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Basic Demand Projection

13th April 2021

IRRP
INTEGRATED RESOURCE AND RESILIENCE PLANS

Presenters

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Overview

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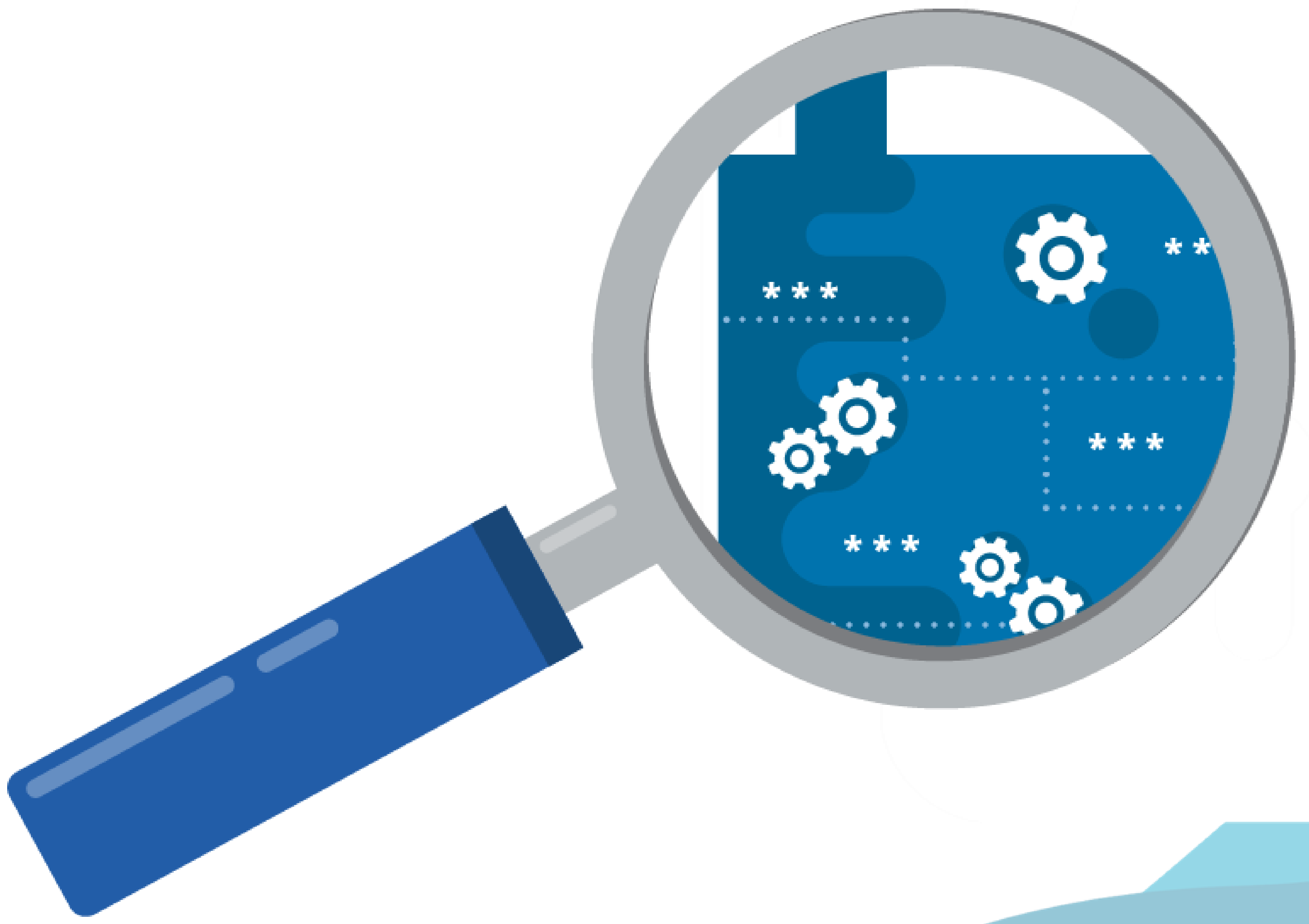
- Introduction
- Loads
- Load Forecasting
- Factors to Consider
- Demand Projection Techniques
- Closing Remarks



Questions

What is the probability of a coin toss being heads or tails? 50%

What is the probability that you will always get it correct? 0%

Why is the forecast different from the actual? avoid

Why does the forecast fail to capture these features from the actual? encourage

Many decision making processes today are still difficult to capture in a probabilistic form.

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Introduction

History

- Forecasting is a necessary and important function in any industry.
- The first oil crisis of the 1970s caught the attention of policymakers.

Introduction to Load Forecasting

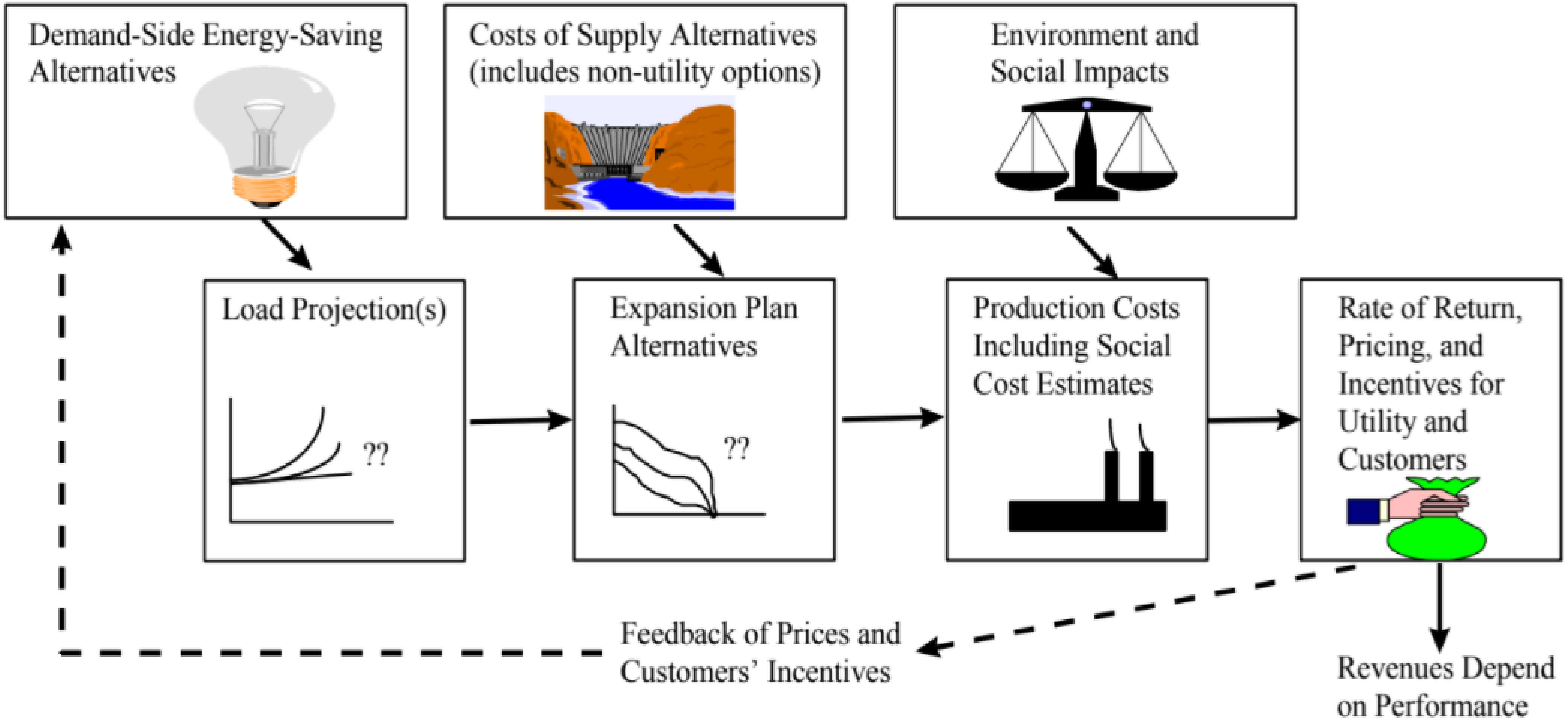
- Energy/demand forecasting is the first step in the energy planning process.

- Who needs/uses it:
  - Electric Utilities
  - Policy Makers
  - Manufacturers and Suppliers

Introduction to Load Forecasting

- *Demand* and *consumption* are also used instead of *load*.
- Energy (MWh, kWh) and power (MW, kW).
- Demand forecast - To determine capacity of generation, transmission and distribution required.
- Energy forecast - To determine the type of generation facilities required.

Linking to the IRRP



Load Forecasting Objective

- Objective is to **minimize errors**.
- Consider the plethora of **risks** facing the utility and the sector.

