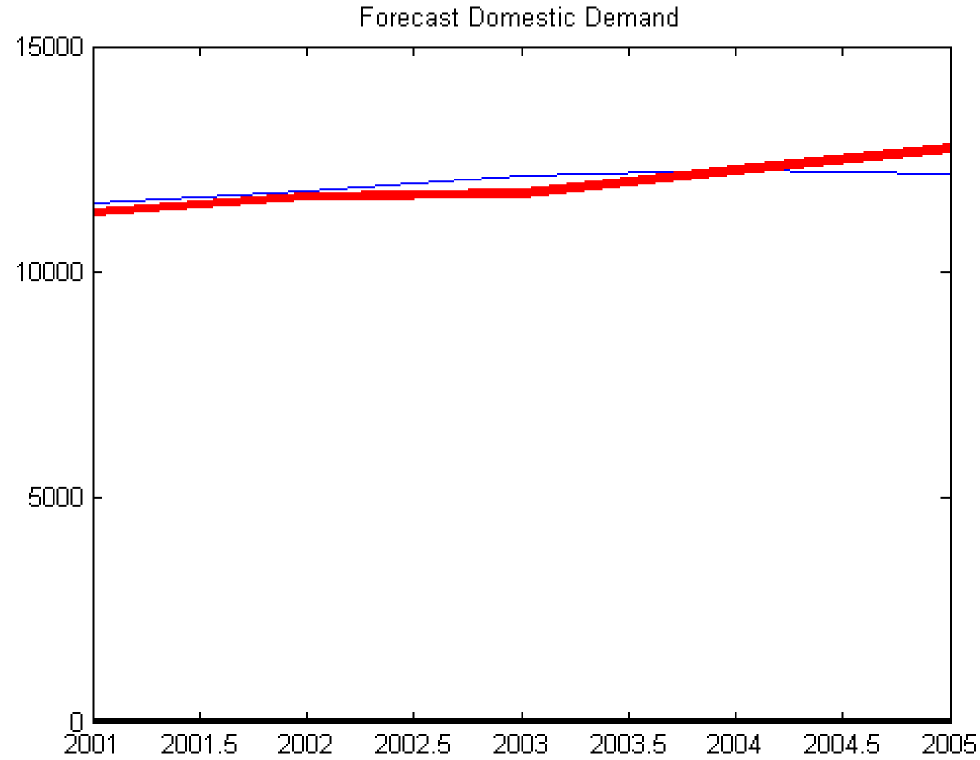
[1] While annual growth responds only marginally in response to year on year differences in average temperatures, it should be recognised that changes in temperature can have a significant effect on short term demand and on peak load. i.e. a 1 degree difference in average temperature over the course of a year has only a small impact on total annual GWh consumption, however the impact of a temperature change on demand over the course of a day (that associated with a southerly front moving up the country for example) can be very large.



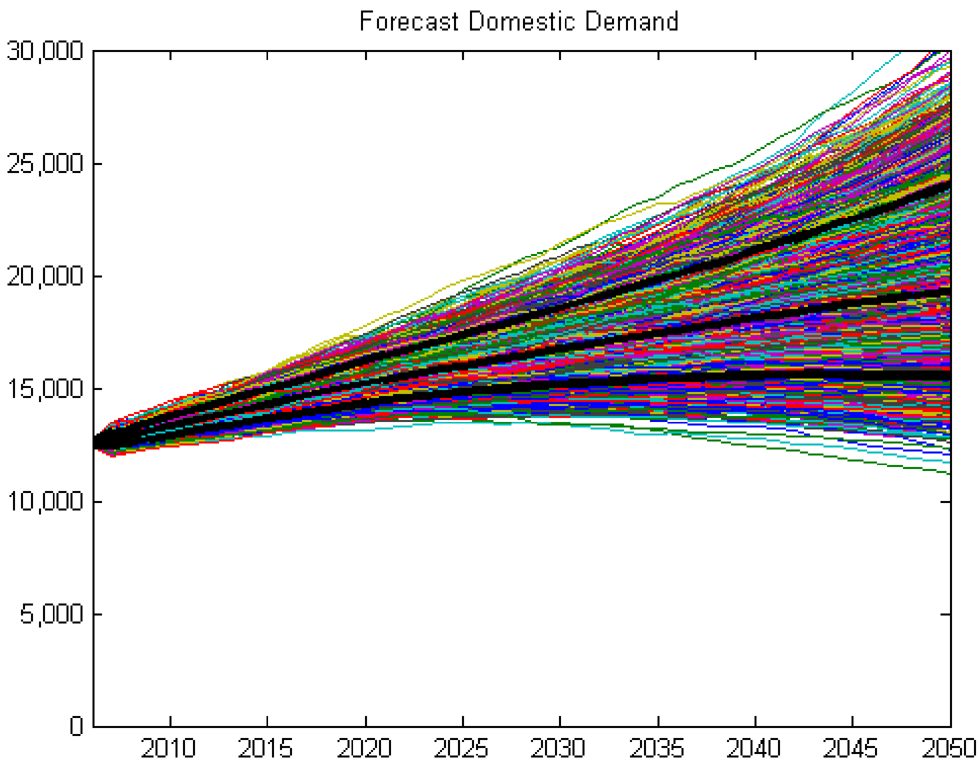
Fitted demand vs. actual residential demand is shown below (actual demand is in black).



The following graph shows the performance of the model when the historical data is truncated to 5 years ago, the model is re-estimated, and the resulting forecasts compared to actual demand for the past 5 years (actual demand is in red).



Modelling error is estimated using a Monte Carlo technique where a synthetic distribution is created for each input series based on the variation in each series compared to a 5 year moving average. Total forecast error is modelled based on estimated distributions for the forecasts of the key drivers used in the sector model. Total forecast uncertainty for residential demand is shown below, with 90% confidence limits shown in black.



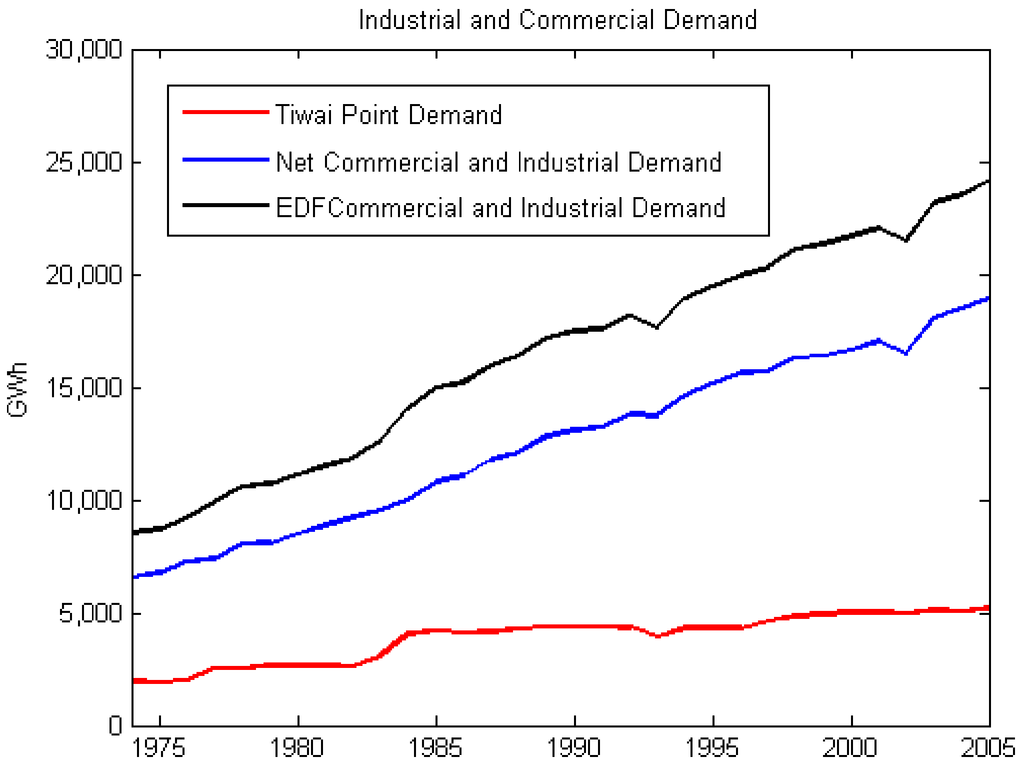
Additional information on the 2004 assessment of alternative model types can be found in the 2004 **Electricity Demand Forecast Model Review** document

Commercial and Industrial Forecasts

The commercial and industrial input series were reviewed following the NZEIR report covered briefly above.

The original series used in the 2004 modelling was constructed by netting off heavy industrial demand from the published MED total commercial and industrial demand series. The Centralised Dataset prepared by the Commission contains half hourly meter data for heavy industrial loads going back (in some cases) to 1972. The definition of demand included in the original heavy industrial series used by Transpower is unclear prior to 2002. To ensure consistency across the period covered by the data, meter data for the direct connect heavy industrial loads was extracted from the dataset, and netted off the original MED series.

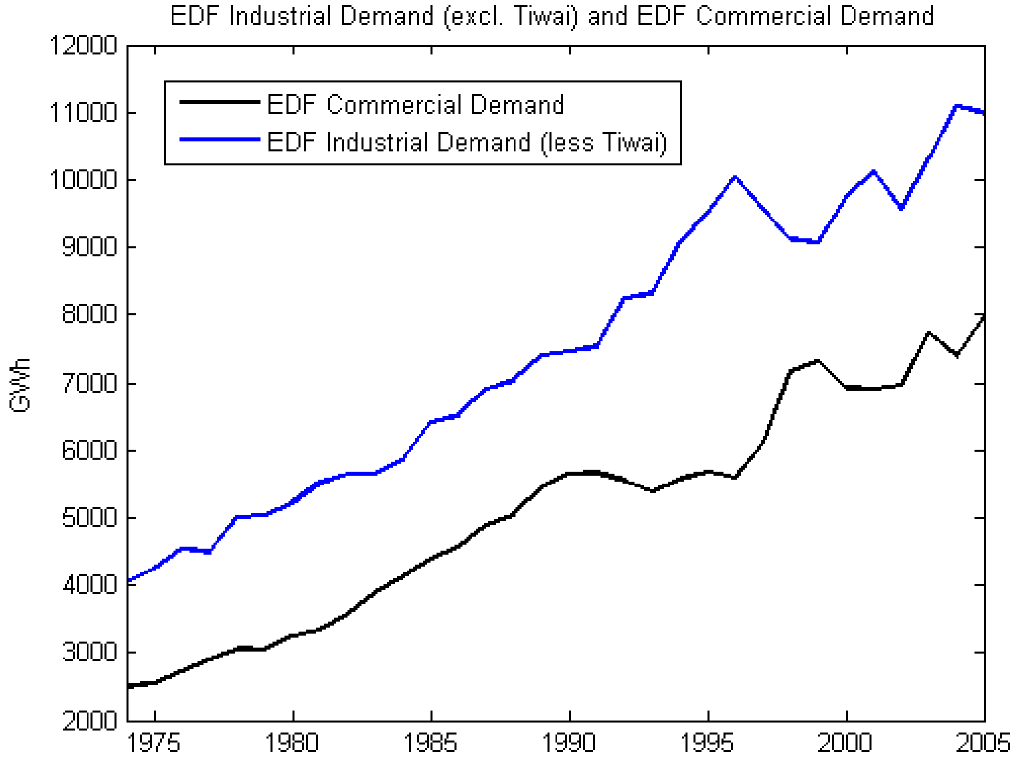
Data for the Tiwai Point Aluminium Smelter exists in a consistent dataset going back to 1972. The following graph shows the MED Energy Data File (EDF) commercial and industrial series less Tiwai Point.



The resulting net series shows remarkably constant growth over the period covered by the data. From a modelling perspective this presents a number of problems as the series remains relatively unresponsive to changes in the key drivers that would be expected to influence demand growth.

The MED publishes national demand data at an ANZSIC level, although long term data is limited to the two summary level industrial and commercial series. Breaking the industrial and commercial demand into their two separate component series did not produce dazzling results unfortunately. The graph below shows the two separate series.

There some clear movements in both series from the early 1990s but these appear to be largely mirror images of the movements in the opposing series (reflected by the fact that when the series are added together they form a fairly straight line). We were unable to draw on any compelling reasons as to why industrial demand would increase and commercial demand decrease significantly at the same time and then reverse at the times shown in the data. This suggests that the apparent year-on-year changes in each series are categorisation issues between the two series rather than real changes.



The apparent categorisation problems lead to the conclusion that modelling incorporating these series should be restricted to the combined series. Spurious changes caused by misclassification of the data in individual years means that both individual series appear (falsely) to respond to changes in the underlying drivers in those years – one series in one direction and the other in the opposite.

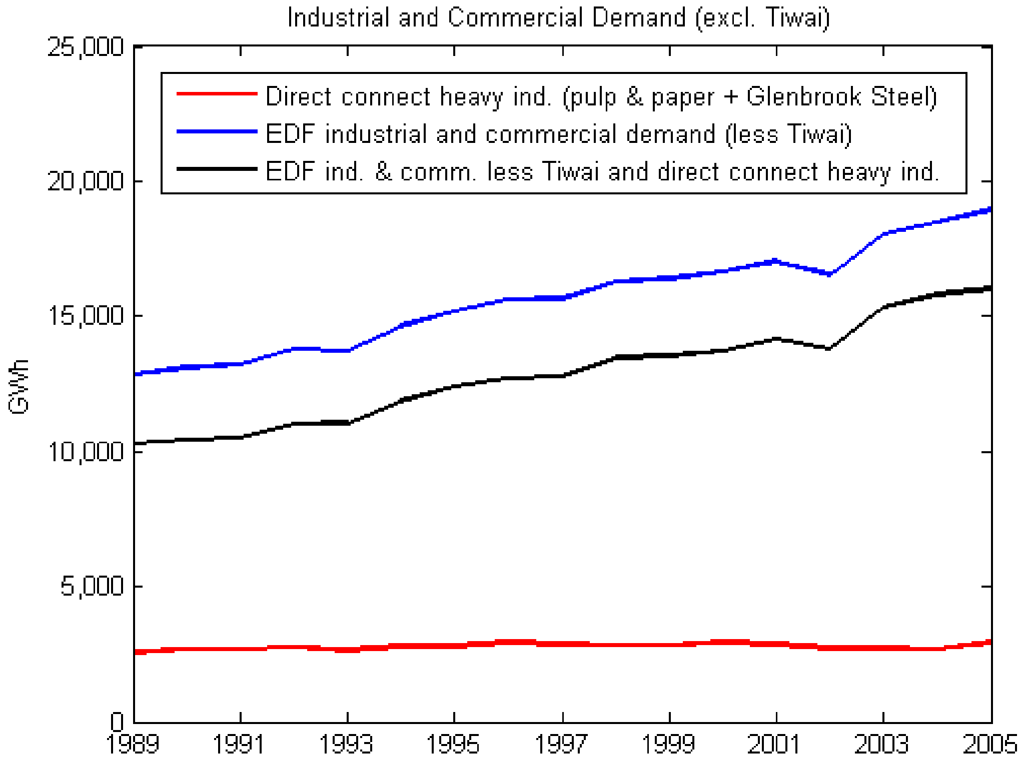
While the various models assessed by the Commission were expanded to allow the separate modelling of the industrial and commercial sectors, the modelling results were generally poor. Individual results are discussed further below.

An additional option explored was to split out those direct connects where sufficient, consistent, meter data was available.

Meter data for the non-Tiwai heavy industrial direct connect loads is available from 1987 onwards (although some series are not present for the entire period). This does not cover the full period that EDF series cover, but it does provide an alternative modelling series where shorter (post 1988) historical series have been chosen because of the substitution issue noted above.

The following graph shows industrial and commercial demand, excluding Tiwai, and excluding the other direct connects for which consistent data series are available (direct connect pulp and paper plant and the Glenbrook steel mill).

It is evident that non-Tiwai direct-connect growth has been relatively flat over the period covered by the data. As a result, the impact of subtracting the direct connects did not have a significant impact on the characteristics on the underlying commercial and industrial series.



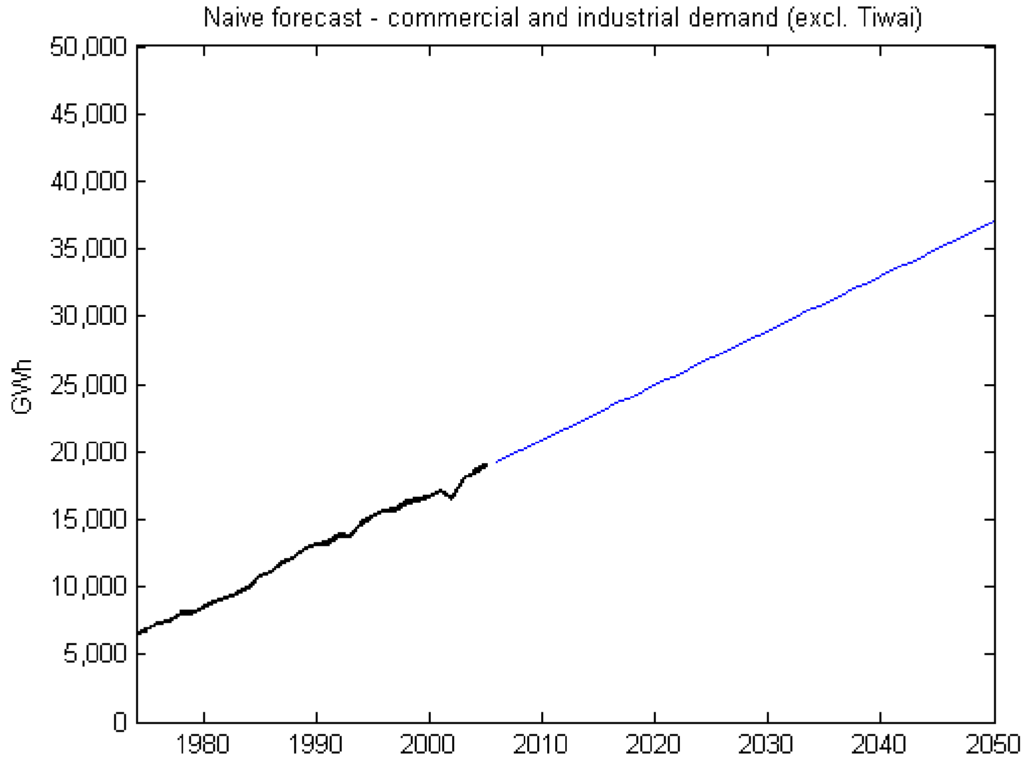
Similar to the splitting of the industrial and commercial series above, the Commission's models were expanded to separately split out the direct connect data from the industrial and commercial series.

