Methods for Forecasting Supply and Demand

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Some material in this presentation was borrowed from Douglas Gotham,
State Utility Forecasting Group, Purdue University
OUTLINE

- Modeling techniques
- Projecting peak demand from energy forecasts
- Determining capacity needs from demand forecasts
- Incorporating load management and conservation measures
- Uncertainty
MODELING TECHNIQUES

Time Series
  • trend analysis

Econometric
  • structural analysis

End Use
  • engineering analysis

Statistically Adjusted End-Use
  • combine elements of econometric and end-use models
TIME SERIES FORECASTING

Pick patterns in historical data and assume the pattern will persist into the future

A simple example
TIME SERIES FORECASTING

A more difficult example

<table>
<thead>
<tr>
<th>1000</th>
<th>1100</th>
<th>1210</th>
<th>1331</th>
<th>1464</th>
<th>1611</th>
<th>?</th>
<th>?</th>
<th>?</th>
</tr>
</thead>
</table>

![Graph showing a time series forecast]
A more realistic example

One may opt to remove randomness with a smoothing techniques

• Exponential Smoothing
• Moving averages
• Hodrick-Prescott filter

However, this is admitting that one can not predict deviations from the trend
A more realistic example with seasonality

When fitting a time trend, remove seasonality

- Exponential Smoothing
- Moving averages
- Census X11 or X12
- Hodrick-Prescott filter

Reapply seasonal factors to prediction
TIME SERIES FORECASTING

Linear Time Trend
• Fit the best straight line to the historical data and assume that the future will follow that line
  • works perfectly in the 1st example
• Many methods exist for finding the best fitting line; the most common is the least squares method

Polynomial Time Trend
• Fit the polynomial curve to the historical data and assume that the future will follow that line
• Can be done to any order of polynomial (square, cube, etc.) but higher orders are usually needlessly complex

Logarithmic Time Trend
• Fit an exponential curve to the historical data and assume that the future will follow that line
  • works perfectly for the 2nd example
Most commercial statistical software packages and spreadsheets include functions for fitting data to a time trend

- Statistical software will often help the user determine which specification has the best fit

Time trends may not work well if there is substantial variability in the data. Smooth data prior to fitting time trend

- Randomness
  - What does not fit the prediction is called prediction error
- Seasonality
  - Be sure to reapply seasonal factors to predictions
TIME SERIES FORECASTING

Strengths:

• Low data requirements
• Simplistic implementation
• Well established approaches
• Can be exceedingly accurate in short-term forecasts

Weakness:

• May result in imprecise forecasts
• Long-term viability of forecasts are questionable
• No capacity for what-if scenarios
Econometric models attempt to quantify the relationship between the variable of interest and a number of factors that affect the output variable.

**Example**

- Output variable
- Explanatory variable
  - Economic activity
  - Weather (HDD/CDD)
  - Electricity price
  - Natural gas price
  - Fuel oil price
  - Population
  - Technology (Time)
ECONOMETRIC FORECASTING

- Each explanatory variable affects the output variable in different ways
- The relationships can be calculated via any of the methods used in time series forecasting
  - Can be linear, polynomial, logarithmic, moving averages, …
- Each relationship is determined holding constant other influences to find an overall best fit set of relationships
- Relationships are commonly known as sensitivities
Example of electricity demand sensitivities for state of Mississippi

<table>
<thead>
<tr>
<th>A 10 percent increase in:</th>
<th>Results in this increase in electricity sales</th>
</tr>
</thead>
<tbody>
<tr>
<td>Electricity price</td>
<td>-3.0 percent</td>
</tr>
<tr>
<td>Cooling degree days</td>
<td>+0.7 percent</td>
</tr>
<tr>
<td>Real personal income</td>
<td>+7.8 percent</td>
</tr>
</tbody>
</table>
Estimates of sensitivities can suffer biasness

- Data error
- **Model misspecification**
  - Functional form
    - Linear/log-log/linear-log/log-linear
    - Omission of constant term
  - Omitted variable bias
- **Influential observations/Regime switch**
- **Simultaneous equation bias**
  - If any independent variable is correlated with prediction errors, the coefficients will be bias
- View a graph of the model errors to identify systematic prediction errors
ECONOMETRIC FORECASTING

Strengths:

• Low data requirements
• Flexible design to meet user needs
• Well established approaches

Weakness:

• May result in imprecise forecasts
• Approach often lacks detail necessary to conduct policy simulations or demand-side management evaluations
End use forecasting looks at individual devices, aka end uses (e.g., refrigerators).