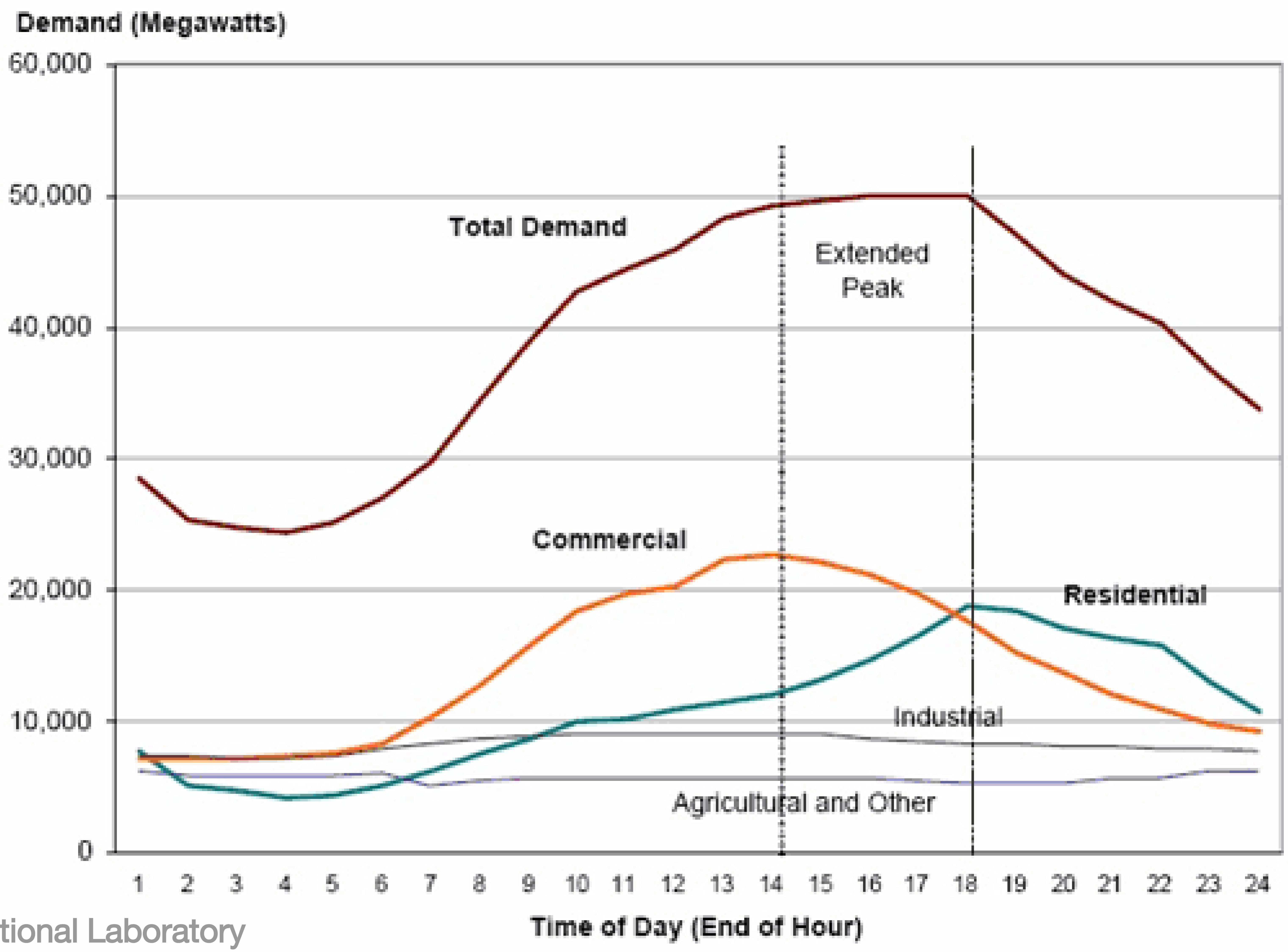
From a planning perspective demand forecasts should be slightly higher.

Uses of Load Forecast

- **Cost of Service** - to determine full costs of providing electricity for all customers. Used by utility and regulator.
- **Development of Rate Design** - requires a projection of the kWh consumption in each rate class over a horizon of about one or two years.
- **Demand Response** - consumers incentivized to participate in grid management modifying their consumption profile.
- **Energy Efficiency** - managing and restraining the growth in energy consumption.

Loads

Load Profile



Lawrence Berkeley National Laboratory

Definitions

- **Demand:**
  - Load averaged over a specific time.
  - Load can be kW, kVAr, KVA or A.
  - Time interval important (usually 15 minutes)
- **Maximum Demand:**
  - Largest demand over time period.
  - Must state demand interval, period and units e.g. 15 mins. Max kW demand for week = 150kW
- **Average Demand:**
  - Average of the demands over a specific period (day, week, month).

Definitions

- Demand Factor:
  - Ratio of maximum Demand to total connected load.
- Diversity Factor:
  - = Max. non-coincident Demand / Max. diversified Demand
- Load Factor:
  - = Avg. Demand of any individual (or group) customers / Max. Demand for the same period

Load Classification

Domestic/Residential
Demand factor: 70-100%
Diversity factor: 1.2-1.3
Load factor: 10-15%

Commercial
Demand factor: 90-100%
Diversity factor: 1.1-1.2
Load factor: 25-30%

Industrial
Small-scale: 0-20 kW
Medium-scale: 20-100 kW
Large-scale: 100 kW and above
- Demand factor: 70-80%
- Load factor: 60-65%

Others
eg. Streetlights
Demand factor: ~100%
Diversity factor: ~1.0
Load factor: ~50%

Load Growth

New Customers

- Increased electrification initiatives
- New construction
  - Urbanisation (housing, commercial centres)
  - Industrial facilities
- Population movement
  - Relocation
  - In-land migration

New Usage

- New appliances
  - Electric stove
  - Air conditioning
  - Electric vehicles
  - Energy storage
  - RE technologies

Load Forecasting

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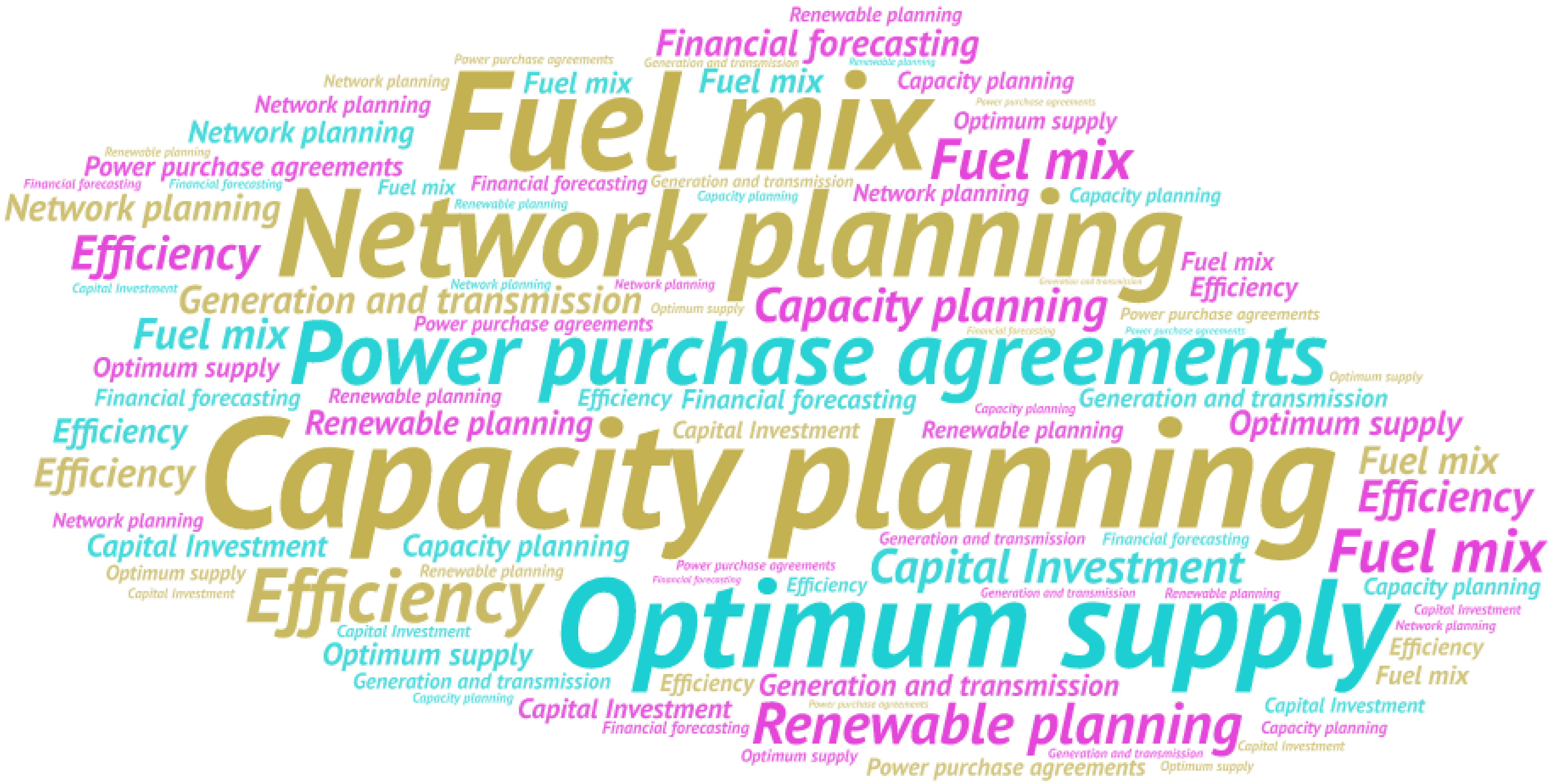
Load Forecasting



A systematic procedure for quantitatively defining future loads.

Types of Load Forecasting

Short Term Load Forecasting

Medium Term Load Forecasting

Long Term Load Forecasting

No single forecast that can satisfy all of the needs of a utility.
A common practice is to use different forecasts for different purposes.

Short Term Load Forecasting

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- This forecasting method is usually has period ranging from one hour to 1 to 2 weeks. Workdays + weekends.
- Limited by horizon of temperature prediction.
- Mean Absolute Percentage Error (MAPE) < 5% acceptable.

- Short term forecasting is used to provide obligatory information for the system management of daily operations, security analysis, economic dispatch, fuel scheduling, system maintenance and unit commitment.

Techniques: Time series analysis (AR, ARX, ARMA etc) | Multiple linear regression | Expert systems approach (neural networks, fuzzy logic, particle swarm optimization)

Medium Term Load Forecasting

- This forecasting method has its period ranging from one week to one year.
- The forecasts for different time horizons are important for different operations within a utility company.

- Medium term forecasting is used for the purpose of scheduling fuel supplies, maintenance of the power system and unit management.