Assessment of commercial/industrial models

Because of the changes in the base demand series the model used to forecast demand for the commercial and industrial sectors was fully re-evaluated. A number of alternative econometric models were constructed. The results for each of the models tested are summarised briefly below.

Naïve forecast

Demand growth for the industrial and commercial sector has been very stable since 1972 as illustrated in the above graphs. To provide a reference point, a simple straight-line forecast was prepared by regressing demand against time (i.e. year). The graph below shows historical commercial and industrial demand (less Tiwai) and a simple straight line extrapolation based on data since 1972.



The above projection provides a useful benchmark for comparing other forecast results. It should be noted thought that the above projection represents constant absolute growth, rather than a constant annual percentage growth (the straight line growth shown above is equivalent to a slowly diminishing annual percentage growth rate).

Linear Models

Model 1: Demand = A+ B*GDP + C*Shortage

This model simply relates demand to total GDP. The statistics for the model are generally good at face value (there is a significant element of non-stationarity in the model – see the First Difference modelling below) although the coefficient for the shortage variation is poor. The forecasts the model produces are sensitive to the period being modelled. Because of the impact of fuel substitution up to the mid 80s, the relationships between GDP and demand are suspect in the earlier years that data is available for. The model produces a very high forecast in 2025 (34859) if all data is included. If the data from 1989 onward is only included the forecast in 2025 is 27022 Gwh. The fit for the model when using the entire data set was also poor as the model tended to respond to changes in GDP while actual demand growth remained reasonably steady. The truncated forecast overshot actual demand over the past 5 years.

Model 2: Demand = a+ b*GDP + c*Price + d*Shortage

This model gave generally similar results. Like the Linear V1 model, it was sensitive to the period being modelled. The price statistic is poor to marginal when the shorter time period of data is used (it is very poor when the full dataset is used) and the shortage statistic is poor. The truncated forecast was reasonably close to actual demand. Again the fit for this model when using the entire data set was poor.

Model 3: Demand/Capita = a + b*GDP/Capita +c*Shortage

The model statistics were good for GDP although shortage statistic was poor, both for the entire data set and the reduced data set. The truncated forecast for the reduced data set was higher than actual demand. Generally this model did not perform as well as Model 1 above.

This model is sensitive to the data period selected - the forecasts were improbably high when using the full data set.

Model 4: Demand/Capita = a + b*GDP/Capita + c*Price +d*Shortage

This model was very sensitive to the selected modelling period (producing exponential forecasts when including all data to 1972). The T-statistics for GDP are good. Truncated forecast close to actual demand, however generally this model did not perform as well as Model 2 above.

Model 5 : Demand = a+ b*GDP + c*TotalEnergyCost + d*Shortage

Again, this model was sensitive to the selected modelling period, producing a very high forecast when modelled on the full range of historical data. With the exception of the GDP coefficient, statistics for the model were generally poor. The truncated forecast for the full series was close to actual demand.

Log Models

Model 1 : log(Demand) = a + b* log(GDP) + c*Shortage

This model was sensitive to data period selected for modelling, and produced an exponential growth forecast using the full dataset. The historical fit was not good. The t-statistic for the GDP coefficient is good, but was poor for the other coefficients. The truncated forecast was high compared to actual demand.

Model 2 : log(Demand) = a + b*log(GDP) + c*log(Price) + d*Shortage

Model is very sensitive to the period modelled. The model produced extreme growth when full dataset used and the fit to historical data was poor. The GDP coefficient t-statistic was good but was poor for the other coefficients. The truncated forecast was low compared to actual demand.

Model 3: log(Demand/Capita) = a + b*log(GDP/Capita) + c*Shortage

The model produces extremely high exponential growth when full dataset used. The historical fit was poor. The GDP coefficient had a good t-statistic, although the shortage coefficient was poor. The truncated forecast was high compared to actual demand.

Model 4 : log(Demand/Capita) = a + b*log(GDP/Capita) +c*log(Price) + d*Shortage

Again, the model produced exponential growth when the full historical data range was used to estimate the model. The historical fit was poor. The model had poor price and shortage coefficient t-statistics although GDP/Cap was good. The Truncated forecast slightly undershoots actual demand.

Two-stage Models

Model 1: Demand/Capita = a + B*GDP/Capita + C*LaggedSmoothedDemand
where LaggedSmoothedDemand = d + e*Year + f*GDP/Capita

This is the pre 2004 Transpower model. The model proved to be unstable with the revised dataset, producing negative demand growth by 2020 using the full data series (the lag variable had the only good statistics). The forecasts were more reasonable using the shorter post 1989 data series but the model statistics were poor.

Model 2 : Demand = a + b*GDP + c*Shortage + d*LaggedSmoothedDemand
Where LaggedSmoothDemand = e + f*Year + g*GDP + h*Shortage

This is the existing Commission model. The model produced a steady exponential growth with the revised dataset, and had poor co-efficient statistics with the exception of the lag variable. The model produced a forecast similar to the naïve forecast when based on the shortened data set. The truncated forecast was close to actual demand, however the model statistics were poor (including the lag variable).

Linear with Lag

Model 1 : Demand = a + b*GDP + c*Shortage + d*LagggedDemand

The model was sensitive to the period being modelled. The model had average to marginal t-statistics and the truncated forecast was close to actual demand.

Model 2: Demand = a + b*GDP + c*Price + d*Shortage + e*LaggedDemand

The model produced improbably high results when based on the full series. The price coefficient was poor, although the other coefficient statistics were marginal. The model statistics were worse when estimated on the reduced period, although the forecasts were at more reasonable level. The truncated forecast was well under actual demand.

Model 3 : Demand/Capita = a + b*GDP/Capita + c*Shortage + d*LaggedDemand

Similar to Model 2 above, the forecast results were improbably high. The model coefficients were poor to marginal, and the truncated forecast results were lower than actual demand.

Model 4 : Demand/Capita = a + b*GDP/Capita + c*Price + d*Shortage + e*LaggedDemand

As with the previous two models, the forecasts results were high when estimated using the full data series. The model statistics were generally poor. The truncated forecast was well under actual demand.

Model 5: Demand = a + b*GDP + c*Shortage + d* ShortageLastYear + e*LagggedDemand

This is a slight variation on model 1 above intended to adjust demand in years following shortages to account for the fact that the lagged demand is lower than ‘normal’.
This improved the coefficients for some statistics but worsened the coefficient for GDP.

Log with Lag

Model 1 : log(Demand) = a + b*log(GDP)+c*log(Price)+d*Shortage+e*log(LaggedDemand)

Forecast results were very high when estimated across the full data series. This model had poor statistics. The truncated forecast was close to actual demand for the shortened data set.

Model 2: log(Demand) = a + b*log(GDP) + c*Shortage + d*log(LaggedDemand)

The model produced very high forecasts when using the full data series and model statistics were poor to marginal with the exception of the lagged variable which dominated the model. The results were marginal when estimated over the shorter time period. The truncated forecast undershot actual demand slightly.

First Difference Models

The non-stationarity issue mentioned earlier is a significant problem for the data series considered here. This can often be dealt with by taking the first differences of all the data series (in effect modelling annual changes as opposed to absolute values).

Model 1 : ΔDemand = a + b*ΔGDP + c*Shortage

This model gave reasonably stable results although the t-statistics for the model are poor to marginal. The truncated forecast was reasonable.

Model 2 : ΔDemand = a + b*ΔGDP + c*ΔPrice + d*Shortage

The results for this model are marginal. The T-statistic for ΔGDP is poor, although the other coefficients have acceptable t-values. The price coefficient is positive. The fit to historical data is very poor, and the truncated forecast slightly higher than actual demand.

Model 3 : ΔDemand/Capita = a + b*ΔGDP/Capita + c*Shortage

This model had a poor GDP/Capita t-statistic and did not fit the historical data well. The truncated forecast was reasonable.

Mixed Models

Model 1 : Demand = a + b*ΔGDP + c*ΔPrice + d*LaggedDemand

This model was dominated by the lag variable. Model results when estimated on the1989-onwards data set were generally good (all t-statistics over 2) although the price co-efficient was positive. The forecasts the model produced were improbably low (flat after 2 years) – as illustrated in the graph in the summary section below. The truncated forecast was slightly under actual demand.

Model 2 : Demand = a + b*ΔGDP + c*LaggedDemand

The model was dominated by the lag variable, with poor t-statistics for the other variables. The truncated forecast undershot actual demand.

Summary

None of the models performed especially well because of the characteristics of the historical demand series.

Ideally it would be more appropriate to include all of the available data and explicitly model the impact of any substitution. The current lack of data makes this impossible without additional research. The Commission plans to spend further time on investigating this issue, but currently the best option is to truncate the data period the forecast are based on, so that the impact of any historical substitution between fuel types is minimised.

The following tables summarise the results for the best performing models based on data running from 1989 to 2004. The selection of 1989 is a reasonably arbitrary one - this is roughly when most of the substitution between fuel oil and electricity appears to have tailed off - but was necessary to provide a starting point for comparing alternative models.

Model	Linear Model 1				Linear Model 2			
	Variable	coeff.	s.d.	t-stat	Variable	coeff.	s.d.	t-stat
Coefficients, standard deviations, and t-statistics	Constant GDP Shortage	3470.300 0.127 -332.490	689.99 0.01 271.39	5.03 17.71 -1.23	Constant GDP Price Shortage	7140.400 0.117 -298.610 -261.610	2116.10 0.01 164.13 254.44	3.37 13.88 -1.82 -1.03
R^2	0.9582				0.9667			
Adjusted R^2	0.9518				0.9584			
Durbin-Watson	0.8787 (d_L = 1.0154 d_U= 1.5361)				1.4559 (d_L = 0.8968 d_U=1.7101)			

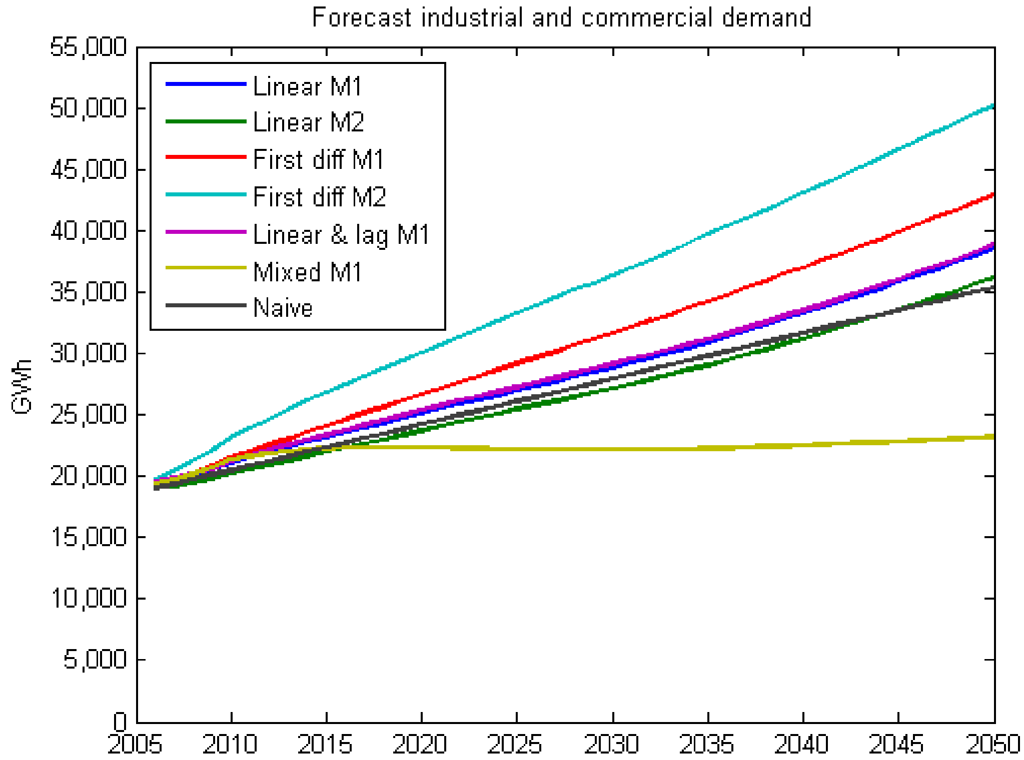
Model	First Difference Model 1				First Difference Model 2			
	Variable	coeff.	s.d.	t-stat	Variable	coeff.	s.d.	t-stat
Coefficients, standard deviations, and t-statistics	Constant ΔGDP Shortage	293.430 0.070 -560.460	169.00 0.05 251.83	1.74 1.46 -2.23	Constant ΔGDP ΔPrice Shortage	438.930 0.065 618.160 -891.310	149.88 0.04 232.47 242.30	2.93 1.63 2.66 -3.68
R^2	0.9623				0.9520			
Adjusted R^2	0.9565				0.9400			
Durbin-Watson	2.0976 (d_L = 1.0154 d_U=1.5361)				1.2425 (d_L = 0.8968 d_U=1.7101)			

Model	Linear with Lag Model 1				Mixed Model 1			
	Variable	coeff.	s.d.	t-stat	Variable	coeff.	s.d.	t-stat
Coefficients, standard deviations, and t-statistics	Constant GDP Shortage Lagged Demand	2178.000 0.075 -456.760 0.417	1086.80 0.03 224.79 0.22	2.00 2.87 -2.03 1.89	Constant ΔGDP ΔPrice Shortage Lagged Demand	1864.200 0.109 766.710 -884.500 0.901	869.61 0.05 234.82 226.34 0.06	2.14 2.39 3.27 -3.91 15.10
R^2	0.9727				0.9679			
Adjusted R^2	0.9659				0.9562			
Durbin-Watson	1.6508 (Durbin h) (d_L = 0.8572 d_U=1.7277)				1.1891 (Durbin h) (d_L = 0.7340 d_U=1.9351)			

In many cases the models assessed were simply using the fairly constant growth exhibited in the demand series and the major explanatory variable, GDP, was largely irrelevant. This is particularly true of the various models incorporating lagged variables or based on first differences.

Most of the models were sensitive to the period selected for modelling. The results for most models were much higher when this earlier data is used.

The following graph compares the forecasts produced by each of the above models.



The mixed model (Mixed M1) was the only one where all the coefficient t-statistics were significant. However, this particular model is a classic example of why choosing a model on the strength of its basic statistics can be misleading. The forecasts produced by the model are unrealistic.

The various models gave conflicting results with respect to price elasticity of demand. The log version of the Linear M2 model suggests a demand elasticity of around -0.18 for the commercial and industrial sectors. However the t-statistics for the price coefficient was only -1.4 for this model (normally t-statistics should have an absolute value higher than around 2 to indicate that the coefficient is significant). Studies focused at demand elasticity have suggested elasticity figures of around -0.3 are typical. The difference based models above produced positive price coefficients for New Zealand - indicating that a year on year increase in price results in increased demand rather than reduced demand - a counter-intuitive, and most likely fallacious, result.

The coefficients for GDP for the two difference based models both had poor t-statistics (between 1.5 and 1.6). The forecasts produced by these models were significantly higher than the naïve forecast. Combined with the counterintuitive price co-efficient, the poor GDP statistic suggests that the First Difference M2 model is not an appropriate model. Similarly, the First Difference M1 model is not sufficiently robust to justify a forecast significantly higher than the naïve.

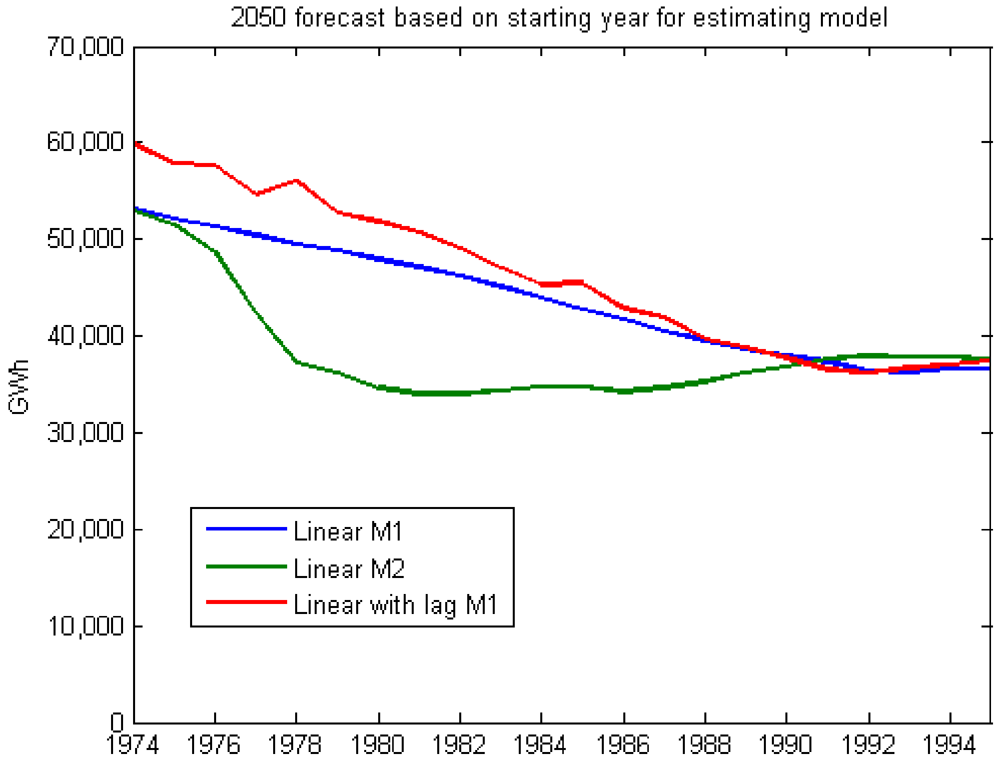
Choosing between the remaining three models is more difficult. The Durbin-Watson statistic for the Linear M1 model conclusively demonstrates that auto-correlation exists in the model residuals. However the t-statistics for the price coefficient in the Linear M2 model is less than 2 and the lag coefficient in the Linear with Lag M1 model is not good.

Because of the sensitivity of the models to the modelling period, the selection of the starting date for estimating the model is a reasonably significant issue. The three ‘short list’ models all produce forecasts of around 30000-35000 in 2045 with starting periods of between 1989 and 1994 for estimating the model.

The Linear with Lag model starts to produce exponential forecast once modelling dates prior to 1989 are used – initially the effect is small, but earlier (pre 1980) dates produce significantly higher forecasts.