- How many refrigerators are out there?
- How much electricity does a refrigerator use?
- How will the number of refrigerators change in the future?
- How will the amount of use per refrigerator change in the future?
- Repeat for other end uses
END USE FORECASTING

Average Energy Consumption for New Refrigerators
(kiloWatt-hours/year)

1972, first oil price shocks (1726 kWh/a)

Average 1980 model had 19.6 cu.ft. of capacity, used 1278 kWh/a and used CFC-blown foam insulation.

By 2001, a typical model has 20 cu.ft. of capacity, features more through-the-door services like ice and water, uses about 63% less energy (476 kWh/a) than the 1980 models and uses ozone-friendly foam insulation.

Average 1961 model had approximately 12 cu.ft. of capacity, used 1015 kWh/a and used fiberglass insulation.

END USE FORECASTING

Strengths:

• Affective at modeling technological changes for forecasting
• Provides basis for simulating policy changes or changes in consumer preference (i.e. electric resistance heating versus heat pump)
• Can incorporate and evaluate the impact of demand-side management/conservation programs

Weaknesses:

• Tremendously data intensive
• Primarily limited to forecasting energy usage, unlike other forecasting methods
• Most long-term planning electricity forecasting models forecast energy and then derive peak demand from the energy forecast
End use models have no systematic way of accounting for stochastic processes

- Sensitivity to degree cooling days or personal income

Statistically adjusted end use models can account for factors other than engineering relationships in predicting demand

- The end use model prediction of demand is one of multiple predictors in a regression equation
STATISTICALLY ADJUSTED END USE

Strengths:

• Systematically adjusts end use predictions to actual observations
• Expands the policy implications under alternative scenarios outside of the control of the utility and regulator

Weaknesses:

• Introduces stochastic process to an otherwise engineered set of relationships
• Imposes additional data requirements to end use models
CHOICE OF MODELING TECHNIQUE

- Time trend models are most appropriate for short-run forecasts.
- Properly-specified econometric models provide sufficiently effective mid-term to long-term forecasts.
- Policy modeling/evaluation requires details most readily found in end use models.
- One can also be creative and adopt elements of all three techniques.

Some studies have shown that more comprehensive approaches do not outperform time-trend methods in the short-run.
ENERGY INFORMATION ADMINISTRATION’S NATIONAL ENERGY MODELING SYSTEM (NEMS)

Projects energy and fuel prices for 9 census regions

Energy demand

- residential
- commercial
- industrial
- transportation
NEMS RESIDENTIAL MODULE

24 end-use services
  • e.g., space heating

Three housing types
  • single family, multi-family, mobile home

50 end-use technologies
  • e.g., electric air-source heat pump

Nine census divisions
NEMS COMMERCIAL MODULE

Ten end-use services
  • e.g., cooking

Eleven building types
  • e.g., food service

64 end-use technologies
  • e.g., natural gas range

Eleven distributed generation technologies
  • e.g., photovoltaic solar systems

Nine census divisions
Seven energy-intensive industries
  • e.g., bulk chemicals
Eight non-energy-intensive industries
  • e.g., construction
Six non-manufacturing industries
  • e.g., coal mining
Cogeneration
Four census regions, shared to nine census divisions
NEMS ELECTRICITY MARKET MODULE

Eleven fossil generation technologies
  • i.e., advanced clean coal with sequestration
Two distributed generation technologies
  • baseload and peak
Eight renewable generation technologies
  • i.e., geothermal
Conventional and advanced nuclear
Fifteen supply regions based on NERC regions and sub-regions
PREDICTING PEAK DEMAND

Recovering peak demand from forecasts depends on the periodicity of the forecasts

- Hourly forecasts creates its own load curve
- Daily forecasts implicitly assumes constant load throughout the day
- Monthly forecasts implicitly assumes constant load throughout the year

To relate daily or monthly forecasts to peak demand forecasts requires a simple transformation of the daily or monthly forecast by dividing by the projected load factor

It is preferable to do this at the sector level

*For time trend and econometric models, one can simply use the peak usage rate as the output variable*
PREDICTING PEAK DEMAND

Day types

- Break overall load shapes into typical day types
  - low, medium, high
  - weekday, weekend, peak day
- Adjust day type for load management and conservation programs

Can be done on a total system level or a sectoral level

Load diversity suggests that peak demand can not be found by simply adding the sectors, but rather load curves by sector must be added to identify peak daily load and time
Each utility does not see its peak demand at the same time as the others

2008 peak demands occurred at:

- Duke Energy – 9/2, 4PM
- Hoosier Energy – 9/2, 6PM
- Indiana Michigan – 7/31, 3PM
- Indiana Municipal Power Agency – 9/2, 3PM
- Indianapolis Power & Light – 9/2, 3PM
- NIPSCO – 7/17, 3PM
- SIGECO – 7/21, 3PM
- Wabash Valley – 7/29, 7PM

Statewide peak – 7/29, 5 PM

Source: State Utility Forecasting Group, Purdue University
Thus, the statewide peak demand is less than the sum of the individual peaks.