Long Term Load Forecasting

- This forecasting method has its period which is longer than a year.
- It is used to supply electric utility company management with precise prediction of future needs for expansion, equipment purchase or staff hiring.
- Top-down | Bottom-up Load Forecasting

Techniques: Trend Analysis | Linear multivariable regression | End use method | Scenario approach

Factors for Consideration

Horizon	Weather	Load	Economy	Data Collection
	Temperature Humidity Wind speed Rainfall Cloud cover	Hourly Daily Weekly Peak Average	Customer income Population size Population growth GDP	Hourly Daily Weekly Yearly Weekdays Weekends/holidays Special events
Short term	X	X		
Medium term	X	X	X	
Long term		X	X	

M. Mustapha, M. W. Mustafa, S. N. Khalid, I. Abubakar and H. Shareef, "Classification of electricity load forecasting based on the factors influencing the load consumption and methods used: An-overview," *2015 IEEE Conference on Energy Conversion (CENCON)*, Johor Bahru, Malaysia, 2015, pp. 442-447. doi: 10.1109/CENCON.2015.7409585

Top-down Load Forecasting

Efficient | Consistent | Business Oriented

- Developing weather indices e.g. hourly temperature, max/min daily temperature, max/min monthly temperature, average daily temperature, average monthly temperature, cooling degree days (CDD above 18 degC).
- Developing macroeconomic e.g. Gross Domestic Product (GDP), number of customers, population, price of electricity, interest rate.
- Developing model(s) for each revenue class e.g. residential load usually has a higher correlation with temperature variables than the industrial load.
- Developing scenarios e.g. weather conditions, economy projections, energy policies, revenue class (separately and collectively)

Bottom-up Load Forecasting

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- Aggregates forecast first at a lower level then vertically integrates to revenue level class.
- Conservative and often higher than necessary. Unrealistic extreme at the top level (over forecasting).
- Becomes inefficient, inconsistent and does not meet business needs when the geographical area is large enough to have variation with employed models, duplication of resources and many iterations to reduce conservativeness.

Over Forecasting & Under Forecasting

	Over Forecasting	Under Forecasting
Upgrading Infrastructure	Increase spending	Insufficient spending
Rates	Increasing more than needed	Decreasing more than needed
Gen | Tran | Dist	More investment than needed	Less investment than needed
Reliability	Improve with higher $	Reduce with lower $
Cost of Service	Higher	Lower
Demand Response	More load to be shifted with less incentives	Less load to be shifted with less incentives
Energy Efficiency	More investment than needed	Insufficient than needed. Missed opportunities for new technologies

Forecasting Horizon

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- The forecast horizon should cover the planning horizon.
- The longer the forecast horizon, the more unpredictable the load.
- The data history should be two to three times of the forecast horizon.
- Access to longer than 30 years of load history is rarely available.

Forecasting Horizon

There are two remedial methods to resolve the insufficient data issue in long term load forecasting:

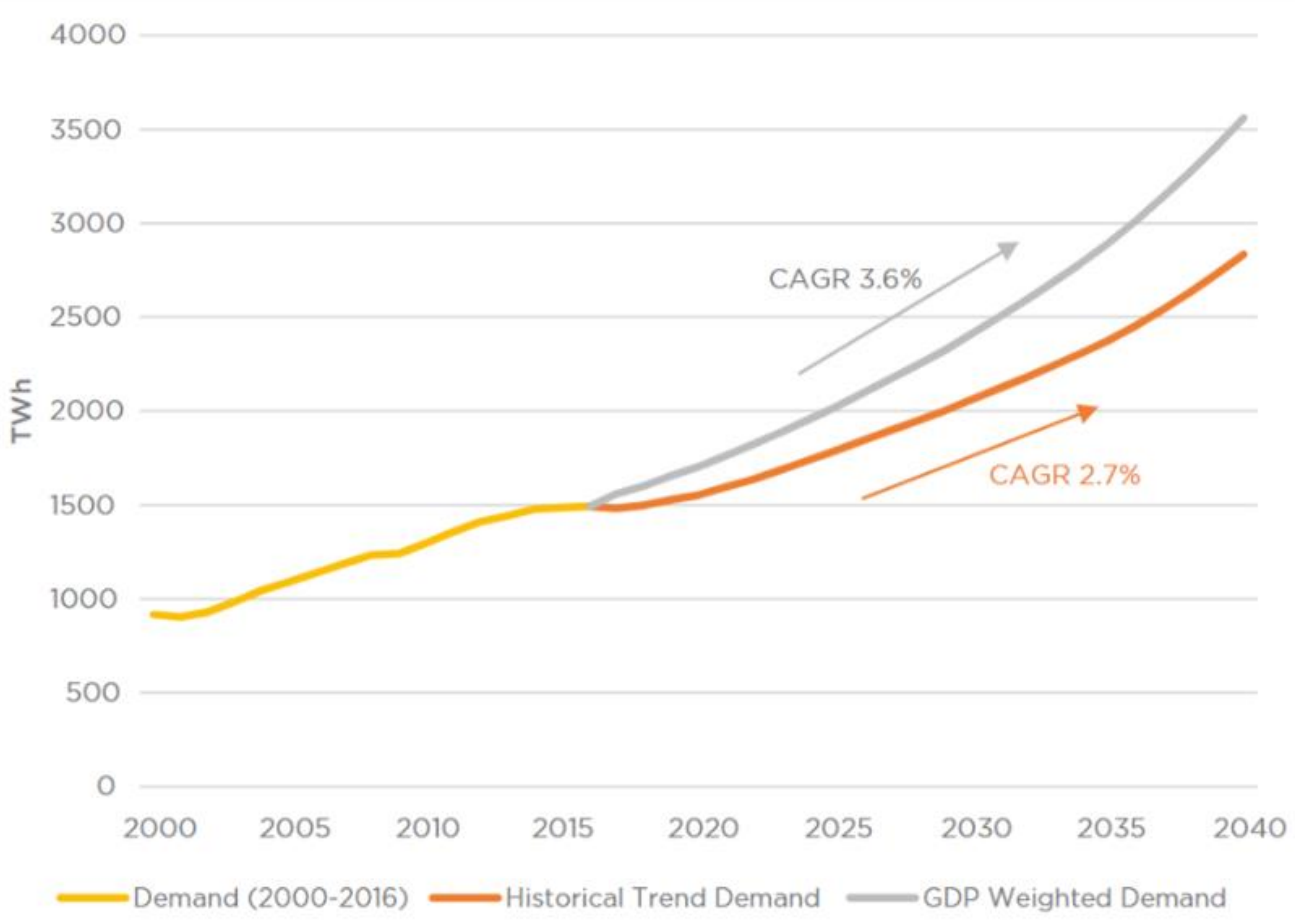
- 1) Make the forecast updating cycle less than half of the length of the data history,
- 2) Probabilistic load forecasts, to better describe the associated uncertainties.

Forecasting Horizon

	Updating Cycle	Forecast Horizon
Financial Planning	1 to 5 years	1 to 20 years
Generation Planning	1 to 2 years	5 to 30 years
Transmission Planning	1 to 2 years	5 to 30 years
Distribution Planning	1 to 2 years	1 to 20 years
Integrated Resources and Resilience Planning	3 to 10 years	10 to 50 years
Renewable Energy Planning	1 to 2 years	1 to 30 years

Long Term Demand Forecast

IDB Load Forecast of LAC (2017-2040)



CAGR - Compound Annual Growth Rate

Long Term Demand Forecast

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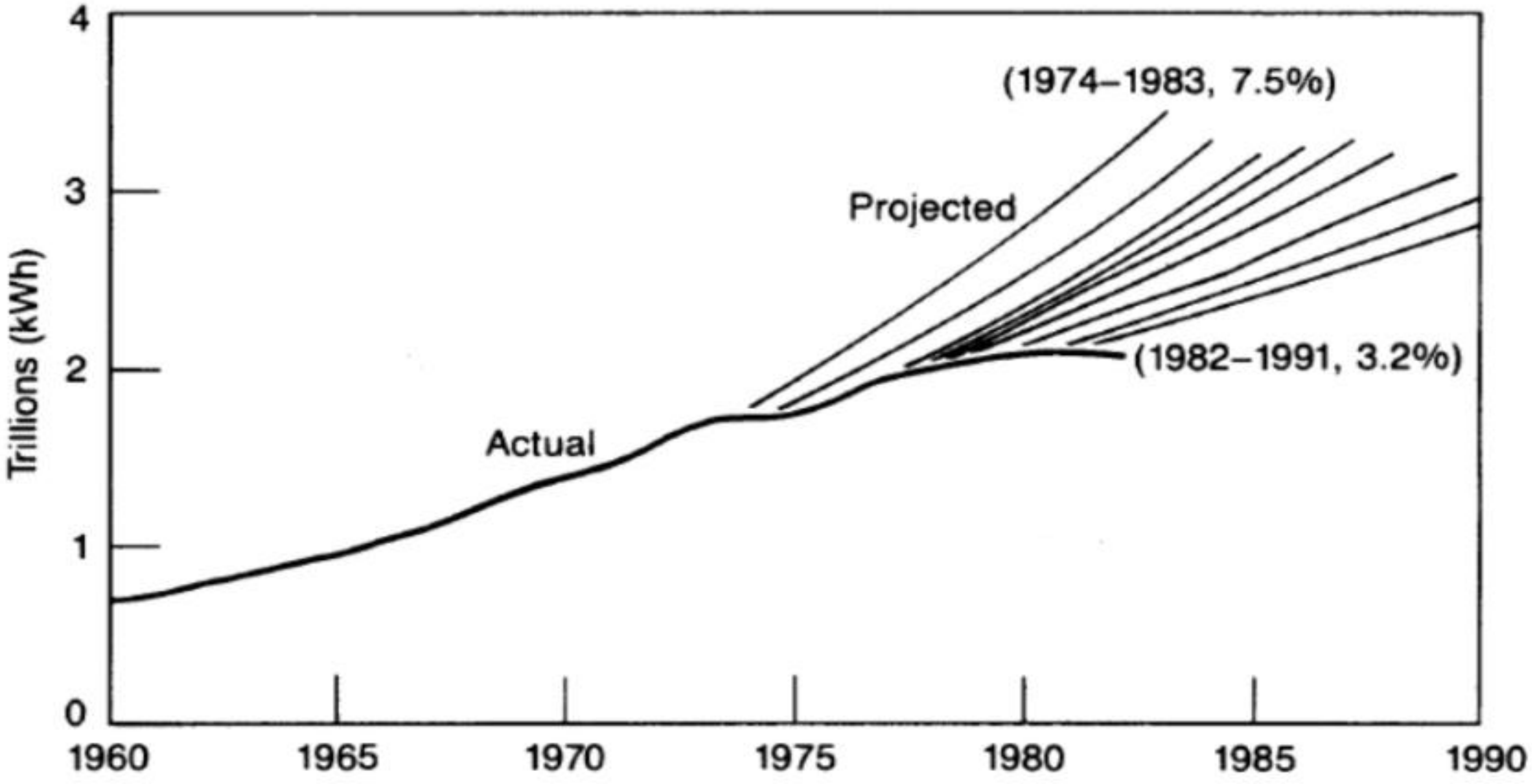