The linear M2 model produces significantly lower forecast as the data period modelled is extended back, although it then rapidly rises again once pre 1977 data is included.

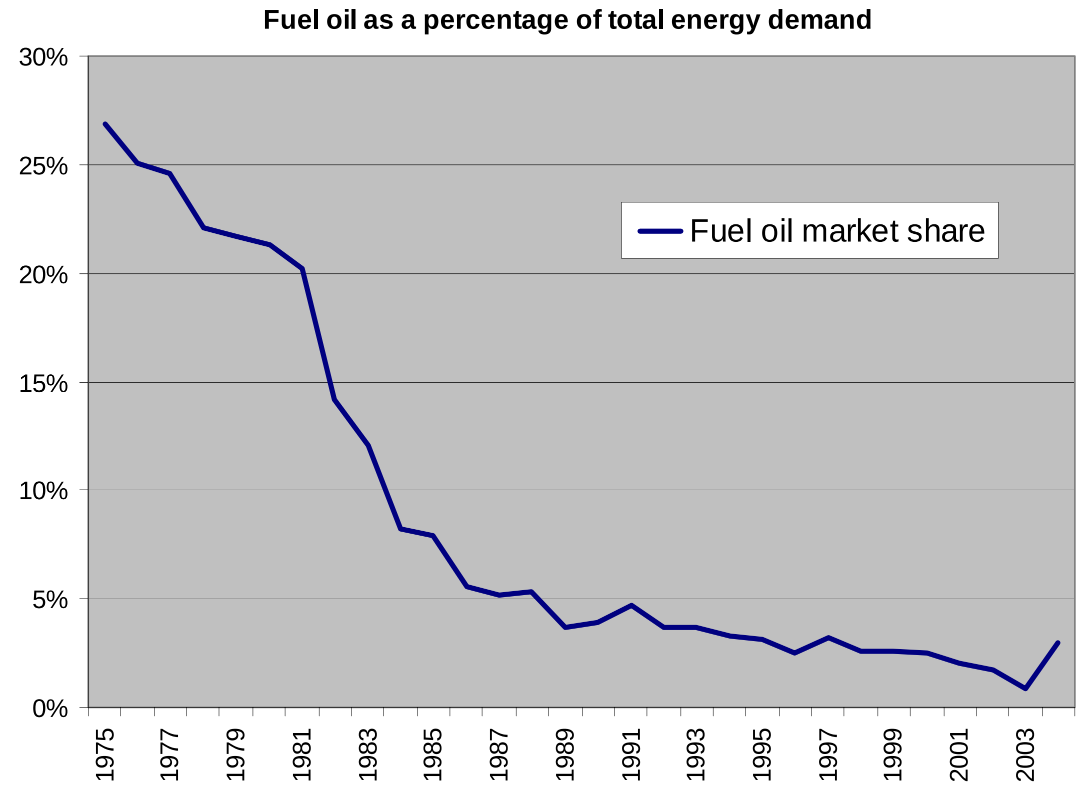
The Linear M1 model is the least sensitive of the three models to changes in modelling period, although it also produces higher forecasts as earlier data is used. The following graph shows the industrial and commercial forecast at 2050 based on the first year each model is estimated from.



The response of the models to changes in the modelled period illustrated above shows the general sensitivity of the modelling that results from the nature of the underlying series.

Ultimately we have selected the period used for modelled based on where the reduction in fuel oil use appear to stabilise. Based on the fuel share data from MED (see the table on page 2 on this report and the graph on the following page) this is roughly 1986, once fuel oil use moves to around 5% of total energy use in the industrial and commercial sectors.

Given the sensitivity of the various models and the nature of the series being modelled, we decided on a model where the relationship between the drivers and demand is kept as simple as possible, accepting that the model statistics may not be ideal. We have selected the Linear M1 model that simply relates GDP to demand, including adjustments for "shortage" years. The relationship between demand and GDP may not necessarily stay stable over the long term. Overseas experience is that there has been a change in the energy intensity of production as economies have matured. This suggests that the relationship between GDP and demand may reduce (i.e. less energy required to produce the same level of output). Certainly, there are policy initiatives in place to encourage such a change.



(Source : Ministry of Economic Development)

Heavy Industrial Growth modelling and assumptions

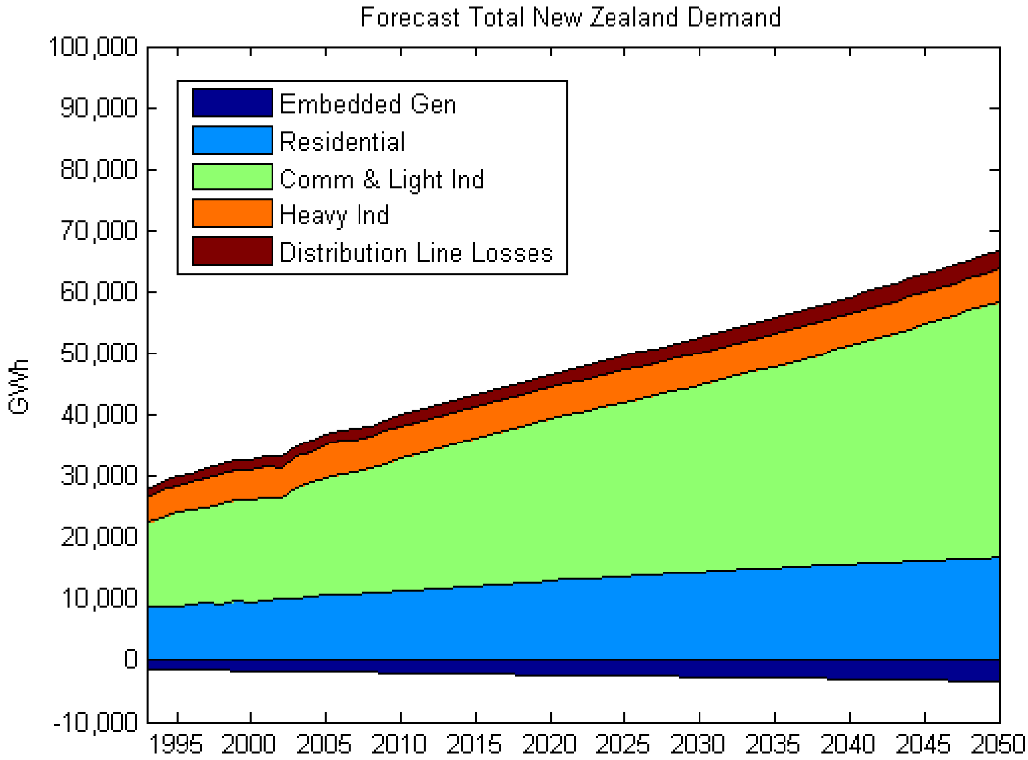
A simple trend was applied to heavy industrial demand for the 2004 forecasts.

For this set of forecasts, only the Tiwai Point aluminium smelter has been separated out from the other industrial and commercial loads (see the commercial and industrial modelling section above). Tiwai Point future demand is assumed to remain constant – i.e. no major expansions or downsizings of the aluminium smelter are explicitly included in the demand forecasts.

An assessment was carried out of the impact of separating out the direct connect heavy industrial loads for which data was available. The non-Tiwai heavy industrial loads were projected forwards based on the relationship between their demand and GDP. There was little impact on the final total demand forecast (as would be expected given that the non-direct connect industrial loads are also projected using GDP). Longer term, the Commission intends to project demand for the major electricity using industries by carrying out industry specific studies. The MED have commissioned an analysis of the major energy intensive industries and it is anticipated that this will provide a useful base for further work.

Total Demand

The following graph shows the components of total forecast demand. Forecasts are at grid exit point. The demand models are based on end use demand, therefore lines company losses need to be added to modelled demand, and embedded generation subtracted.



Embedded generation is assumed to remain at its current proportion of total generation (i.e. it will grow at the same rate as total demand). As embedded generation is roughly 4% of total generation this is equivalent to around 25-30GWh of additional generating capacity each year (roughly 10MW per year of wind generation going into local networks as opposed to being grid connected).

Line company loses have been running at between 5-6% over the past few years. As lines company asset utilisation increases, it would be expected that average losses would increase. However improvements in the quality of local network assets should at least offset this so it is assumed that lines companies losses will remain at their current levels (a figure of 5.75% has been used).

Demand Uncertainty

Forecast uncertainty is modelled using a Monte Carlo based approach where model error and forecast uncertainty are assessed using distributions estimated for the historical input series and forecast input series respectively.

The historical input distributions are synthetic distributions based on the variation between the various inputs (reported GDP, population, households) and a 5 year moving average[2]. Each Monte Carlo run involves adjusted the inputs based on the various synthetic distributions and re-estimating the model.

The forecast input distributions are based on assessments of likely variation for each series. The forecast series are kept internally consistent within each Monte Carlo run (i.e. GDP and household projections are linked to population).

Uncertainty in the various inputs is briefly described below:

[2] The impact of using alternative moving average periods was assessed and found to be minimal.

GDP : GDP had been broken into three components, population, productivity and a random component. The population component is kept consistent with the variation introduced in the population section below. Productivity variation is based on scaling productivity for all years by a factor drawn from a distribution based on an estimated historical range. The third random component provides some year on year change caused by random external causes (such the international environment) and has been based on historical GDP variation.

Households : Uncertainty in households had been broken into two components, population uncertainty (kept consistent with the population variation below) and a household size component. Household size is varied based on a scale factor applied and phased in over the forecast period.

Population : Population variation is handled by applying a factor drawn from a distribution based on the various Statistics New Zealand population scenarios.

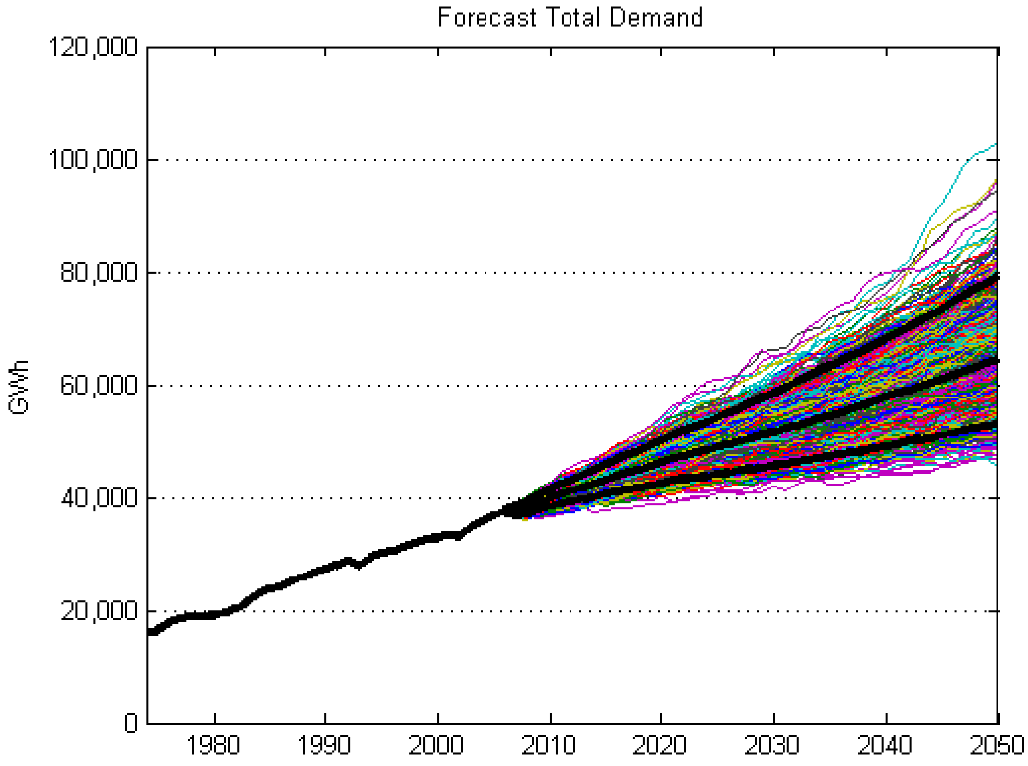
Price : Variation is based on a simple estimated distribution used to scale price is each forecast year.

There are a wide range of other factors that will influence future demand growth. Two primarily issues are future trends in energy intensity, and the balance between grid connected and embedded generation.

Energy intensity changes are reflected in the historical data the models have been estimated from. The forecasts therefore reflect an ongoing underlying rate of efficiency improvement. Step changes in energy efficiency resulting from policy initiatives that are demonstrably different to the historical rates of change have not been modelled explicitly as part of these forecasts. Where a material change from a confirmed policy can be robustly established and independently confirmed, explicit adjustments to future forecasts will be considered. The possible impacts of broader technology and social changes will be dealt with through scenario analysis.

The relative balance between embedded generation and grid connected generation will be determined by changes in technology and input costs. Economies of scale have resulted in smaller scale technologies such as wind farms being built at a size where direct connection to the grid is required rather than into the local networks. Possible changes in the mix of embedded generation vs. grid connected generation have not been assessed as part of the forecasting process but will be handled through scenario analysis

The following graph shows total forecast variation with 90% confidence limits (i.e. 5% of forecasts exceed the upper confidence limit and 5% of forecasts are lower than the lower confidence limit).



Regional Modelling

The current lack of consistent long term regional data makes the development of individual econometric models for each region impractical. Regional forecasts are therefore based on an allocation of the national forecasts.

A number of alternative regional allocation approaches were tested by the Commission earlier this year. The different methodologies tested by the Commission yielded significantly different forecasts across the various regions. The main constraining factor on the allocation approach used was a lack of information of the composition of electricity demand at a regional level. Retailers have since been approached to obtain data on the relative balance of industrial/commercial and residential loads in each region.

Residential allocation : Total national residential demand was allocated on the basis of projection population growth in each area. Population forecasts are available at a local network level (built up from meshblock level to the old Electric Power Board areas) from Statistics New Zealand.

The allocation is based on the following formula:

For each network area,

$$\text{Res.Demand}(FY) = \frac{\text{Population}(FY)}{\text{Population}(BY)} \times \frac{\text{National Res. Demand Per Person}(FY)}{\text{National Res. Demand Per Person}(BY)} \times \text{Res.Demand}(BY)$$

where FY = forecast year, and BY = base year (the most recent year that actual values were available).

Note that residential demand in each network area was only approximated based on the proportion of residential demand in the region compared to total demand.

Demand across all areas is then scaled so that the sum of each of the areas matches back to the national total.

This approach assumes that demand growth within a region due to an increase in population will have the same characteristics as the existing residential demand in that region (i.e. additional population growth in a high usage area will also be high usage). Changes in per person energy intensity will be spread proportionately across the country (i.e. a 10% increase in demand per person at a national level will result in 10% growth across all regions).

Grid exit point (GXP) residential demand is forecast by pro-rating the network area residential demand to each GXP within the network based on the current proportion of total load at the GXP compared to the total local network load. In effect this assumes that the mix of load at each of the GXPs within a local network is the same.

Regional residential demand is calculated by simply summing the residential demand for each network within the region.

Industrial and commercial allocation : Total national industrial demand was allocated on the basis of projected GDP growth in each region. Long term regional GDP projections were obtained from the NZIER.

The allocation is based on the following formula:

For each region,

$$\mathrm{IndCommDemand}(FY) = \frac{\mathrm{GDP}(FY)}{\mathrm{GDP}(BY)} \times \frac{\mathrm{National\ Ind.Comm.Demand\ /\ National\ GDP}(FY)}{\mathrm{National\ Ind.Comm.Demand\ /\ National\ GDP}\ (BY)} \times \mathrm{IndCommDemand}(BY)$$

where FY = forecast year, and BY = base year.

Similar to the residential allocation above, this approach assumes that the energy intensity of additional demand in a region associated with an increase in production (GDP) will be the same as the existing energy intensity within the region. Forecast changes in modelled national level energy intensity are spread proportionately across the country.

Network level demand within each region is allocated on the basis of the current total network demand as a proportion of total regional demand. Demand at a GXP level is allocated based on current GXP demand as a proportion of the total network demand.

Embedded generation growth and local lines losses are simply spread across regions based on total load. While there are likely to be some differences between regions, the variation needs to be taken into context relative to the uncertainty in the forecast drivers of demand (GDP and population).

Adjustment to reflect recent regional demand growth

The main problem with the above allocation methodology is that it does not reflect recent trends within regions resulting from short-term changes in energy intensity. A good example of this is the intensification of farming in some areas which has resulted in high energy consumption growth over recent years relative to changes in GDP and population in those areas. Such changes are not likely to be sustainable in the long run, but it is preferable to incorporate some of the impact into the shorter term forecasts to allow for some continuation of the current trends.

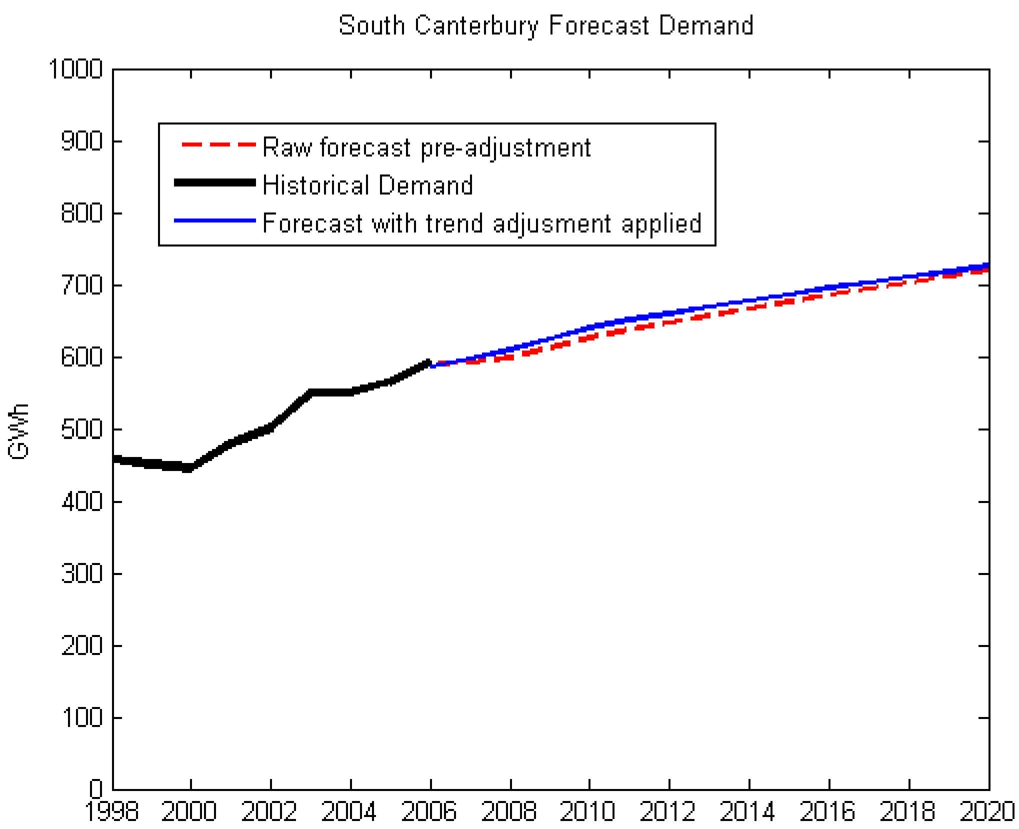
A hybrid approach has been used where forecasts are calculated based on a simple trend for each region using March year data from 1997. A weighting factor is then applied between the trend based forecasts, and the forecasts calculated using the mixed GDP/population based method outlined above. The resulting forecasts in each region are then scaled so that the sum of all the regions matches back to the national level forecasts. Essentially the approach takes some of the demand from slower demand growth regions and allocates it to higher demand growth regions in those cases where the higher growth has outstripped the rate of growth that would have otherwise have been forecast by the model.