Actual statewide peak demand can be calculated by summing up the load levels of all utilities for each hour of the year.

Diversity factor is an indication of the level of load diversity.

Historically, Indiana’s diversity factor has been about 96 – 97 percent.

- that is, statewide peak demand is usually about 96 percent of the sum of the individual utility peak demands.

Source: State Utility Forecasting Group, Purdue University
LOAD AND DIVERSITY FACTORS

\[
LF\% = \left( \frac{\text{Total Demand over } x \text{ period of time}}{\text{Total Demand over } x \text{ period of time at peak rate}} \right) \times 100
\]

\[
DF\% = \left( \frac{\text{Sum of total demand over } x \text{ period of time}}{\text{Sum of total demand over } x \text{ period of time at peak rates}} \right) \times 100
\]

Factors range between 0% and 100% with higher numbers preferred from an efficiency perspective.
Target reserve margin
Loss of load probability (LOLP)
Expected unserved energy (EUE)
Assigning capacity needs to type
  • peaking
  • baseload
  • intermediate
Optimization
Reserve/capacity margins are relatively easy to use and understand, but the numbers are easy to manipulate

- Contractual off-system sale can be treated as a reduction in capacity or increase in demand
  - does not change the RM margin, but will change the CM
- Similarly, interruptible loads and direct load control is sometimes shown as an increase in capacity
Probabilistic methods that account for the reliability of the various sources of supply

Loss of load probability

• given an expected demand for electricity and a given set of supply resources with assumed outage rates, what is the likelihood that the supply will not be able to meet the demand?

Expected unserved energy

• similar calculation to find the expected amount of energy that would go unmet

Both are used in resource planning to ensure that sufficient capacity is available for LOLP and/or EUE to be less than a minimum allowable level
Once capacity need is determined, the next step is to determine what type of capacity is needed:

- peaking (*high operating cost, low capital cost*)
- baseload (*low operating cost, high capital cost*)
- intermediate or cycling (*operating and capital costs between peaking and baseload*)

State renewable fuel mandates will have increasing influence on this decision.
Assigning Demand to Type
Allocate peak demand to each load type based on:
• The load shape
• characteristics of customers
  • utilities with a large industrial base tend to have a higher percentage of baseload demand
  • those with a large residential base tend to have a higher percentage of peaking demand

Rough breakdown:
• Baseload 65%, intermediate 15%, peaking 20%§

§ Source: State Utility Forecasting Group, Purdue University
Assigning existing resources to load type

• One needs to assign existing generation to three load types based on system criteria
  • Age, capacity, fuel type…
• Consider purchased power contracts
  • Time of execution and the source’s capacity factor
• Also assign power sales contracts
Assigning new capacity needs to type

- compare existing capacity to projected demand
- subtract buy through loads
- add sales contracts
- add retirement of existing units
- add LOLP and EUE if appropriate
LOAD MANAGEMENT AND CONSERVATION MEASURES

Direct load control and interruptible loads generally affect peak demand but not energy forecasts

- delay consumption from peak time to off-peak time
- usually subtract from peak demand projections

Efficiency and conservation programs generally affect both peak demand and energy forecasts

- consumption is reduced instead of delayed
- usually subtract from energy forecast before peak demand calculations
 SOURCES OF UNCERTAINTY

Exogenous assumptions

• forecast is driven by a number of assumptions (e.g., economic activity) about the future

Stochastic model error

• it is usually impossible to perfectly estimate the relationship between all possible factors and the output

Non-stochastic model error

• bad input data (measurement/estimation error)
ALTERNATE SCENARIOS

Given the uncertainty surrounding long-term forecasts, it is inadvisable to follow one single forecast

Source: SUFG 2009 Forecast
FURTHER INFORMATION

State Utility Forecasting Group
- http://www.purdue.edu/dp/energy/SUFG/

Energy Information Administration
- http://www.eia.doe.gov/index.html

Center for Economic Analysis
- http://cea.msu.edu