National Electric Reliability Council forecast vs. actual data

A Short Break

Before we switch presenters

Factors to Consider

Factors

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- Class of customers (residential, commercial, industrial, agricultural, public, etc.)
- Special events (TV programmes, public holidays, etc.)
- Population
- Economic indicators (per capita income, Gross National Product (GNP), Gross Domestic Product (GDP), etc.)
- Electricity price
- Trends in using new technologies

Factors

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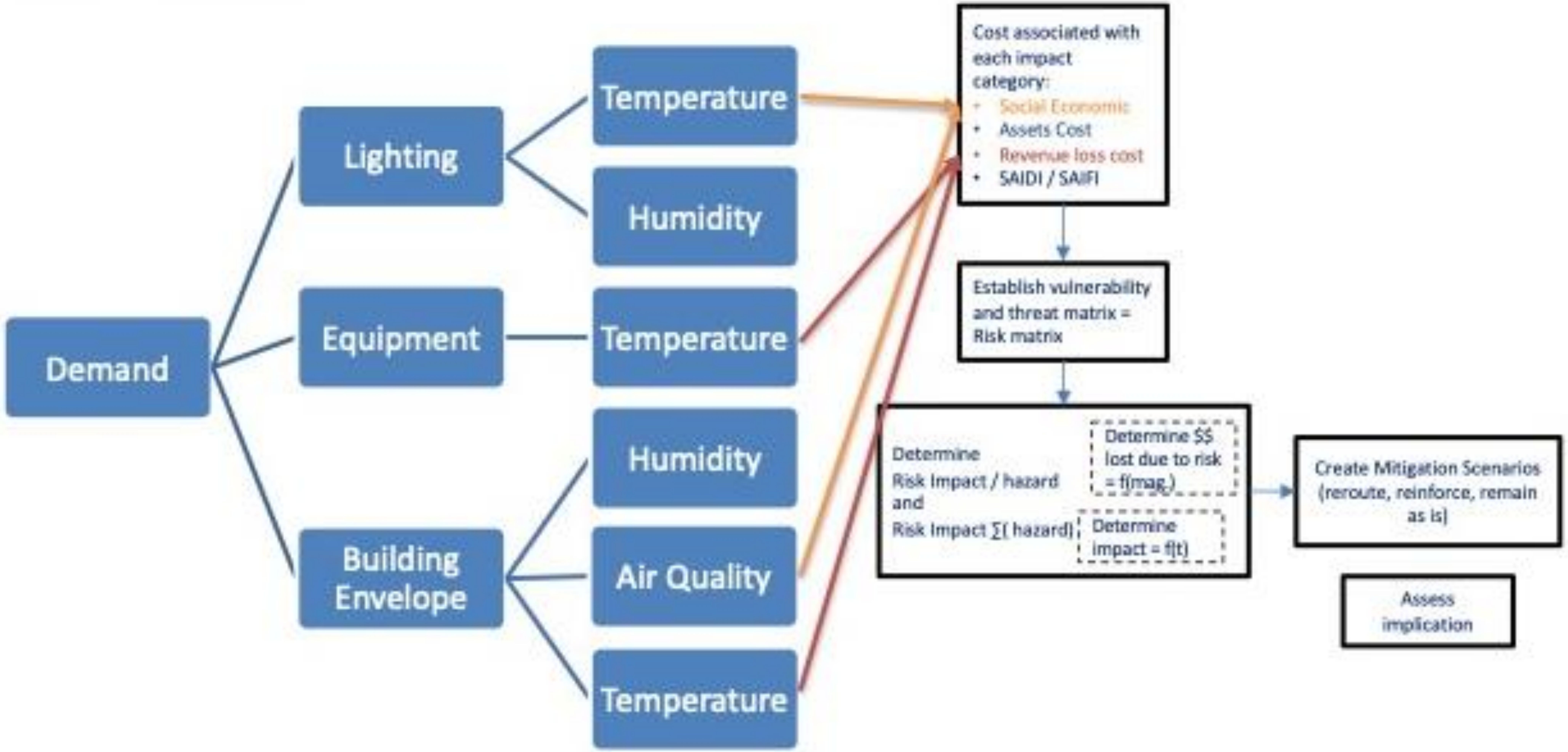
- Hours of the day (day/night)
- Day of the week (week day/weekend)
- Time of the year (season)
- Weather conditions (temperature and humidity)
- Application use

Load Forecasting

- Customer Class
  - Domestic/Residential
  - Commercial
  - Industrial
  - Street Lighting
- Electric Vehicles
- Distributed Generation
  - Renewable Energy Generation + Energy Storage

Building Blocks



Adapted from CCREEE

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Impact of Weather

Present condition of meteorological elements | two weeks

- Causes variations in domestic and commercial loads and public lighting
- Main weather variables that affect the load are:
  - Temperature
  - Cloud cover
  - Visibility
  - Precipitation
  - Rainfall
  - Thunderstorm
  - Flooding
  - Wind speed

affects cooling

affects lighting

- Height of the cloud cover
- Thickness
- Cloud amount
- Time of occurrence and duration

Including Weather Variables

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- Weather variables used differently for short versus long term load forecasting.
- In short term load forecasting, weather forecasts throughout the forecasting horizon are used to produce load forecasts.
- Accuracy of weather forecasts affects the accuracy of load forecasts.

Features presented by the data will guide inclusion.
Importance of accurate dataset.

Including Weather Variables

- In medium and long term load forecasting, weather simulation approach is preferred. Based on historical weather information.
- Create and generate scenarios based load forecasts.
- Resolution of weather data should have same or better resolution as load data.

Studies to confirm validation of including variables other than temperature in long term load forecasting.

Temperature

- Average temperature is the most significant on load variations.
- Temperature and load are non-linearly related. Heating and cooling.
- Non-linearity is further complicated by humidity. E.g. extended periods of extreme heat, air conditioning usage increased

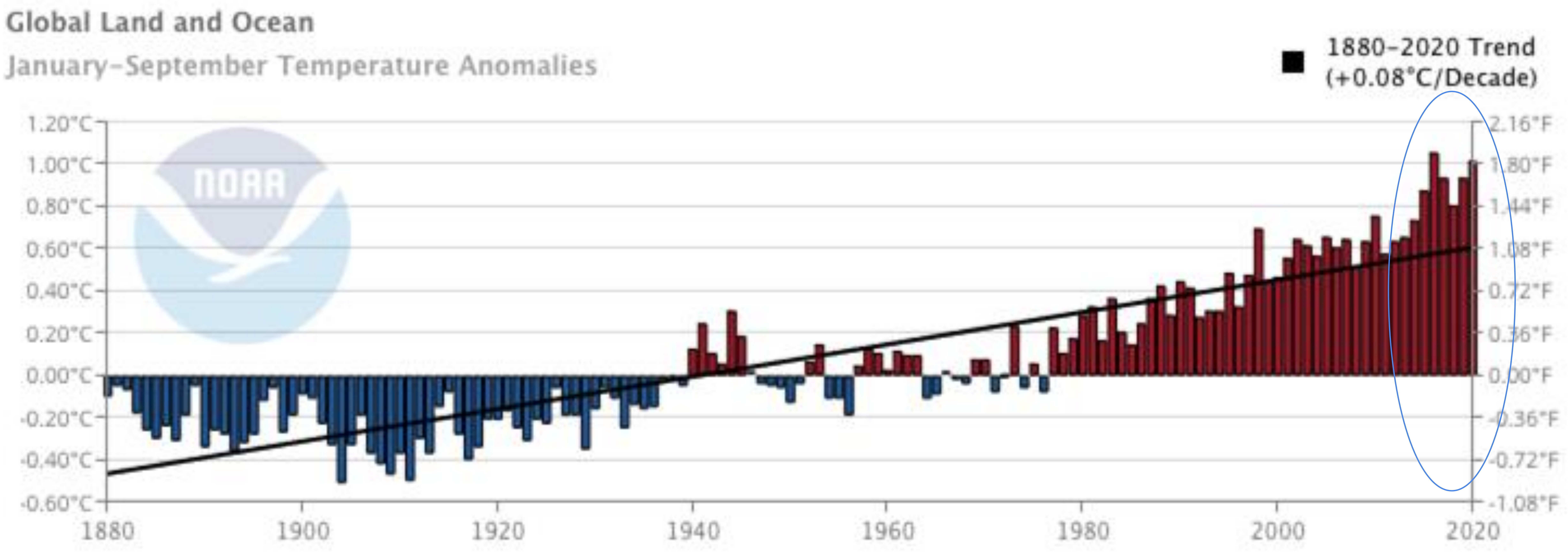
Year To Date

January - September 2020

REGION	ANOMALY (1910-2000)		TREND (1910-2020)		RANK (OUT OF 111 YEARS)		RECORDS		
	°C	°F	°C	°F			YEAR(S)	°C	°F
Caribbean Islands	+1.04	+1.87	+0.09	+0.16	Warmest	2nd	2016	+1.06	+1.91
					Coolest	110th	1910	-0.92	-1.66