The weighting factors used are arbitrary. Three weighting methods were tested.

1) A specified weighting was applied to the trend forecast for each forecast year – we used a linearly reducing rate from 1.0 to 0.2 over 5 years with 0 weighting thereafter: (i.e. 1, 0.8, 0.6, 0.4, 0.2, 0, 0, 0, 0, ...);
2) An exponentially reducing weighting was applied – we used a 0.8 factor (i.e. 1, 0.8, 0.64, 0.51, 0.41, 0.33, 0.26, 0.21, ...); and
3) A fixed weighting to apply to each year – we used 0.5 as an example (i.e. 0.5, 0.5, 0.5, 0.5, 0.5, …).

We selected the exponential weighting method as being the least complicated insofar as it allows the simple phasing out of the trend without specifying an explicit 'expiry' date and path shape (as required by method 1) and without incorporating a continuing trend into the forecasts (method 3).

The following graph shows forecast demand for South Canterbury with and without the trend adjustment to the regional forecast (note that in most regions there was a negligible impact).



The demand forecasting model allows for additional explicit adjustments to be made to demand at a GXP level. This allows for the inclusion of known new major loads where these are committed or certain to go ahead (within reason), and where the loads are significant compared to the existing regional load. Currently the model does not include any specific load adjustments.

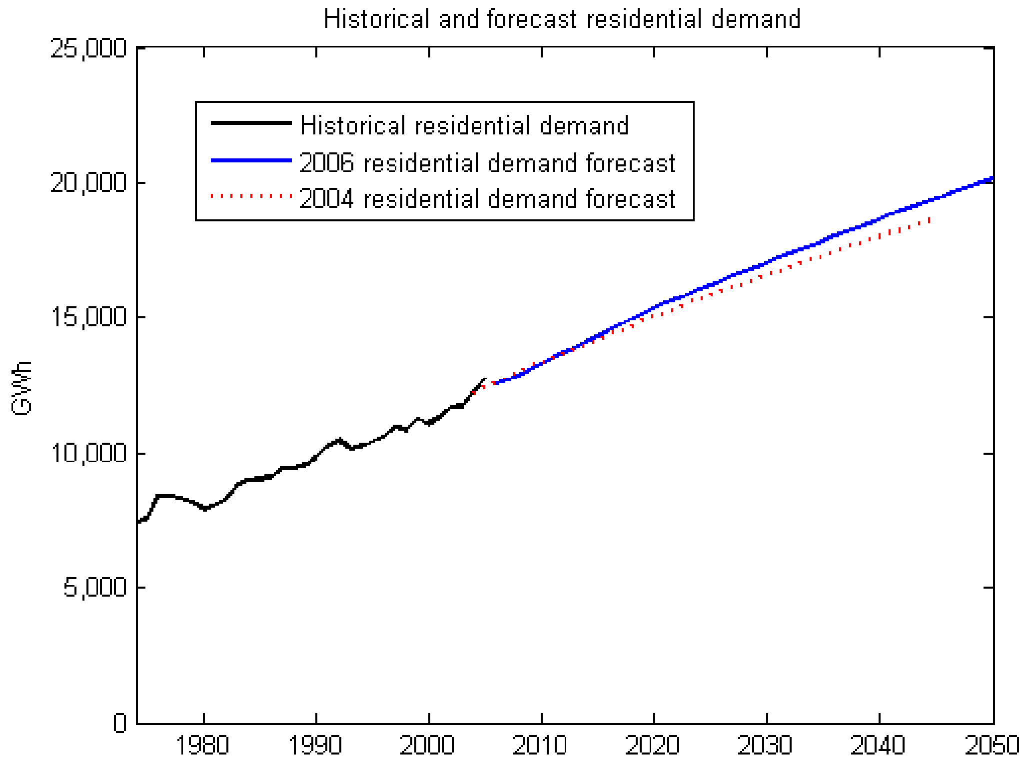
Appendix A shows demand forecast demand for each region and confidence limits based on modelled national level variation.

Comparison vs. previous forecasts

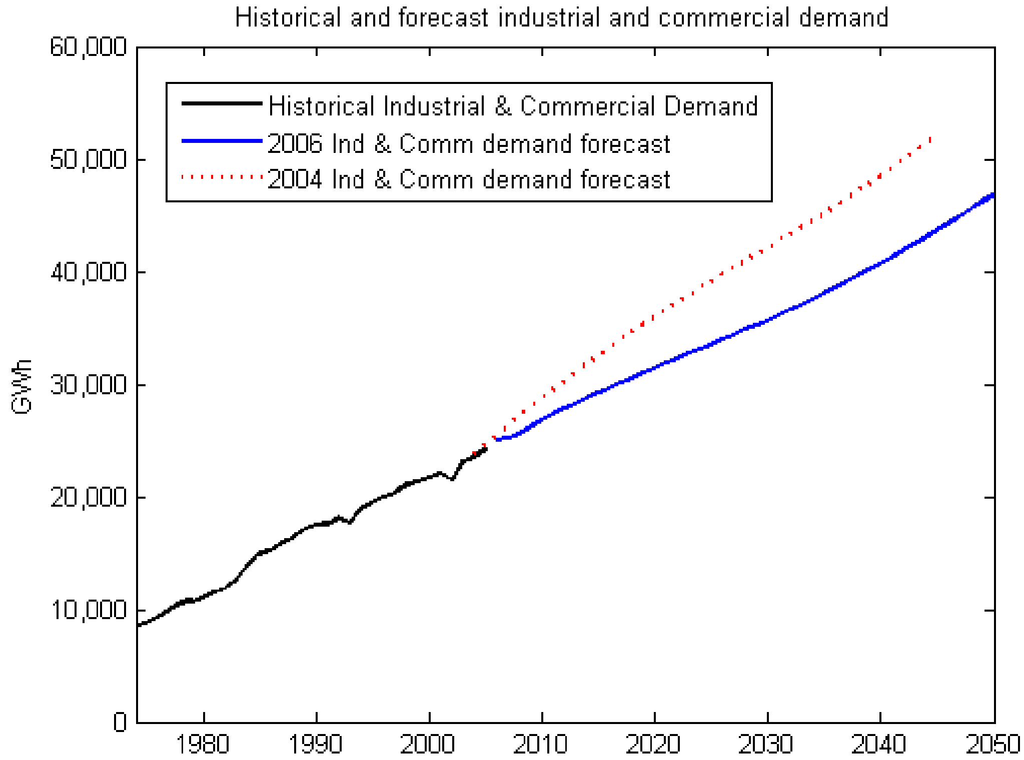
As discussed above, the forecasts for residential and commercial/industrial demand have changes as a result of a number of factors including:

- the review and update of historical input series; and
- the review and re-estimation of the models used for the industrial and commercial sectors .

The following graphs compare the previous forecasts published in the 2005 Statement of Opportunities and the new forecasts resulting from the review outlined in this paper.

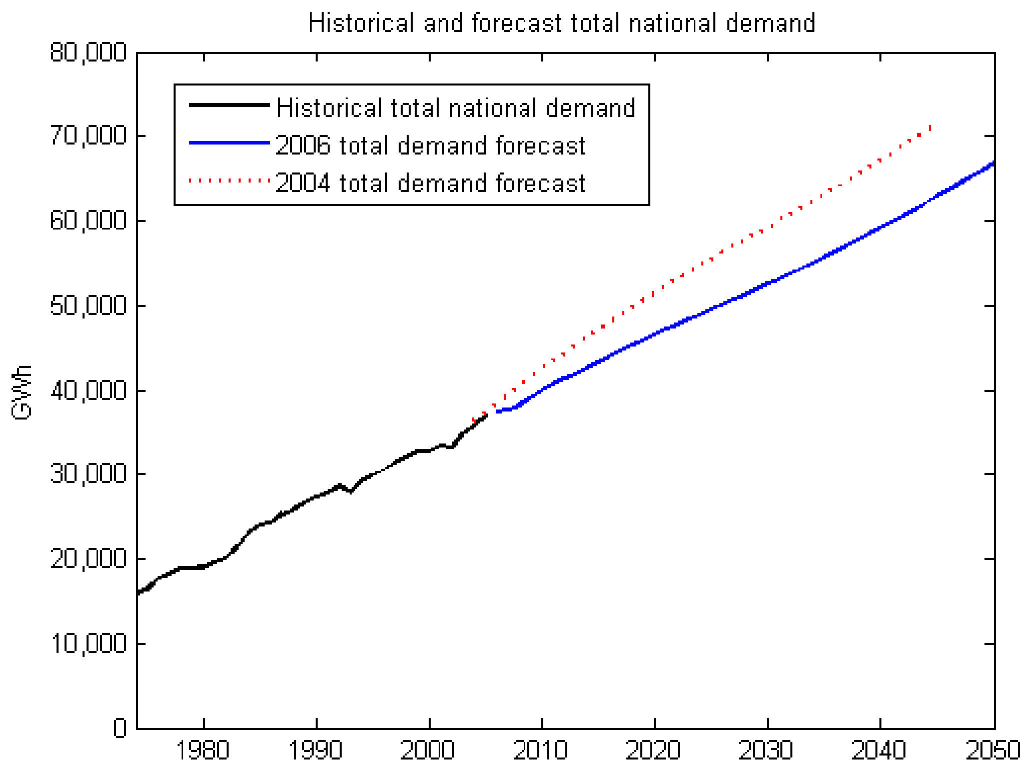


The main driver for the change in the residential demand forecast is higher long term population growth. This mainly arises from the adoption of a net 10000 immigration average scenario as the ‘medium forecast’ by Statistics New Zealand as opposed to the previous 5000 net immigration figure.

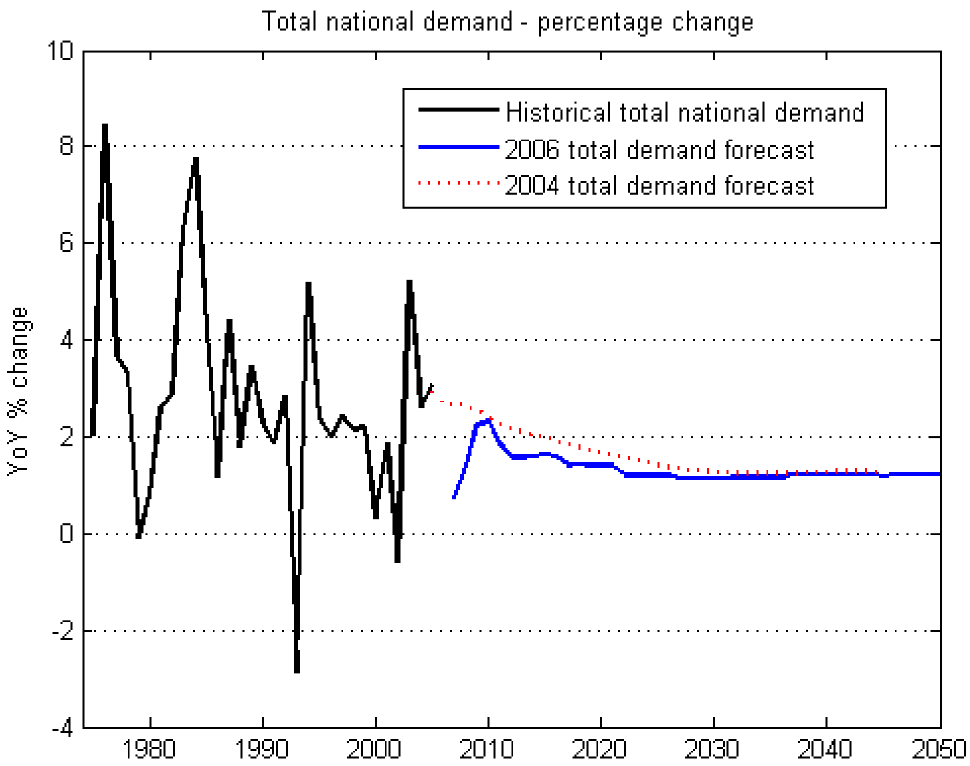


The main drivers for the change in forecast industrial and commercial demand are the change the model and modelling period for the industries apart from Tiwai, and the adoption of a flat forward forecast for the smelter.

The net impact of the changes on total forecast demand is shown in the following graph:



The difference in forecasts is shown in percentage terms below.



The very low growth evident in the early years forecast is mainly due to the low GDP forecast for the year ended March 2007 (0.8% forecast GDP growth).

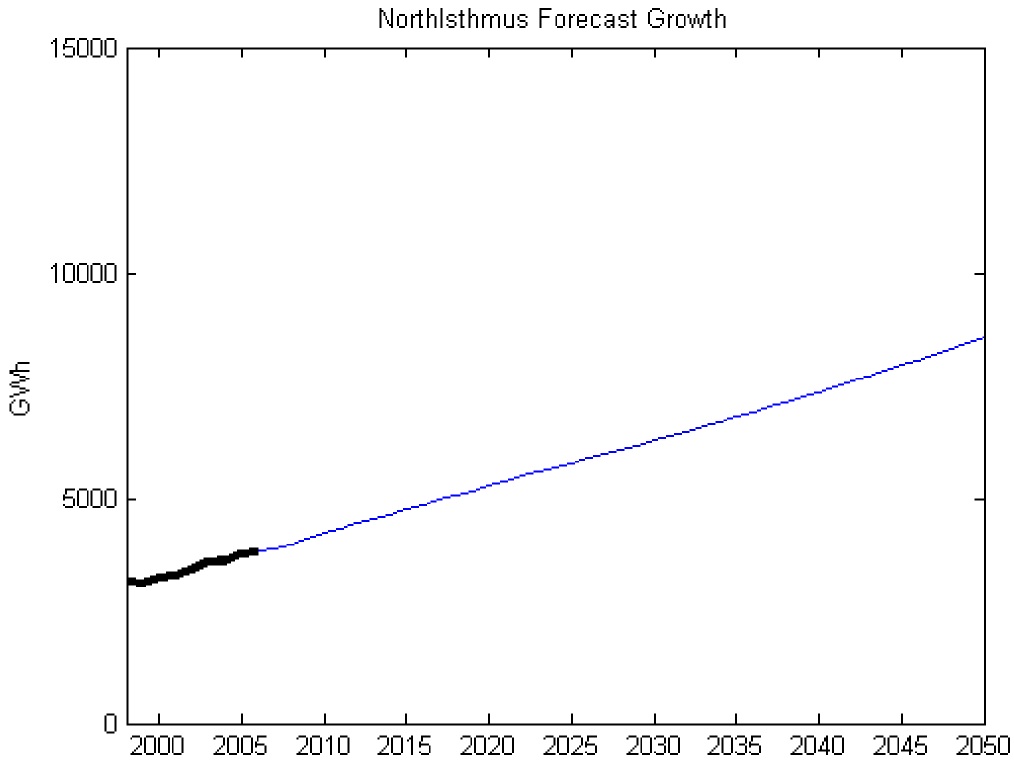
Peak Forecasts

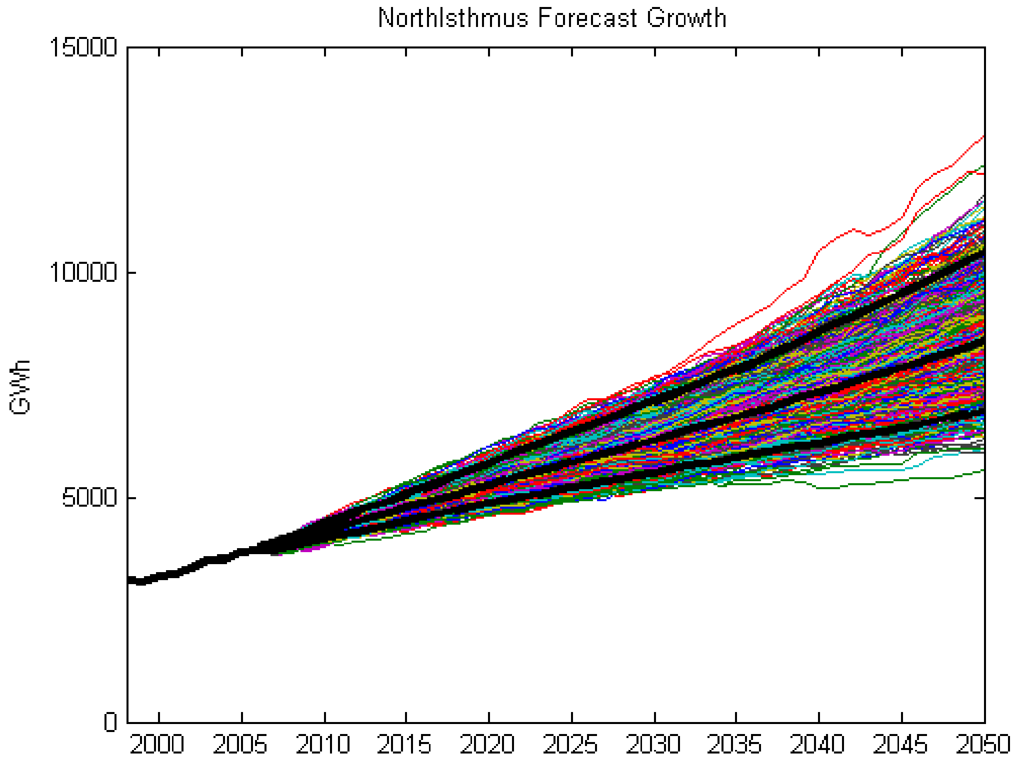
Peak forecasting is not addressed in this report. There are a number of issues that require further investigation before an approach for forecast peak demand can be finalised.