https://www.ncdc.noaa.gov/sotc/global-regions/202009#region-year-to-date

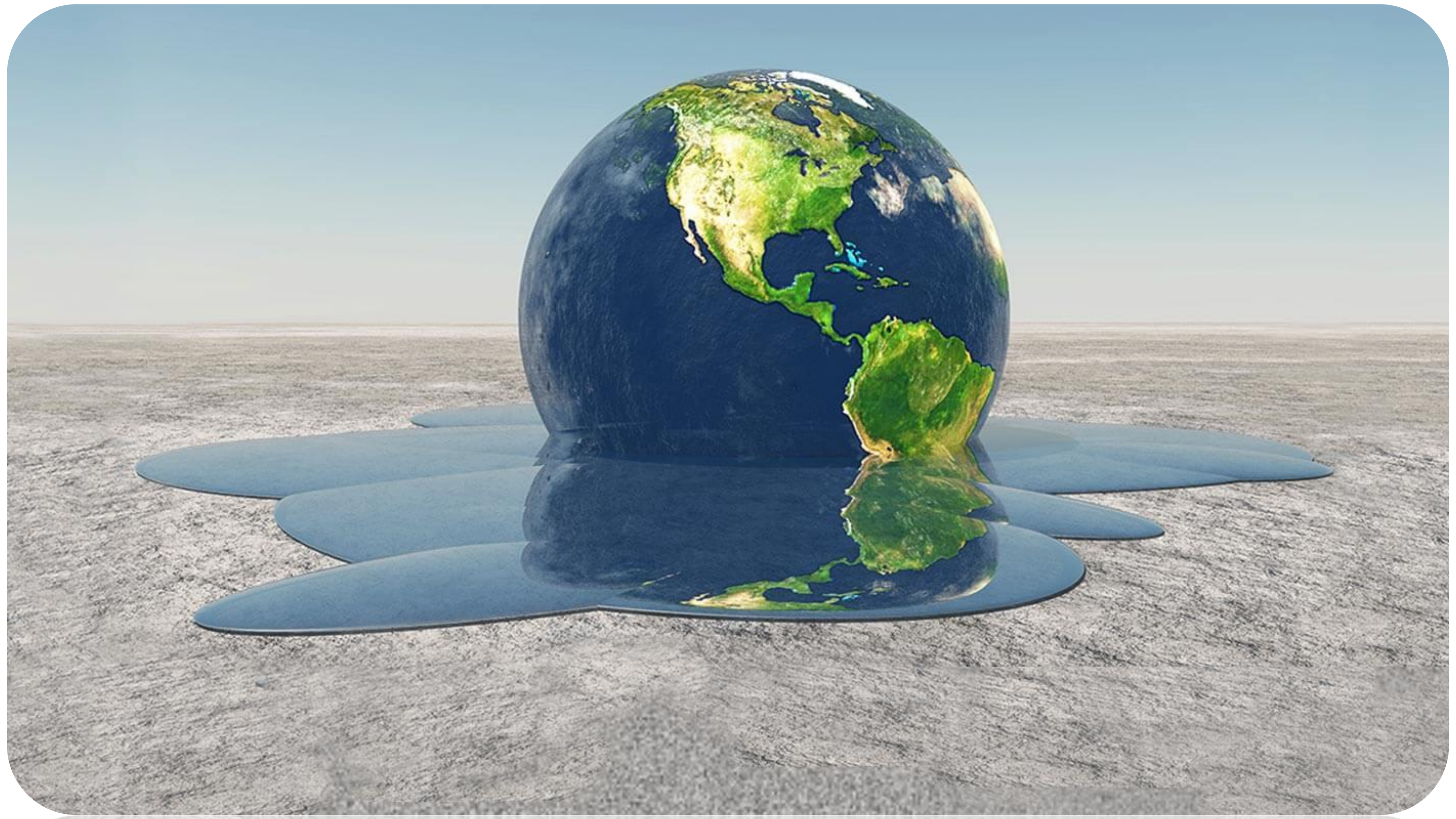
Temperature



https://www.ncdc.noaa.gov/climate-monitoring/

Model Weather Variables

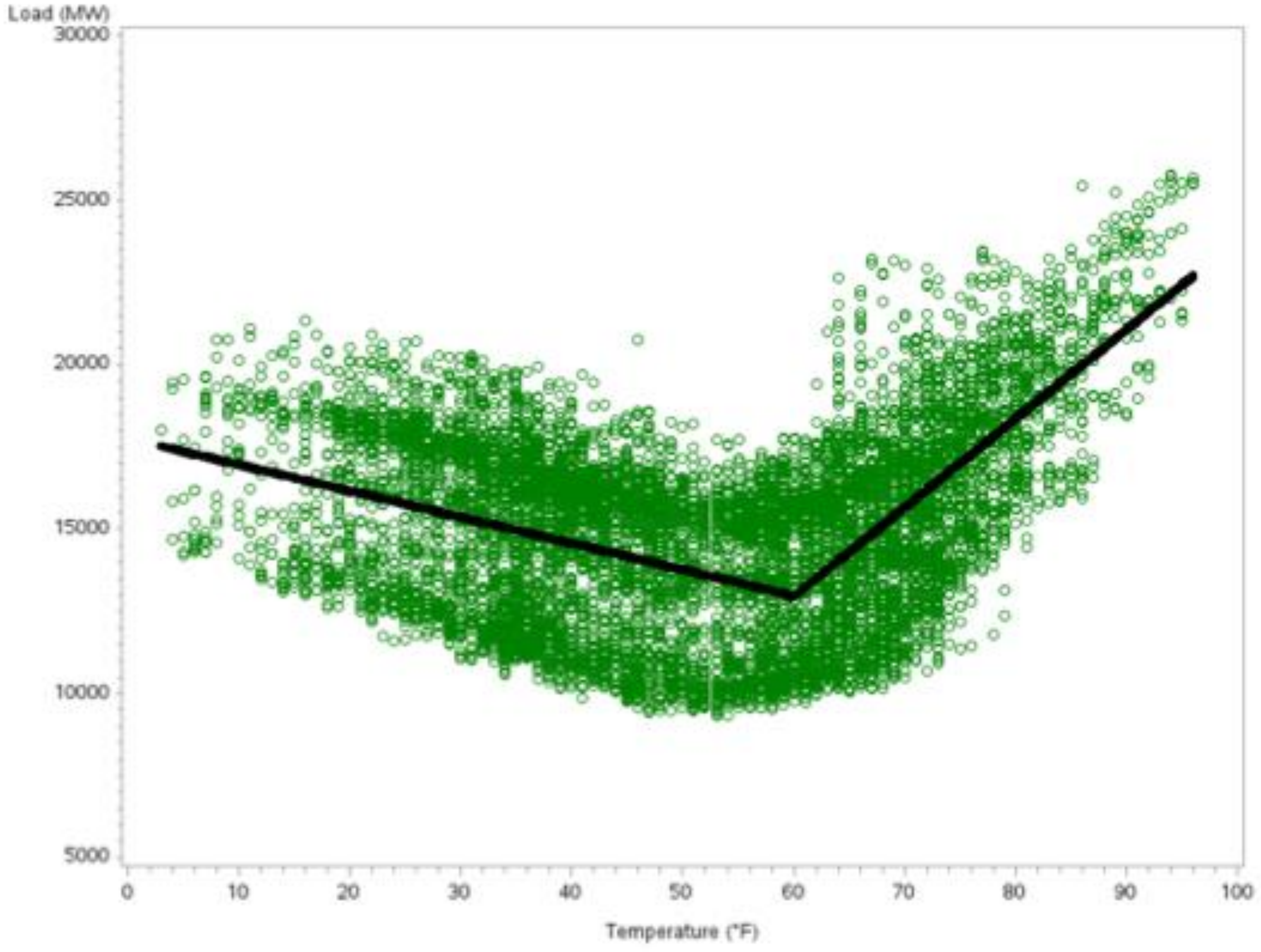
To determine impact of weather variables (climate change) on load demand, it is essential to **analyze data** concerning different weather variables and calculate **regression models** for inclusion into the models.



https://images.app.goo.gl/HfS1nD7mT2DuDgVK8

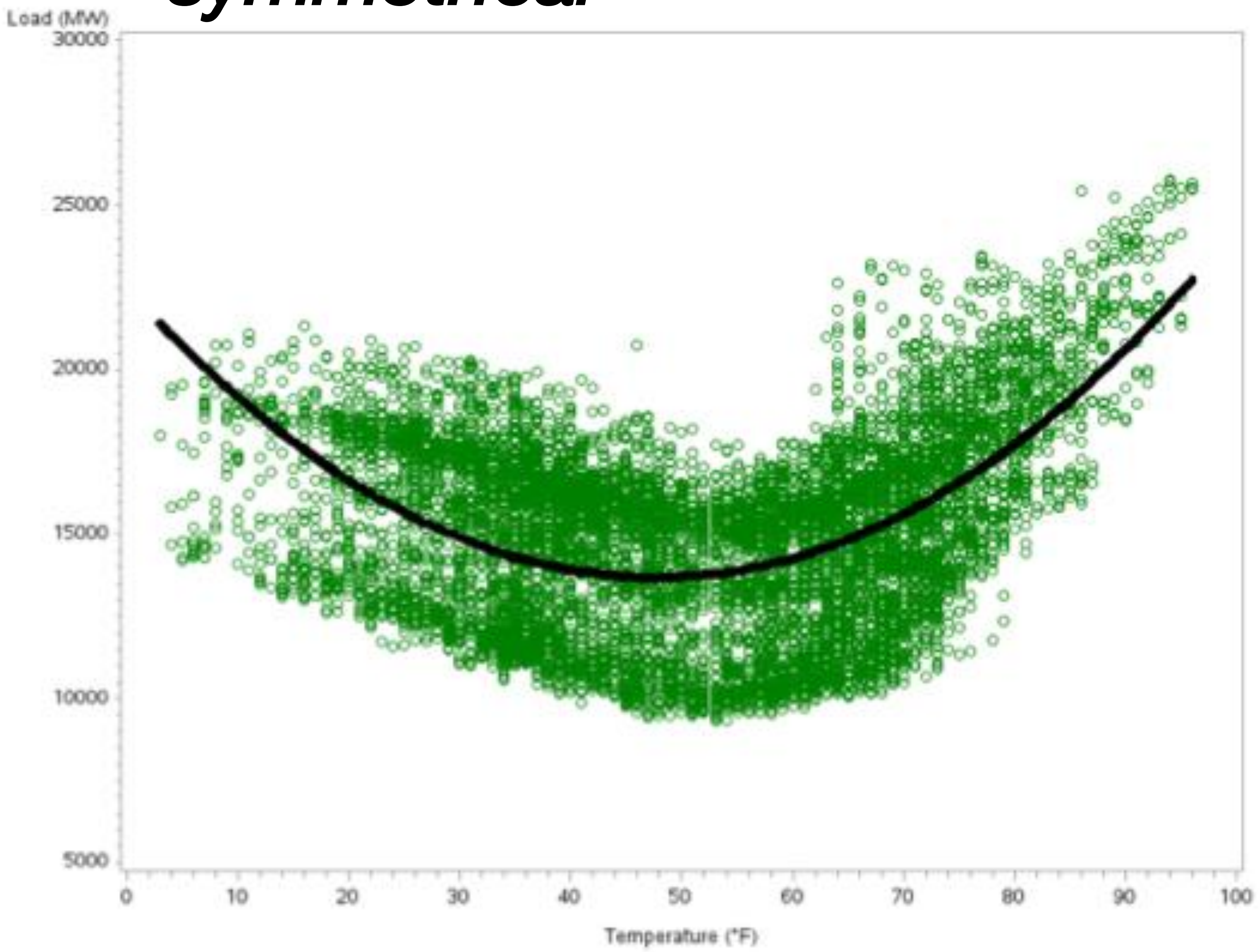
Load vs Temperature Relationship

linear



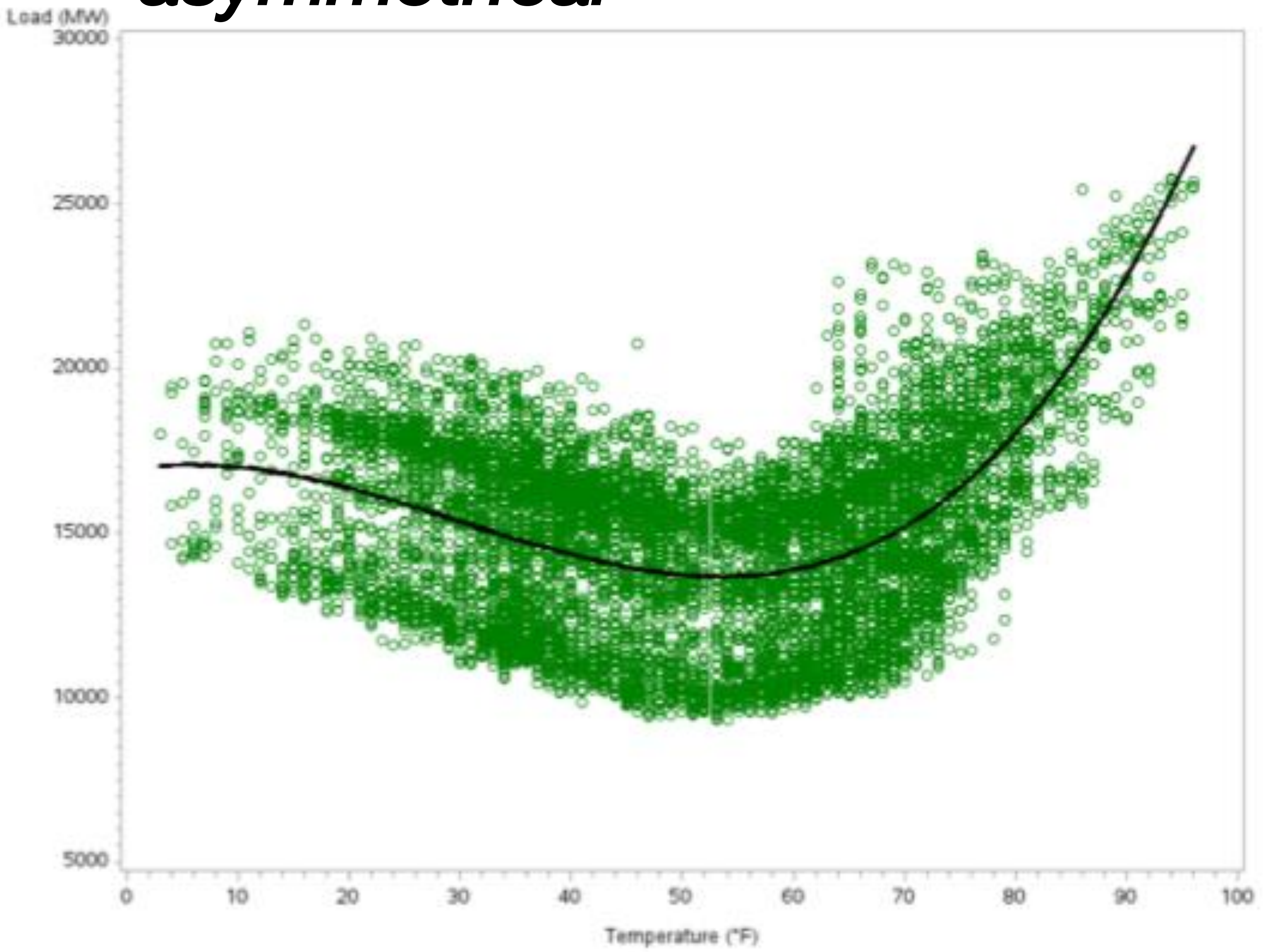
Piecewise linear models

symmetrical



2nd order polynominal regression model

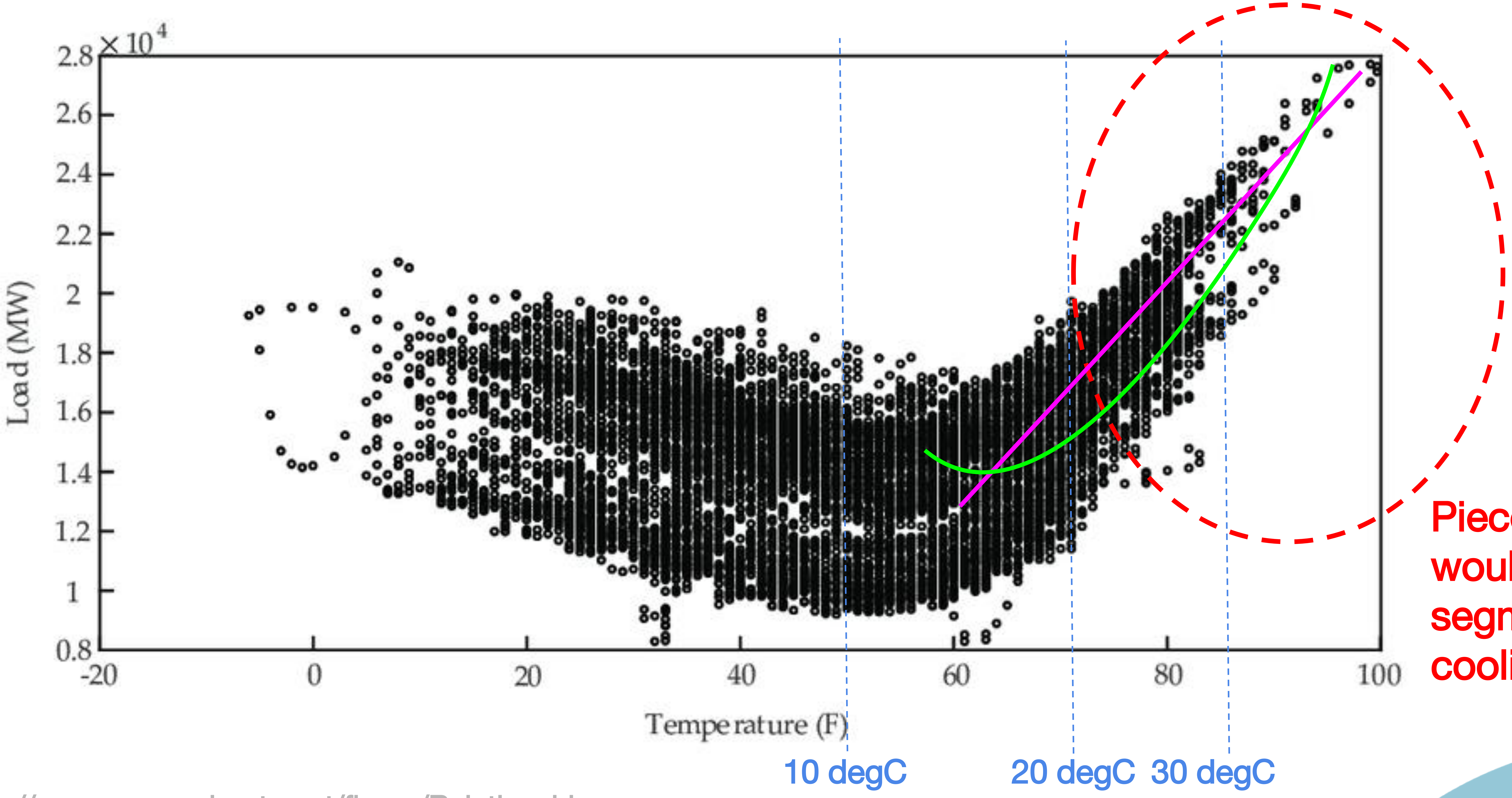
asymmetrical



3rd order polynominal regression model

"Load Forecasting Case Study", Tao Hong, University of North Carolina at Charlotte and Mohammad Shahidehpour, Illinois Institute of Technology, 2015.