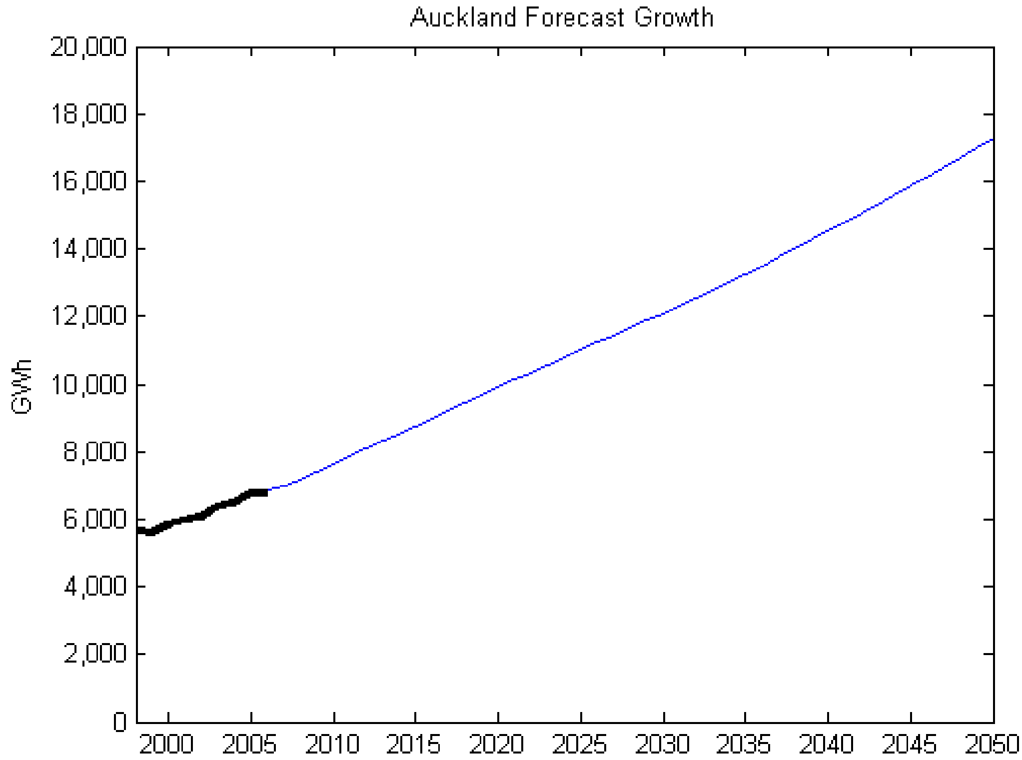
In general, peak growth is lower than average demand growth over the long term due to the effect on the diversification of load behind grid exit points and active peak load management. However, it is possible for peak growth to be significantly higher than average demand growth over the short term, in response to changes in consumer behaviour, year to year weather conditions and the like.

At this stage it is tentatively proposed that peak forecasts be based on long run growth rates, plus a margin to reflect the potential annual variation in peak growth rates.

Appendix A: Regional Forecasts






Auckland Forecast Growth
GWh
20,000
18,000
16,000
14,000
12,000
10,000
8,000
6,000
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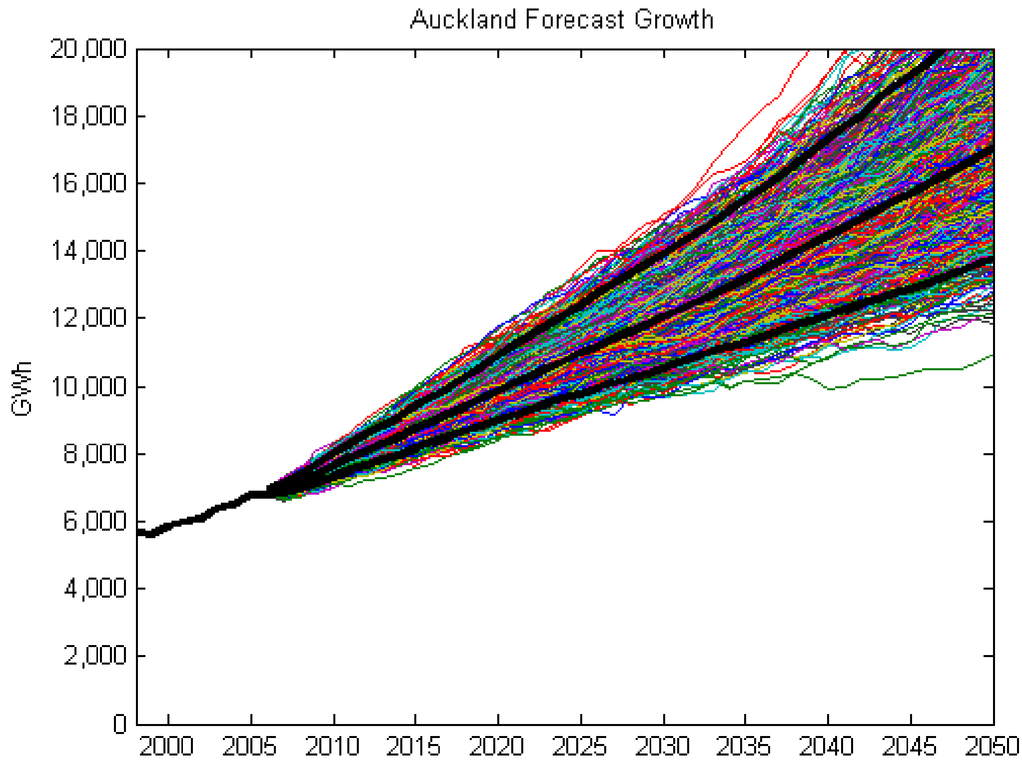
Auckland Forecast Growth
GWh
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18,000
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14,000
12,000
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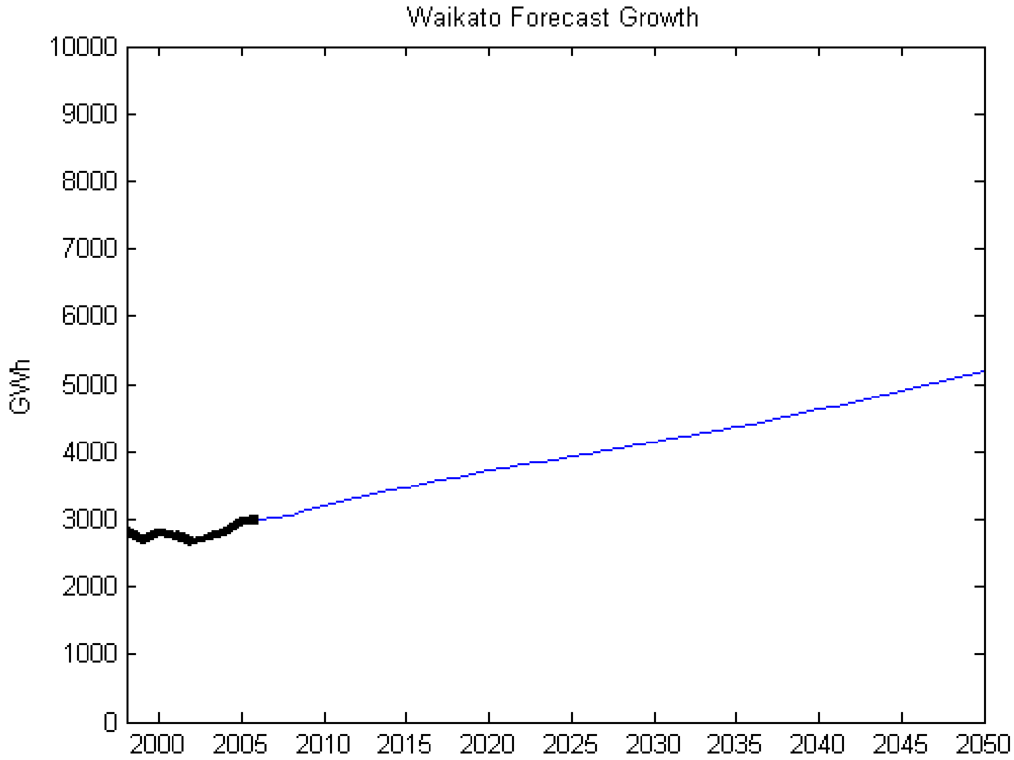
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GWh
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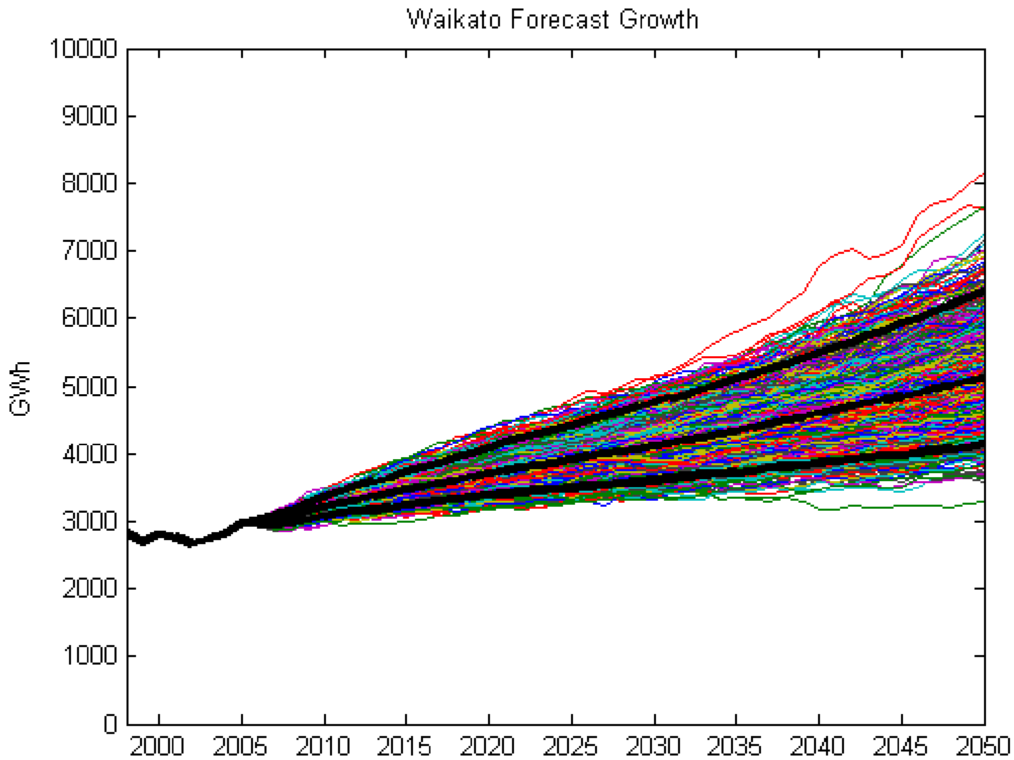
Waikato Forecast Growth
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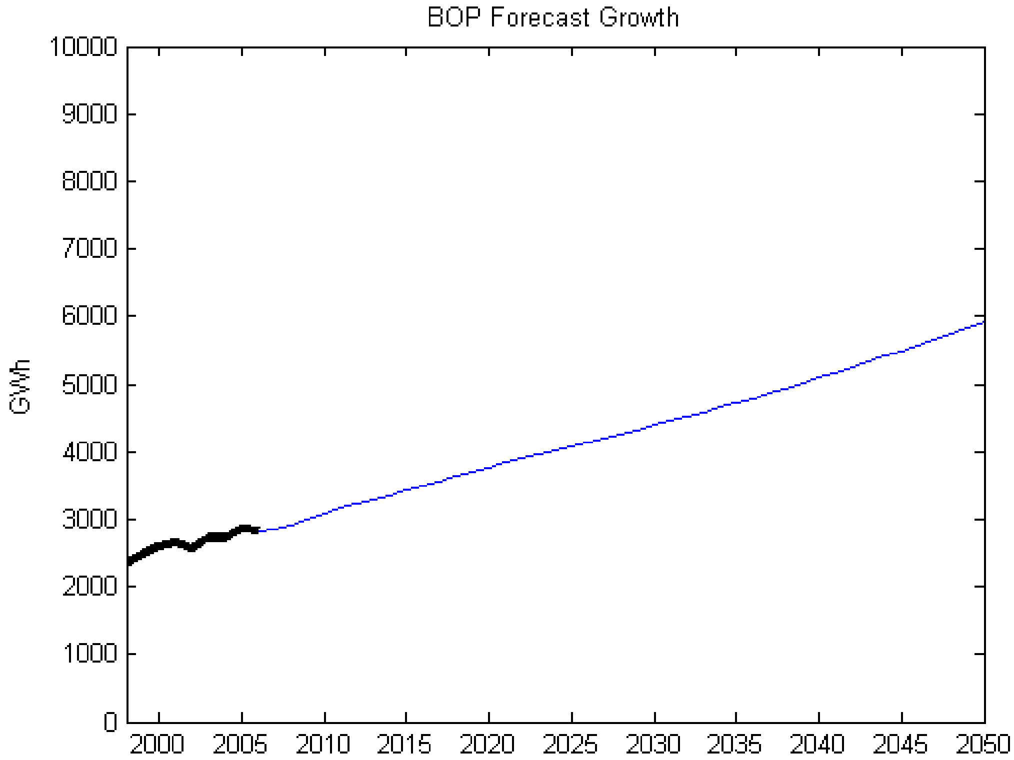
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GWh
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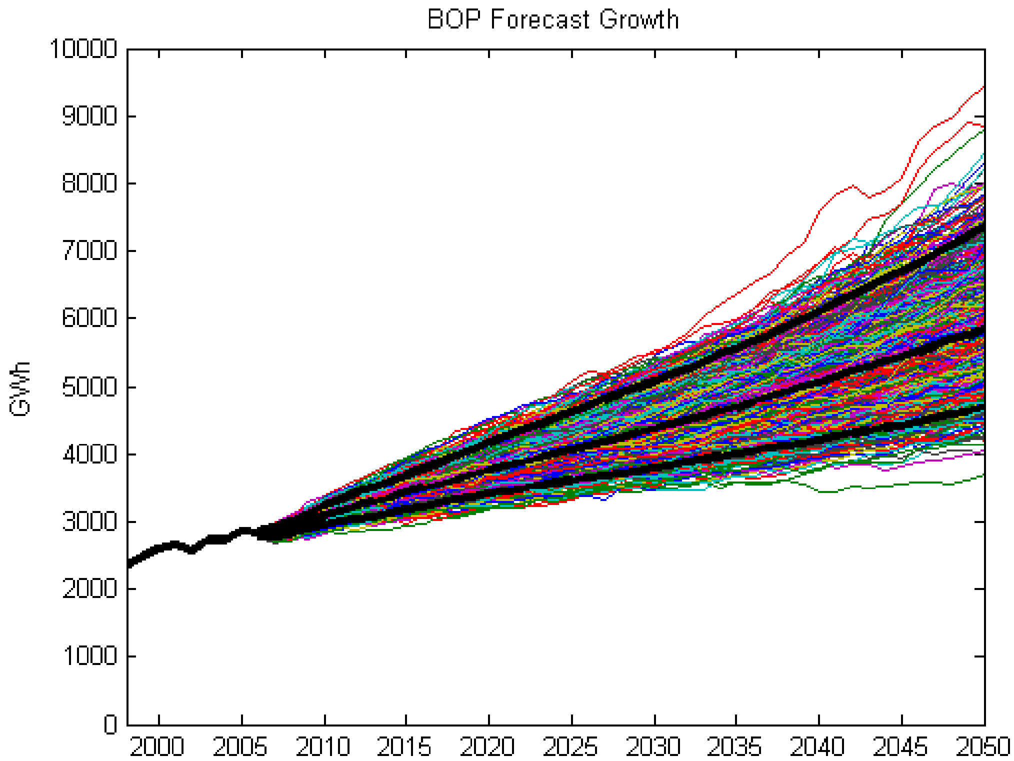
BOP Forecast Growth
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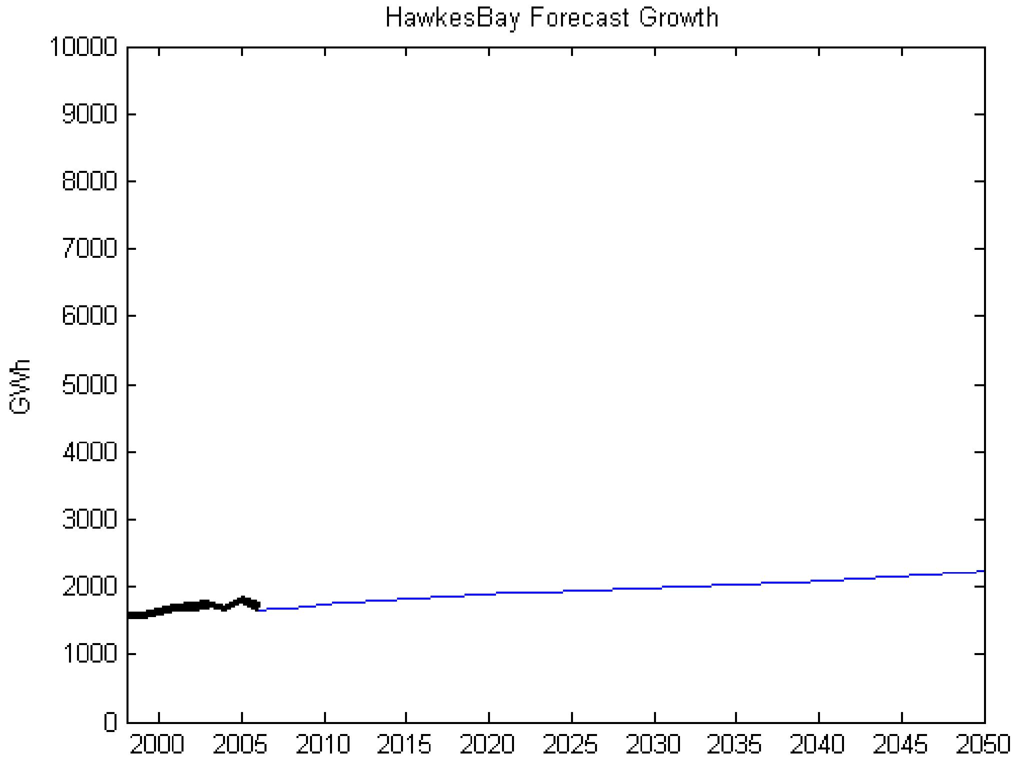
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GWh
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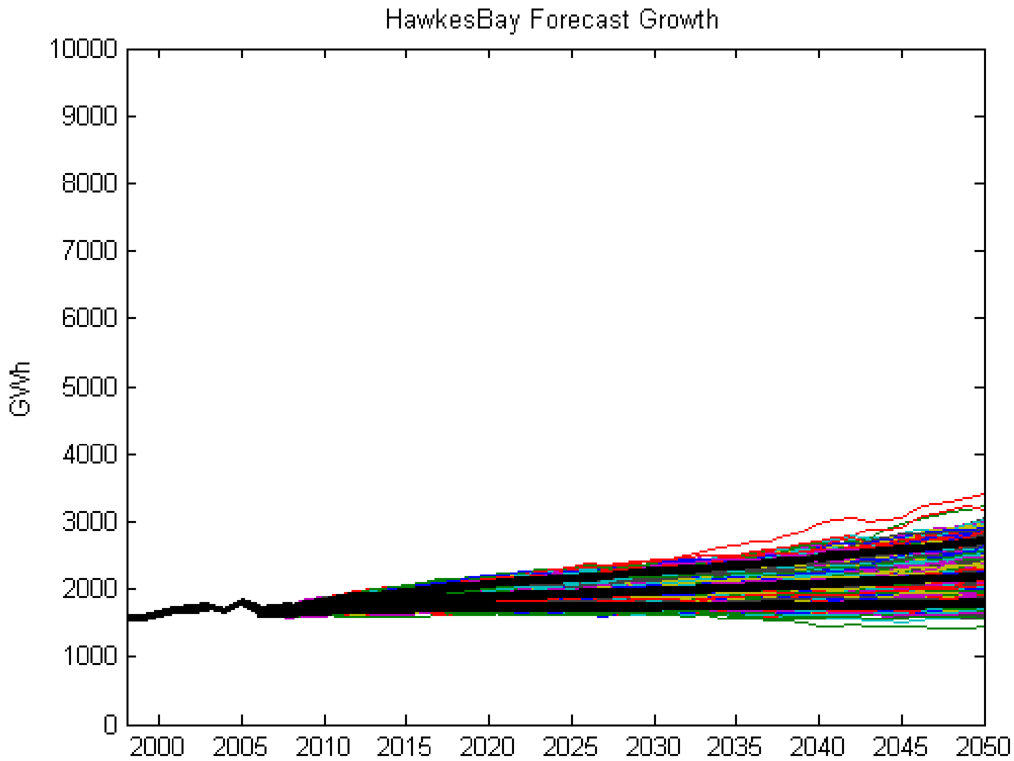
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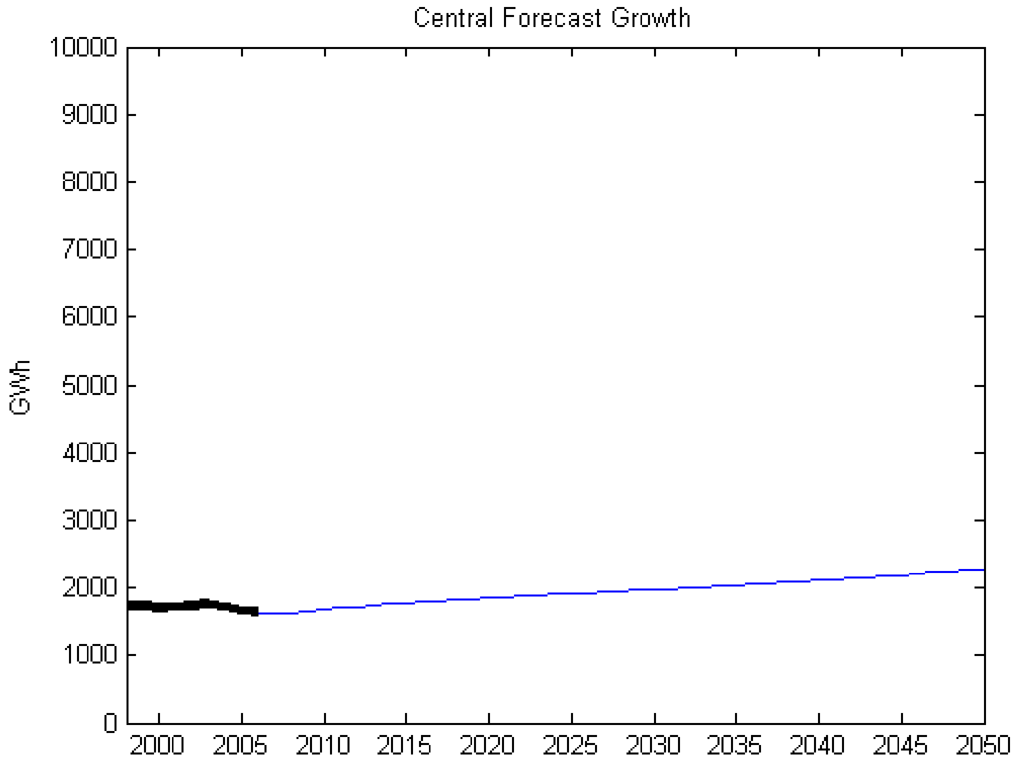
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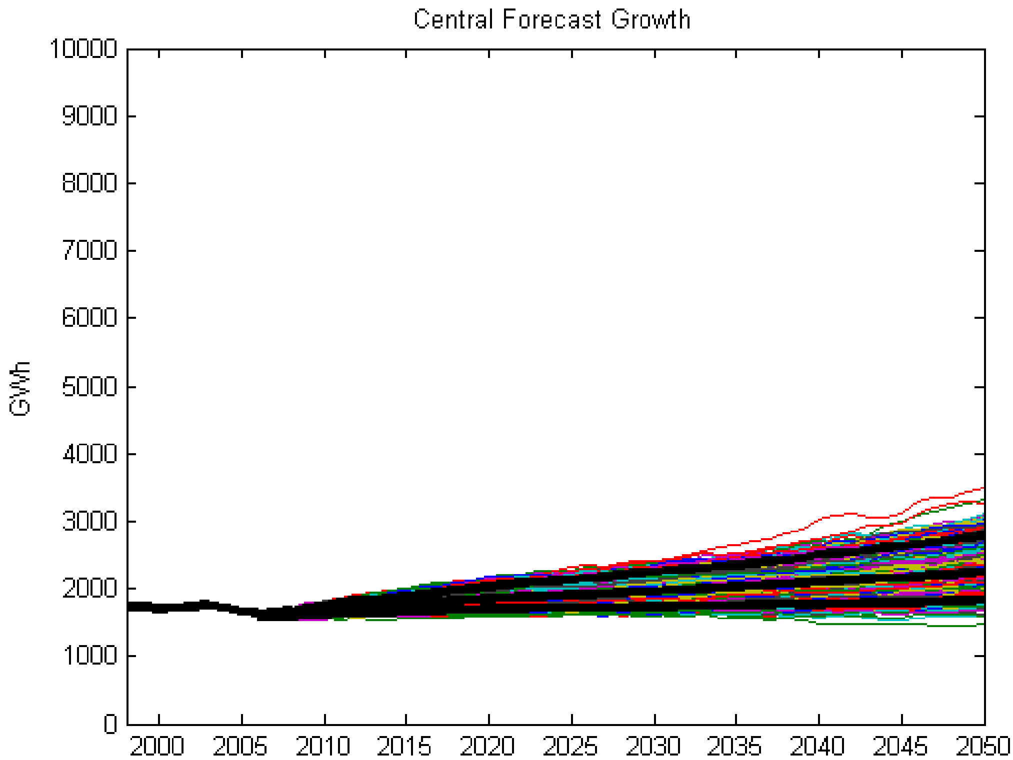
Central Forecast Growth
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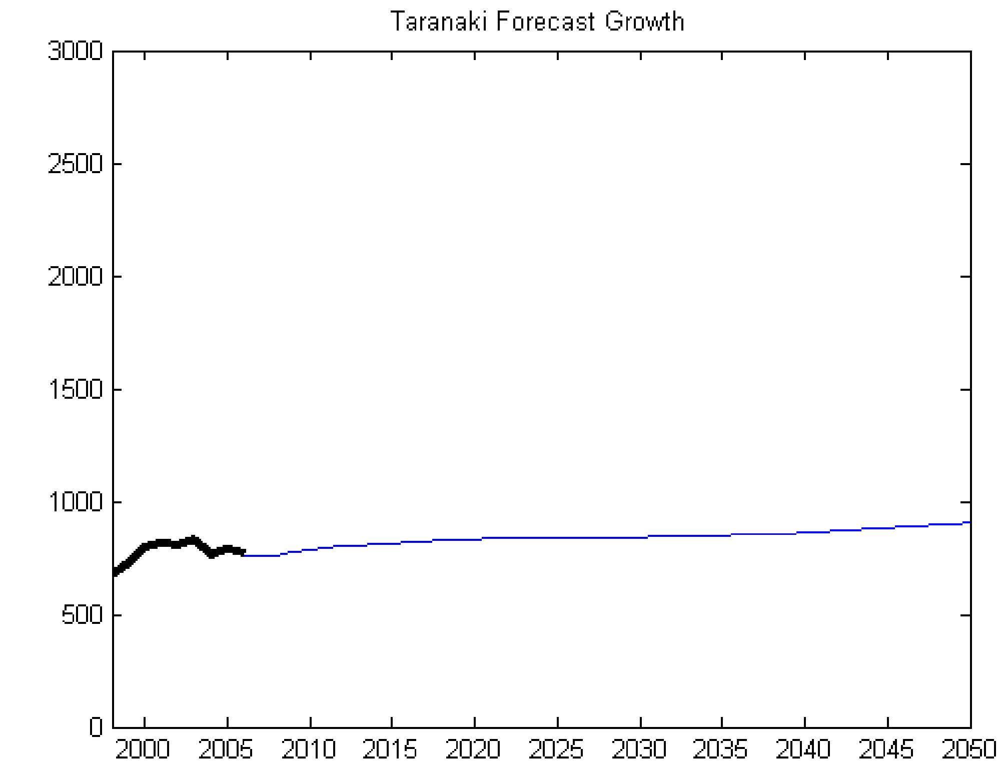
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1500
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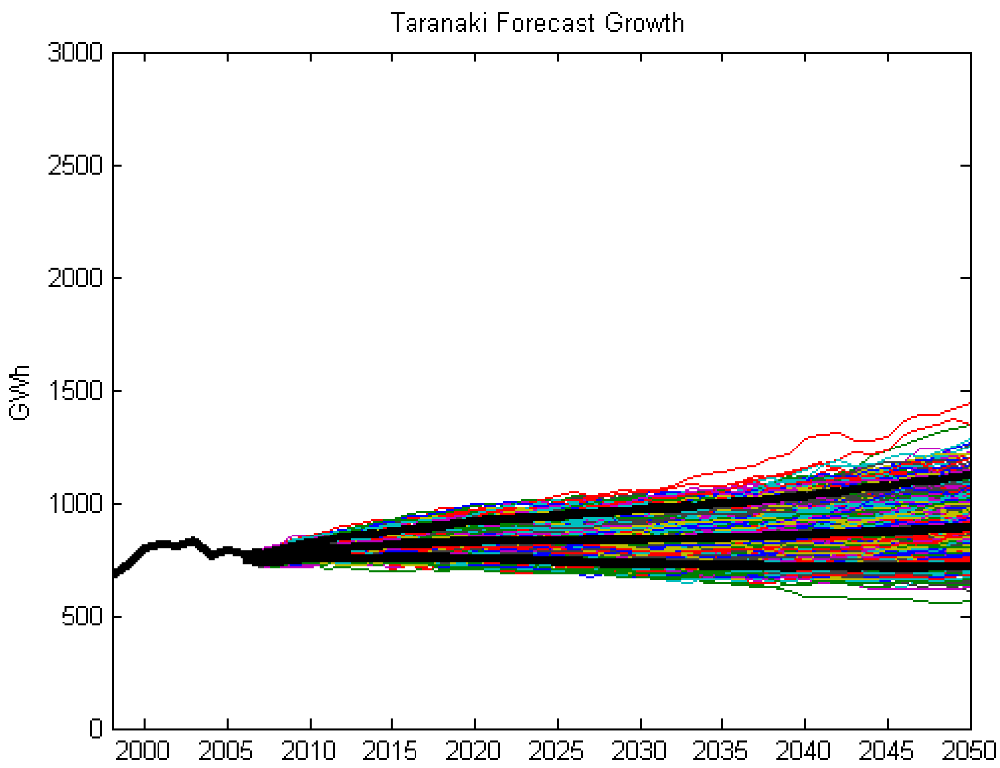
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GWh
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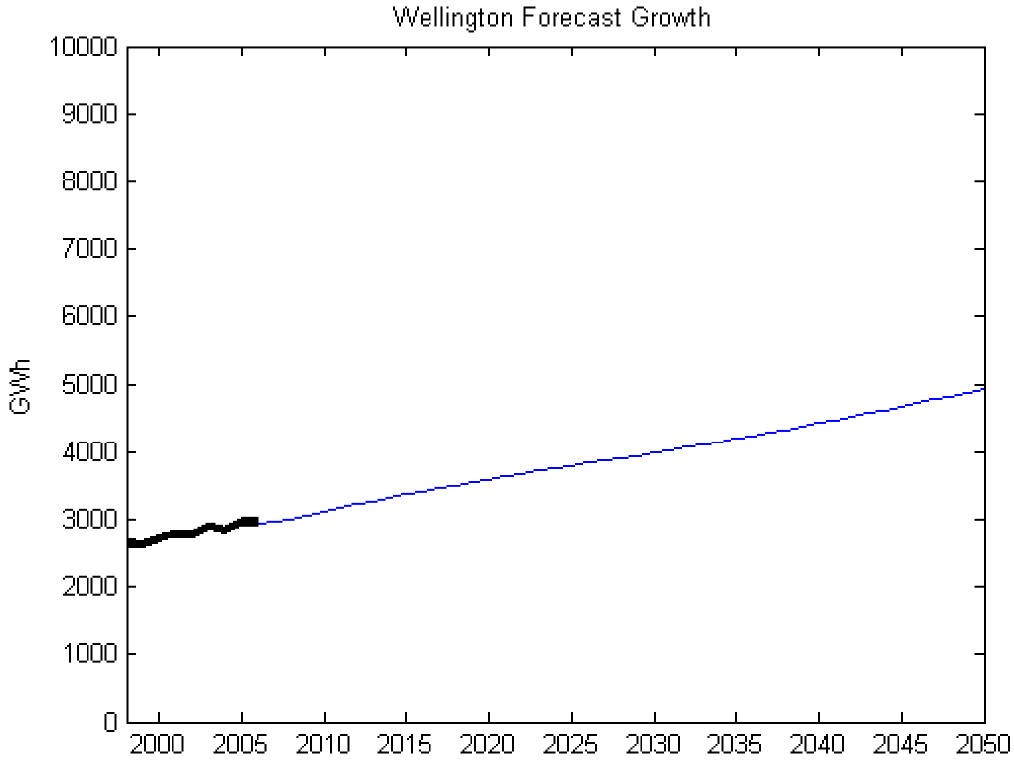
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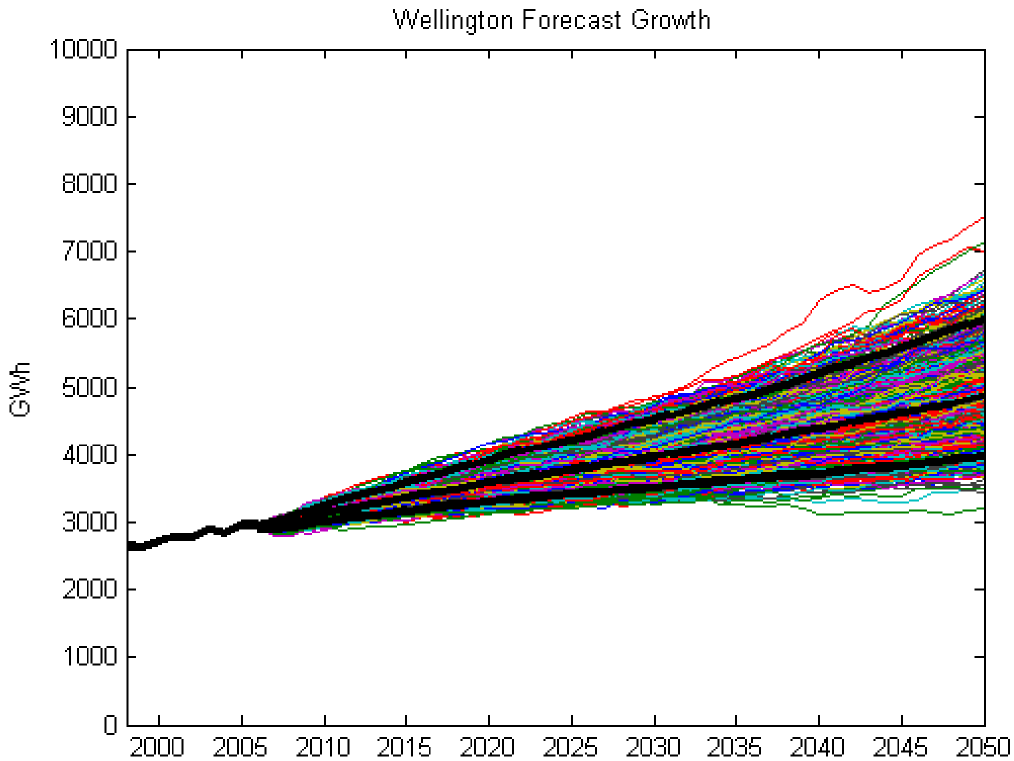
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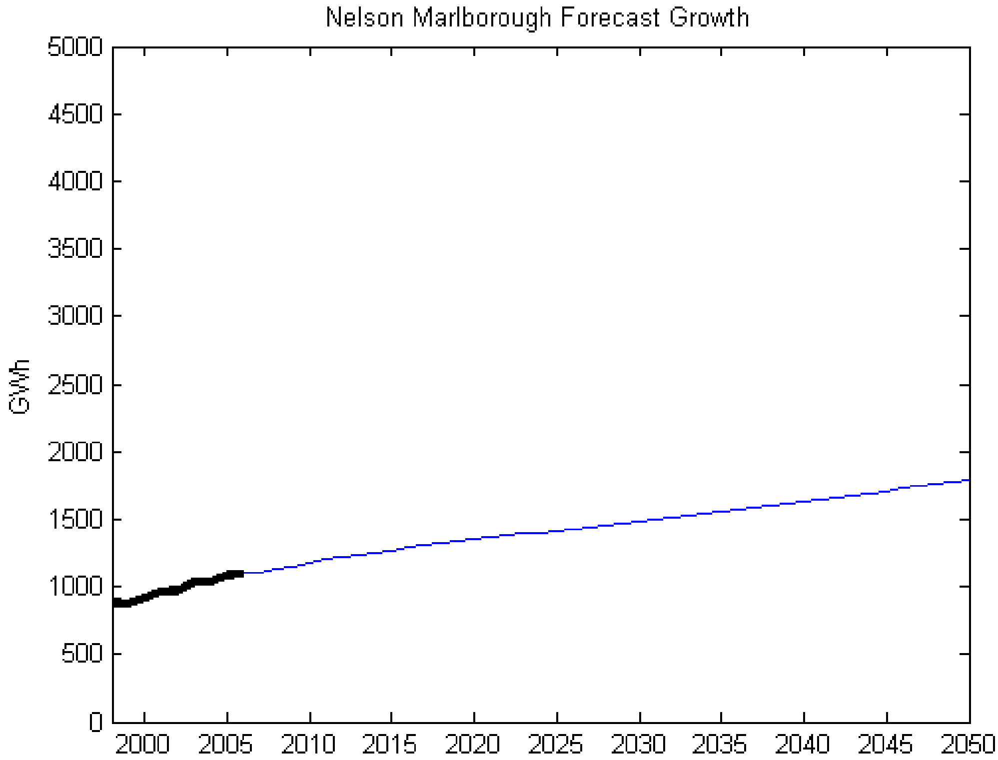
Nelson Marlborough Forecast Growth
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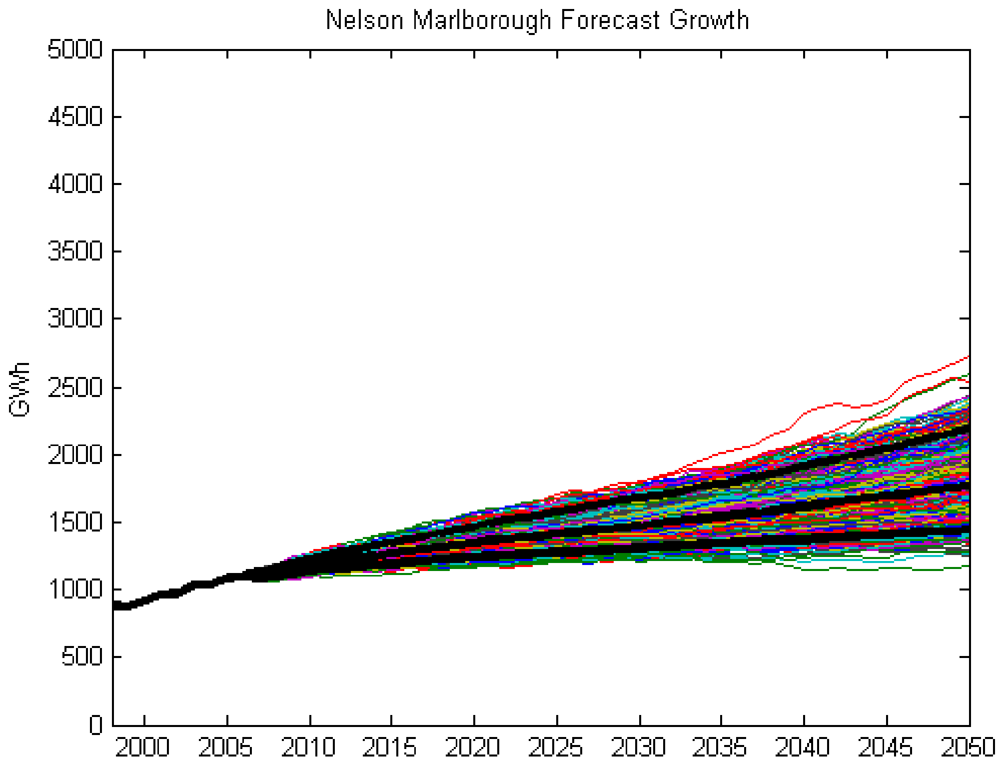
Nelson Marlborough Forecast Growth
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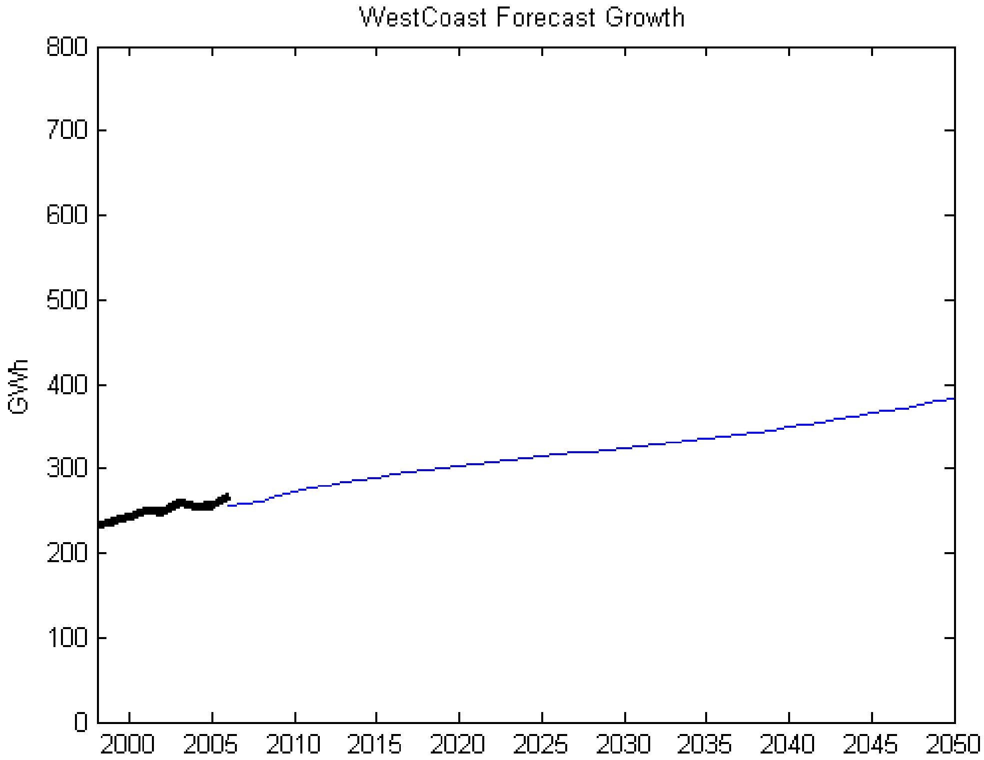
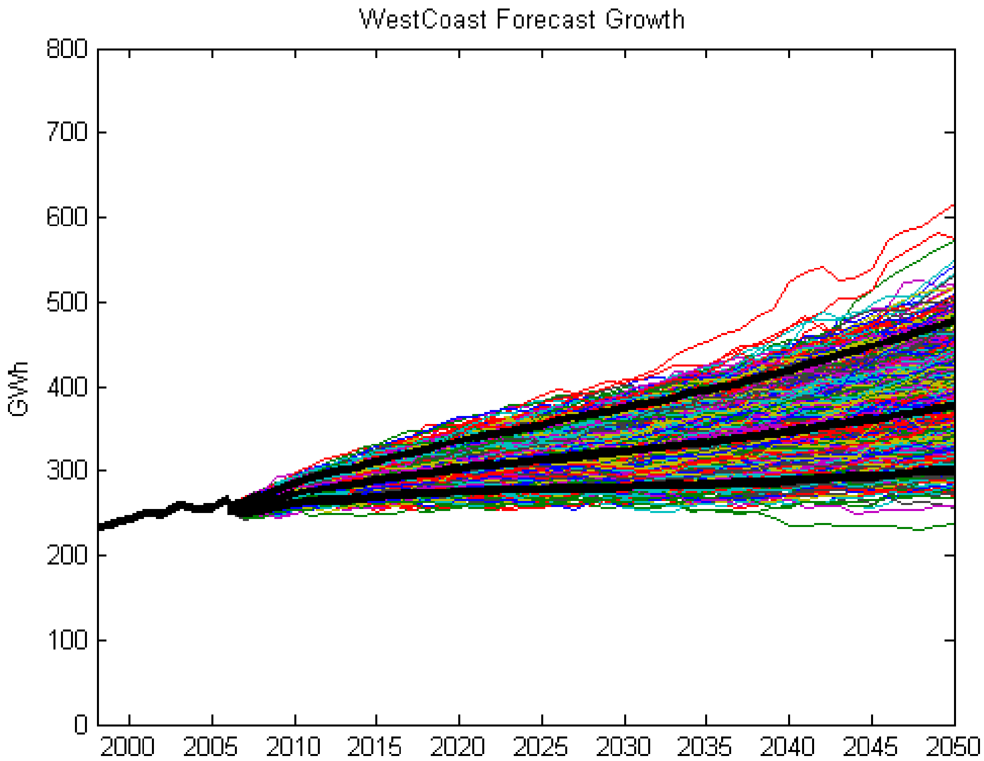
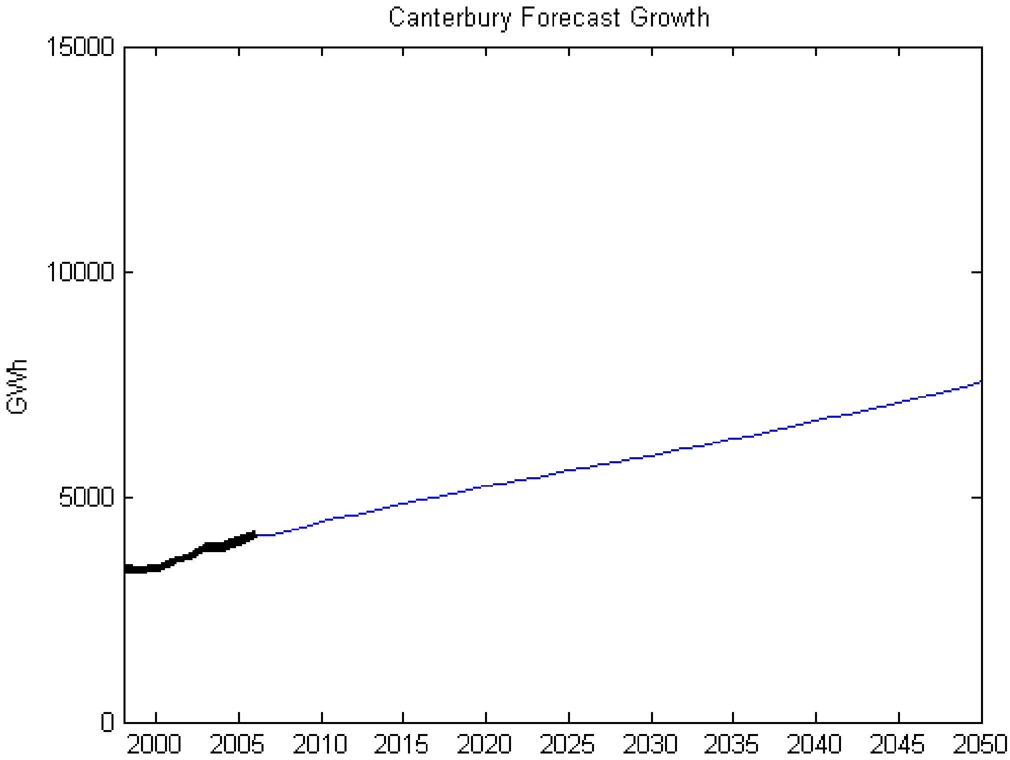
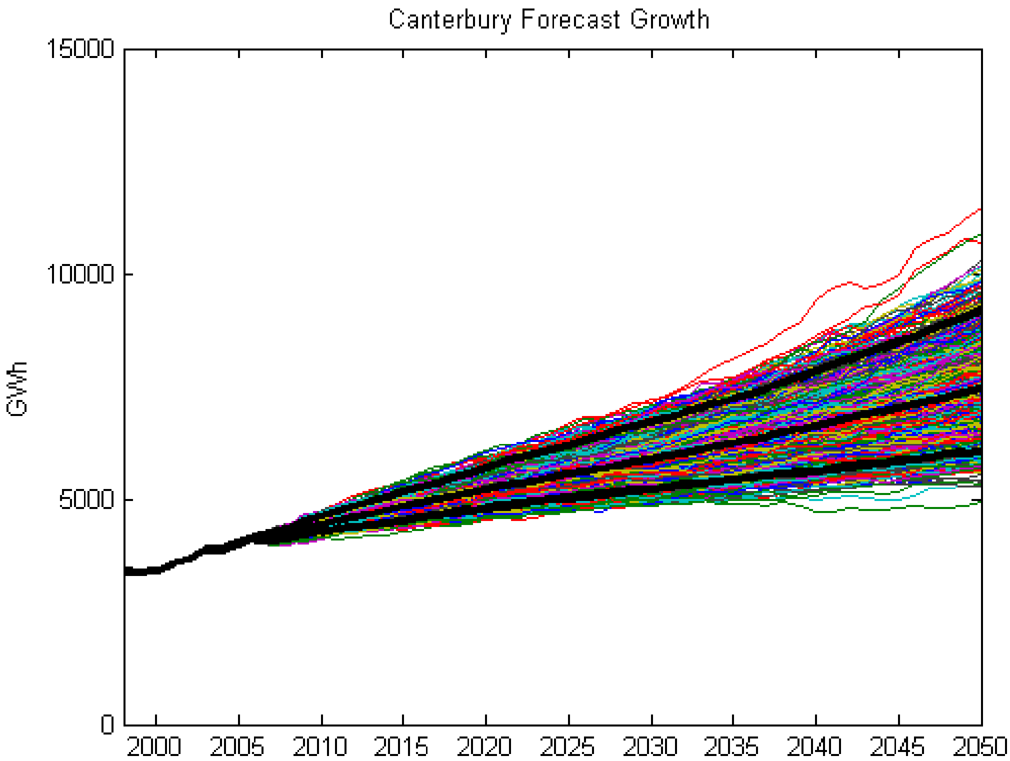
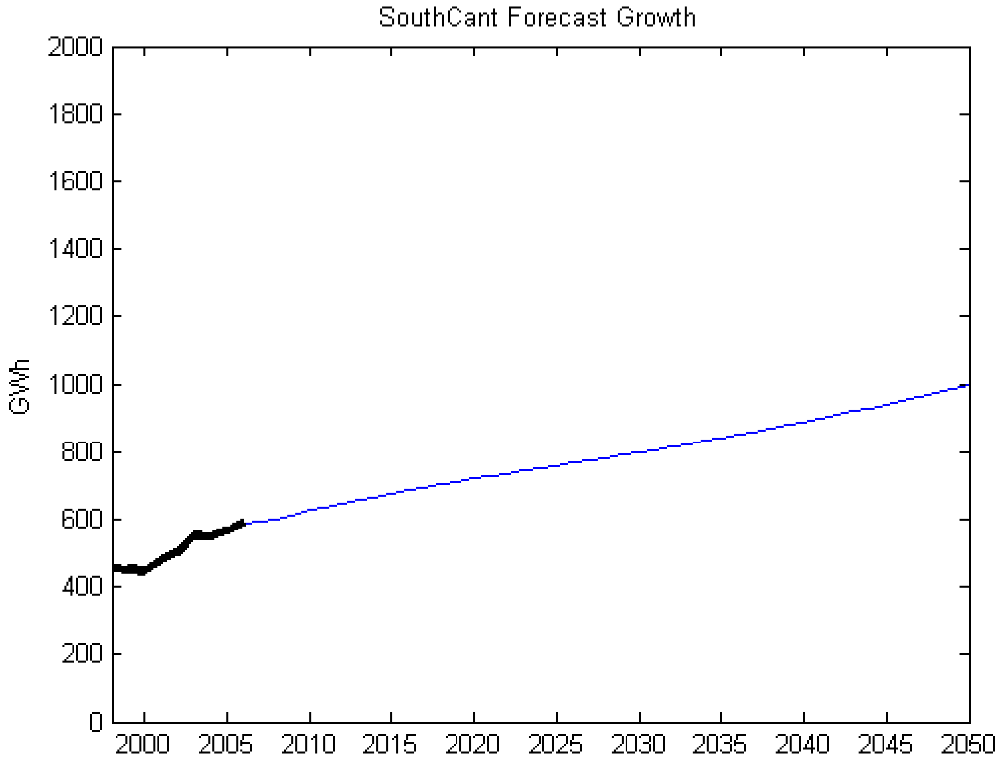
2045
2050