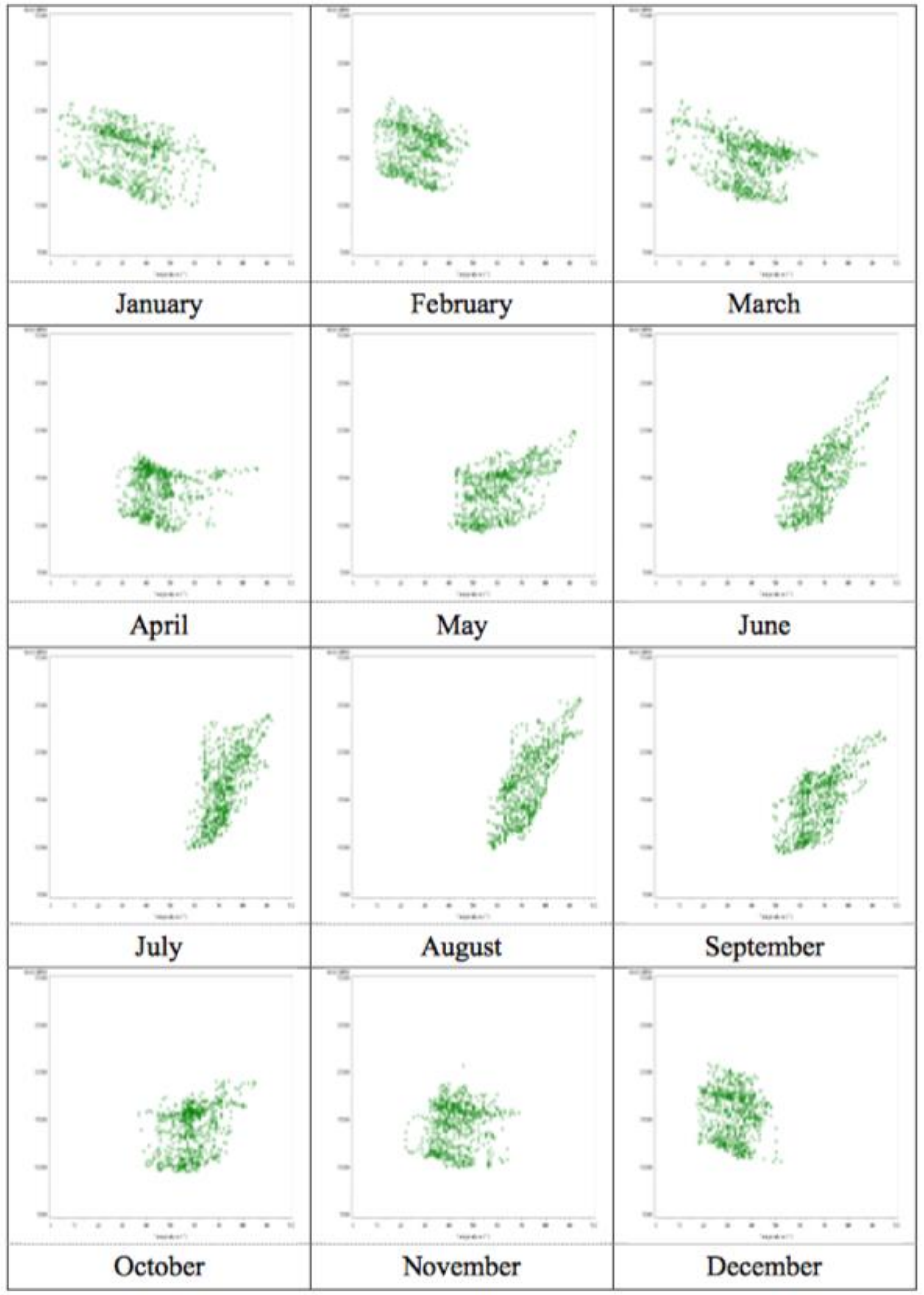
Load vs Temperature Relationship

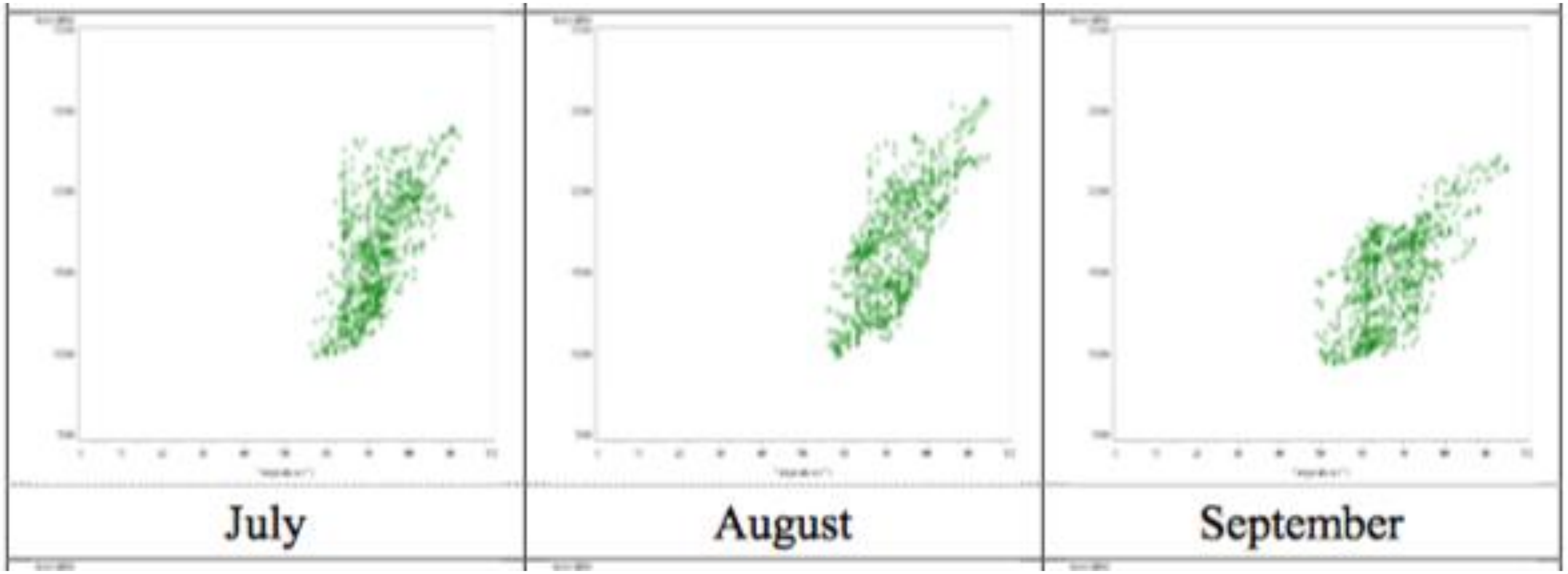


Piecewise linear models would yield the segments required for cooling only.

https://www.researchgate.net/figure/Relationship-between-load-and-temperature_fig2_310834746

Monthly

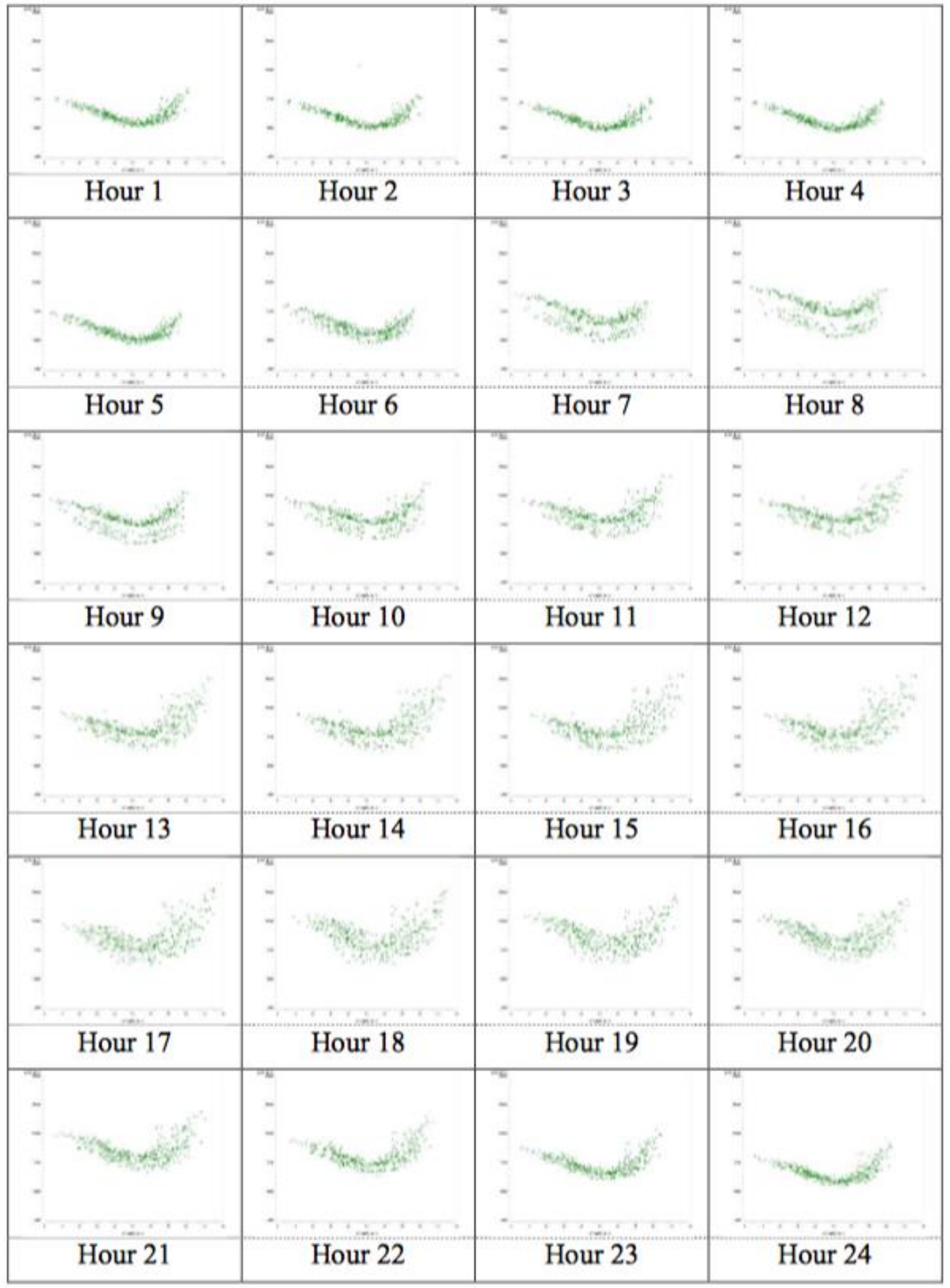




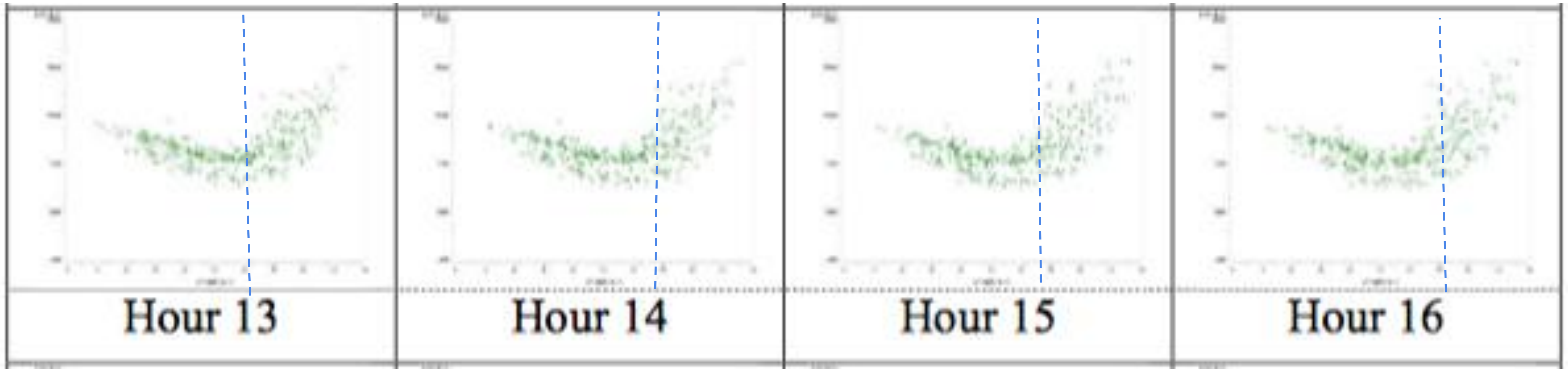
This example is cooling

"Load Forecasting Case Study", Tao Hong, University of North Carolina at Charlotte and Mohammad Shahidehpour, Illinois Institute of Technology, 2015.