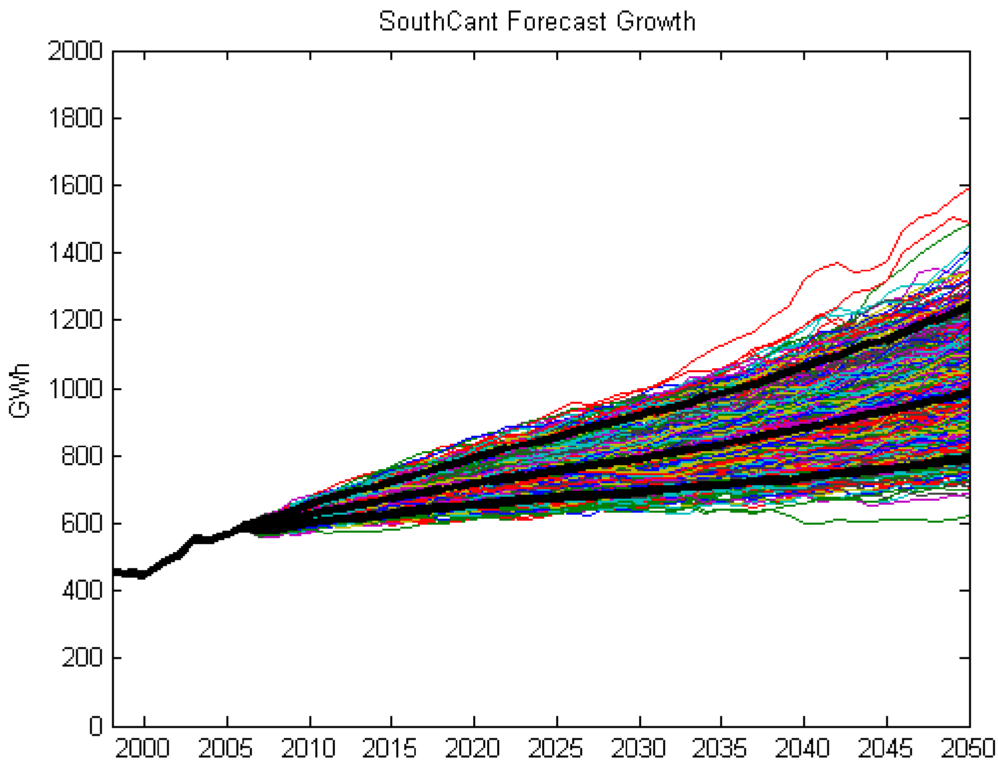

WestCoast Forecast Growth
GWh
0
100
200
300
400
500
600
700
800
2000
2005
2010
2015
2020
2025
2030
2035
2040
2045
2050

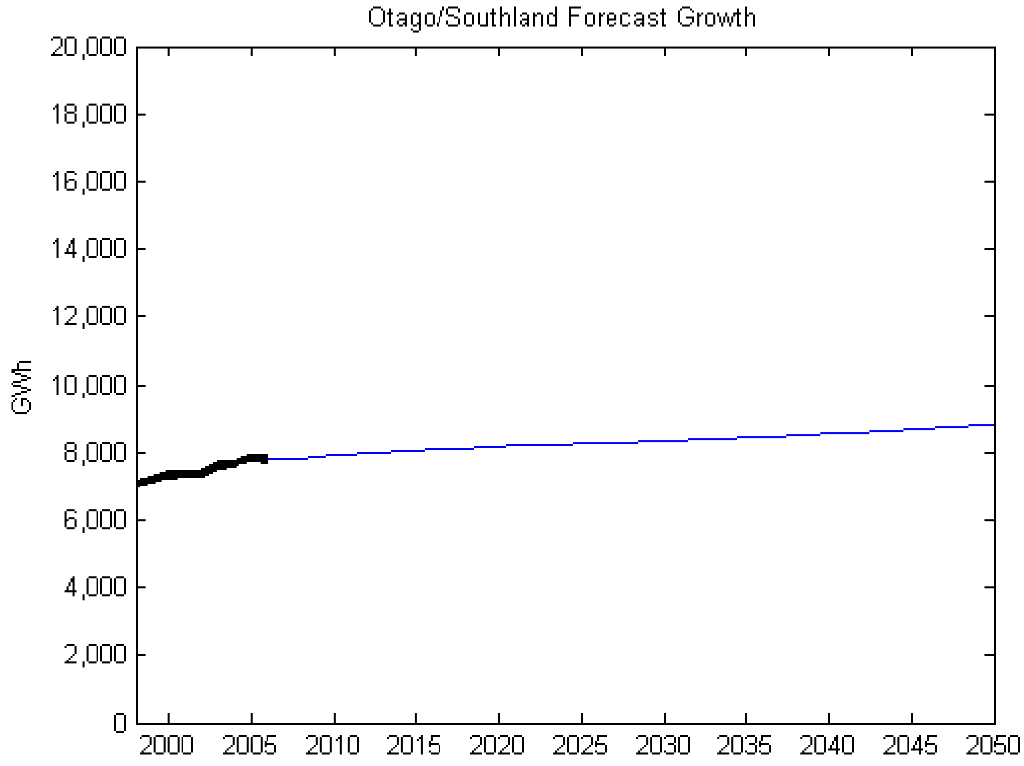

WestCoast Forecast Growth
GWh
0
100
200
300
400
500
600
700
800
2000
2005
2010
2015
2020
2025
2030
2035
2040
2045
2050

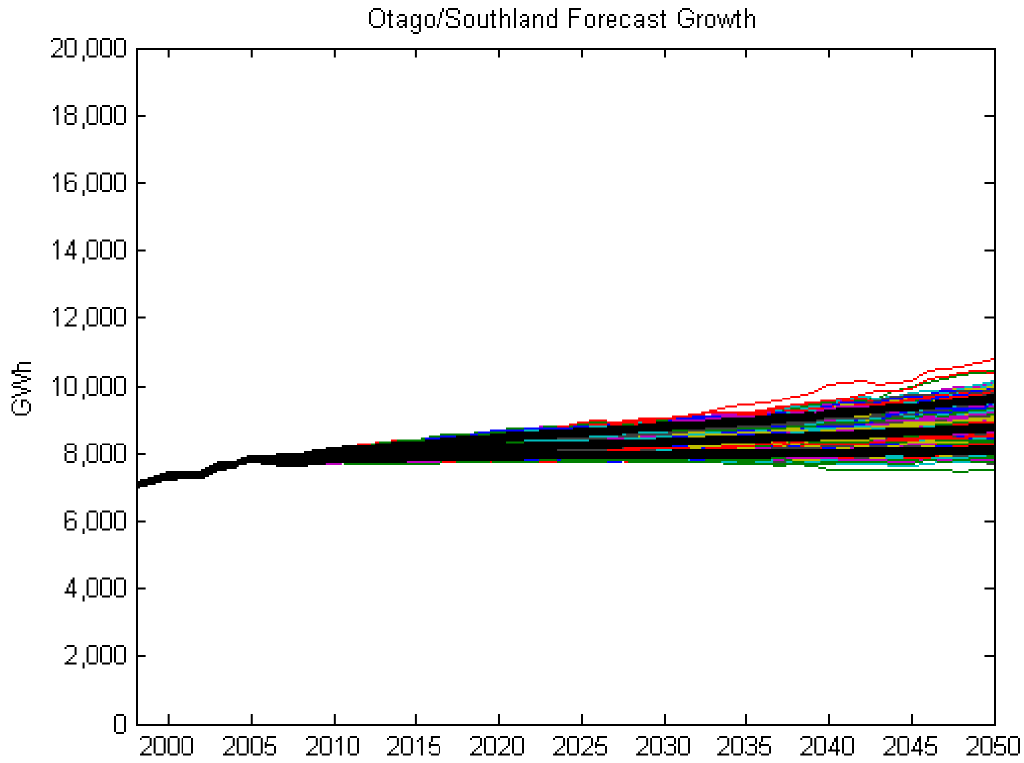

Canterbury Forecast Growth
15000
10000
5000
0
GWh
2000
2005
2010
2015
2020
2025
2030
2035
2040
2045
2050

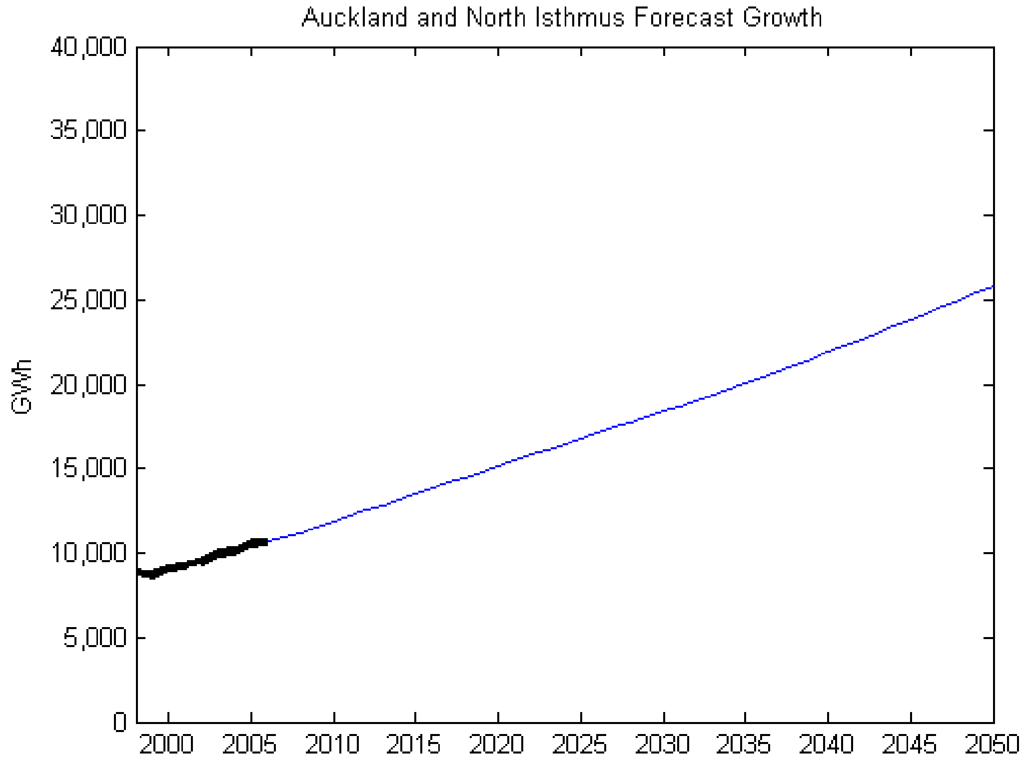

Canterbury Forecast Growth
15000
10000
5000
0
GWh
2000
2005
2010
2015
2020
2025
2030
2035
2040
2045
2050

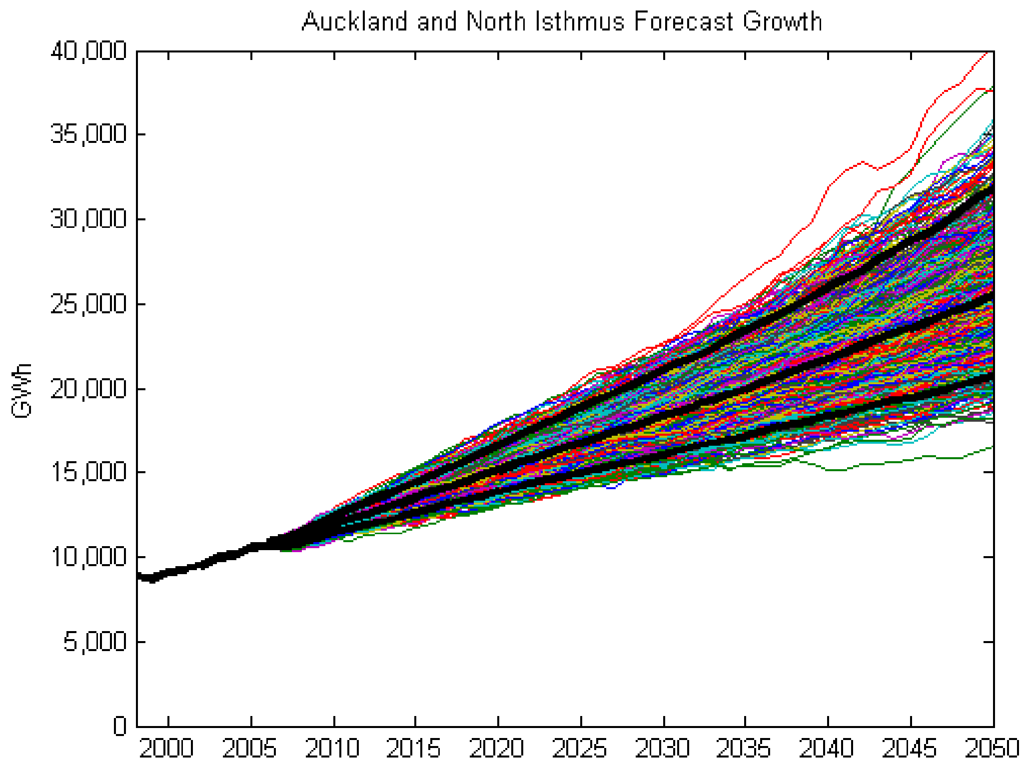

SouthCant Forecast Growth
GWh
0
200
400
600
800
1000
1200
1400
1600
1800
2000
2000
2005
2010
2015
2020
2025
2030
2035
2040
2045
2050

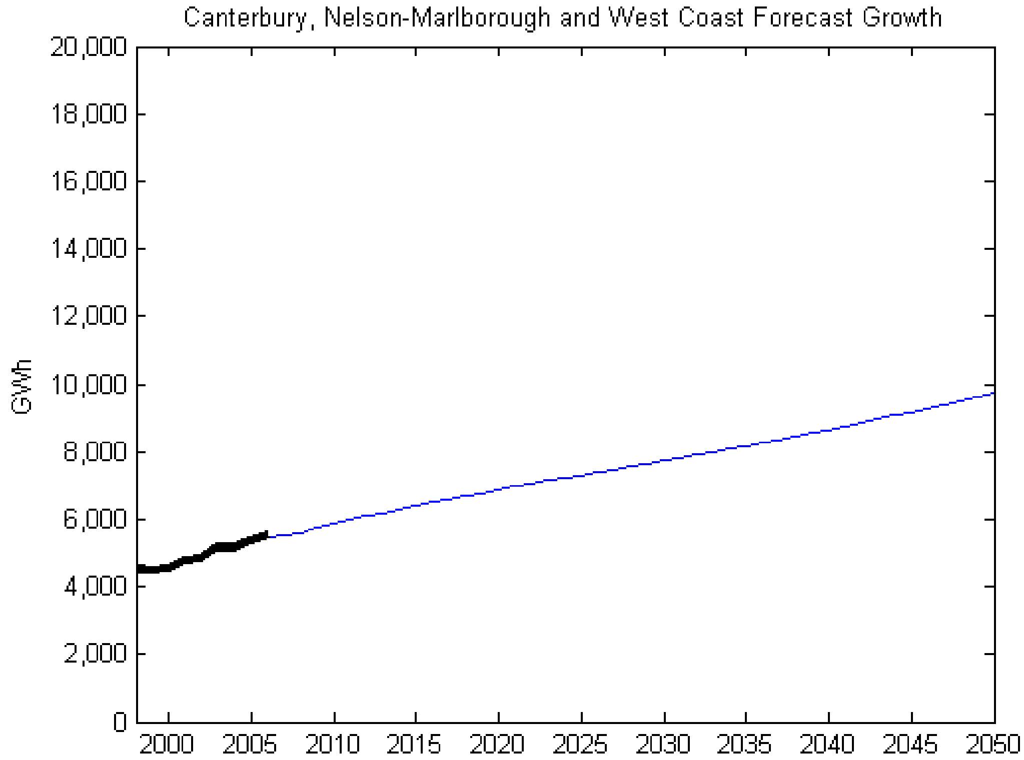

SouthCant Forecast Growth
GWh
0
200
400
600
800
1000
1200
1400
1600
1800
2000
2000
2005
2010
2015
2020
2025
2030
2035
2040
2045
2050


Otago/Southland Forecast Growth
GWh
20,000
18,000
16,000
14,000
12,000
10,000
8,000
6,000
4,000
2,000
0
2000
2005
2010
2015
2020
2025
2030
2035
2040
2045
2050

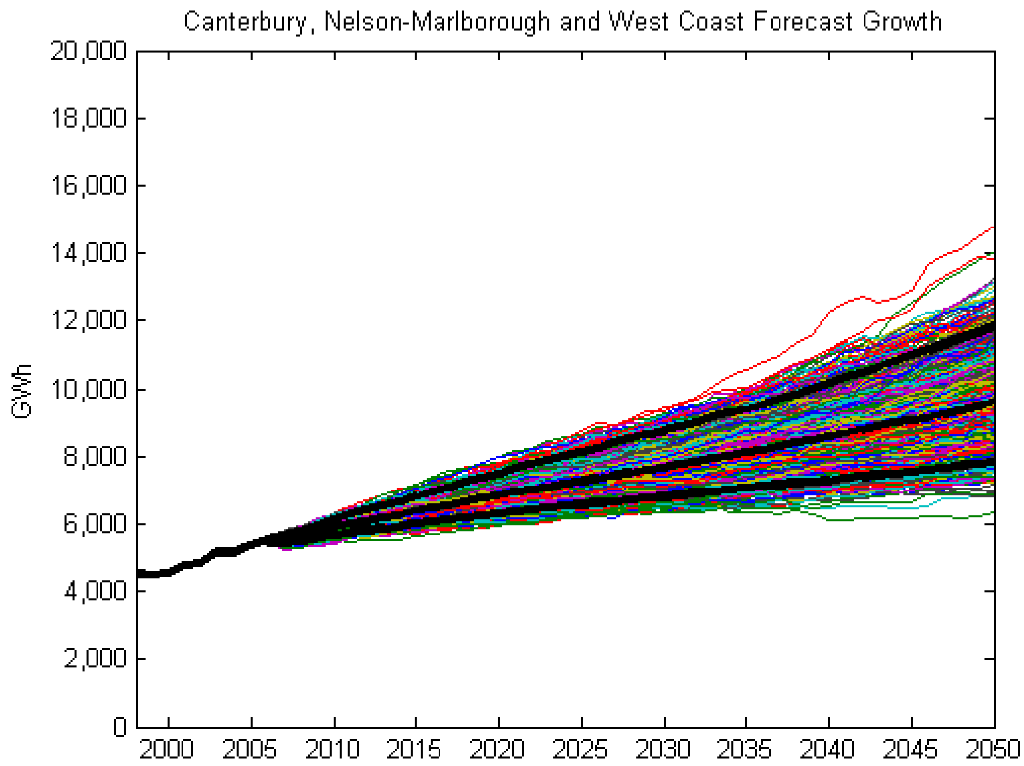

Otago/Southland Forecast Growth
GWh
20,000
18,000
16,000
14,000
12,000
10,000
8,000
6,000
4,000
2,000
0
2000
2005
2010
2015
2020
2025
2030
2035
2040
2045
2050


Auckland and North Isthmus Forecast Growth
GWh
40,000
35,000
30,000
25,000
20,000
15,000
10,000
5,000
0
2000
2005
2010
2015
2020
2025
2030
2035
2040
2045
2050


Auckland and North Isthmus Forecast Growth
GWh
40,000
35,000
30,000
25,000
20,000
15,000
10,000
5,000
0
2000
2005
2010
2015
2020
2025
2030
2035
2040
2045
2050



Canterbury, Nelson-Marlborough and West Coast Forecast Growth
GWh
20,000
18,000
16,000
14,000
12,000
10,000
8,000
6,000
4,000
2,000
0
2000
2005
2010
2015
2020
2025
2030
2035
2040
2045
2050



Canterbury, Nelson-Marlborough and West Coast Forecast Growth
GWh
20,000
18,000
16,000
14,000
12,000
10,000
8,000
6,000
4,000
2,000
0
2000
2005
2010
2015
2020
2025
2030
2035
2040
2045
2050