Hourly



Recency Effect - temperatures of the current and preceding hours affect the load.



This example is heating and cooling

"Load Forecasting Case Study", Tao Hong, University of North Carolina at Charlotte and Mohammad Shahidehpour, Illinois Institute of Technology, 2015.

Lagged Temperature Variables

Temperature of hour *t*

$$T_{avg,d} = \frac{1}{24} \sum_{i=24d-23}^{24d} T_{t-i}$$

Average temperature of the *d*th 24-hour period

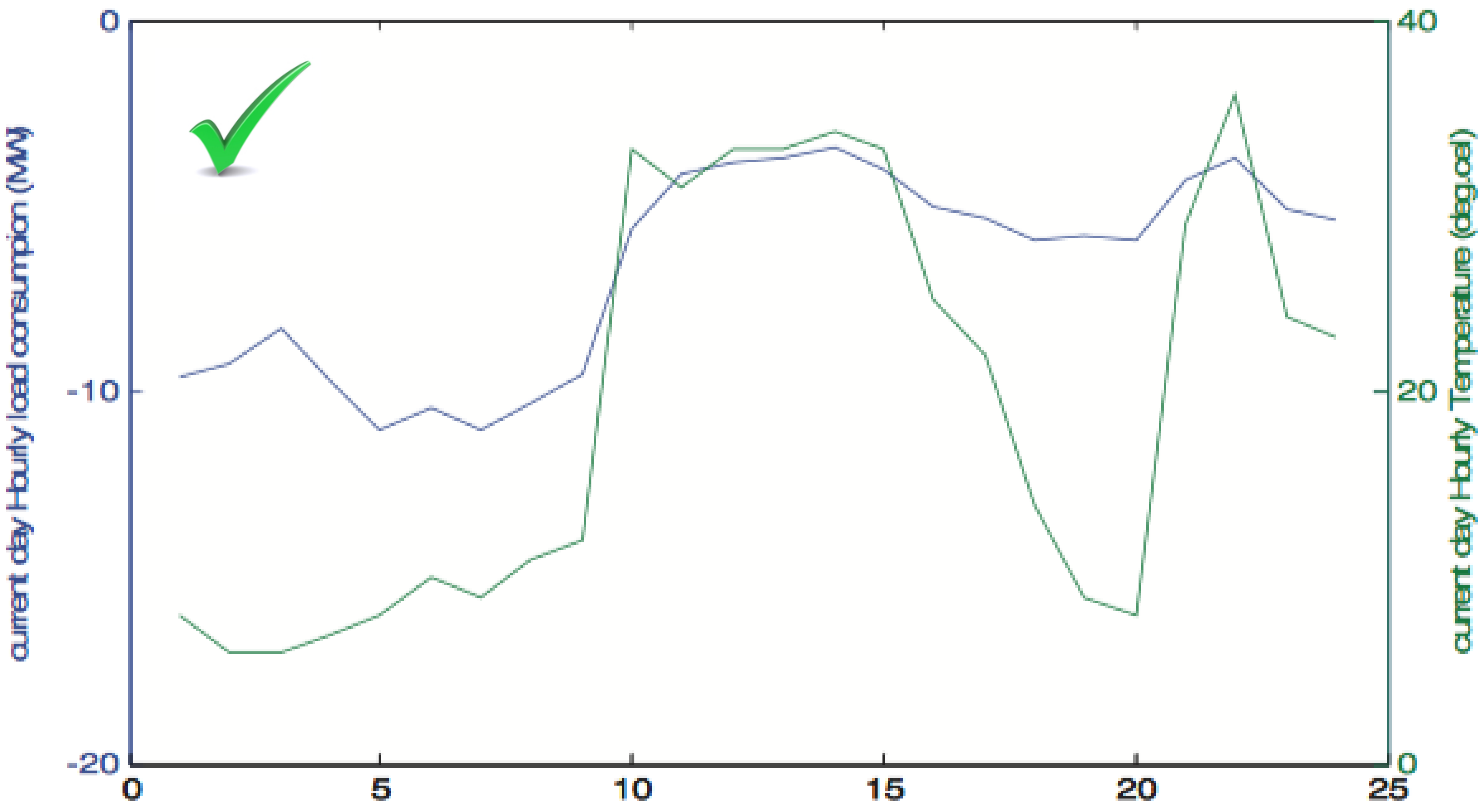
$$T_w = \frac{\sum_{k=1}^{24} \alpha^{k-1} T_{t-k}}{\sum_{k=1}^{24} \alpha^{k-1}}$$

Exponentially weighted temperature to assign higher weights to the recent hour temperatures.

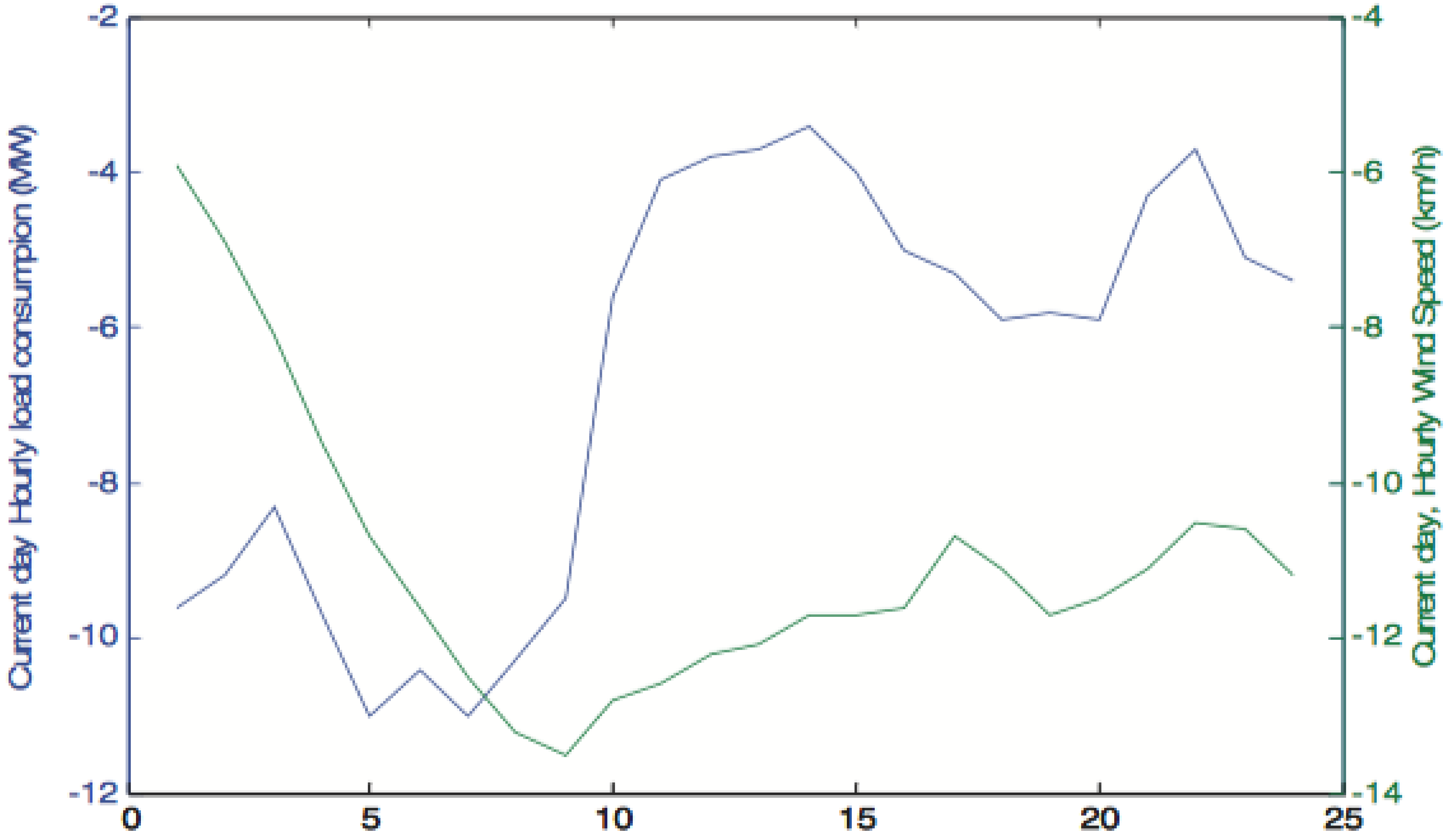
Where α is the base for the exponential weights with the typical range from 0.8 to 1.

Correlation

High correlation near 1



Hourly Temperature and Hourly Load
R=0.8493



Hourly Wind Speed and Hourly Load
R=0.2538

Classification of electricity load forecasting based on the factors influencing the load consumption and methods used: An overview.

Econometric Model

- Econometric models are constructed from economic data with the aid of the techniques of statistical inference.
- Equations that are estimated from the data are usually derived from first-order conditions from an optimization problem (utilisation or profit maximization).
- The data on behaviour (purchases of goods) is used to infer the underlying structure of technology or tastes. Once the underlying structure is known, the model can be used to predict the quantity of a particular commodity that will be consumed at any set of relative prices and income or output.
- In other words, the entire schedule is inferred from a discrete set of observations on agent behaviour.

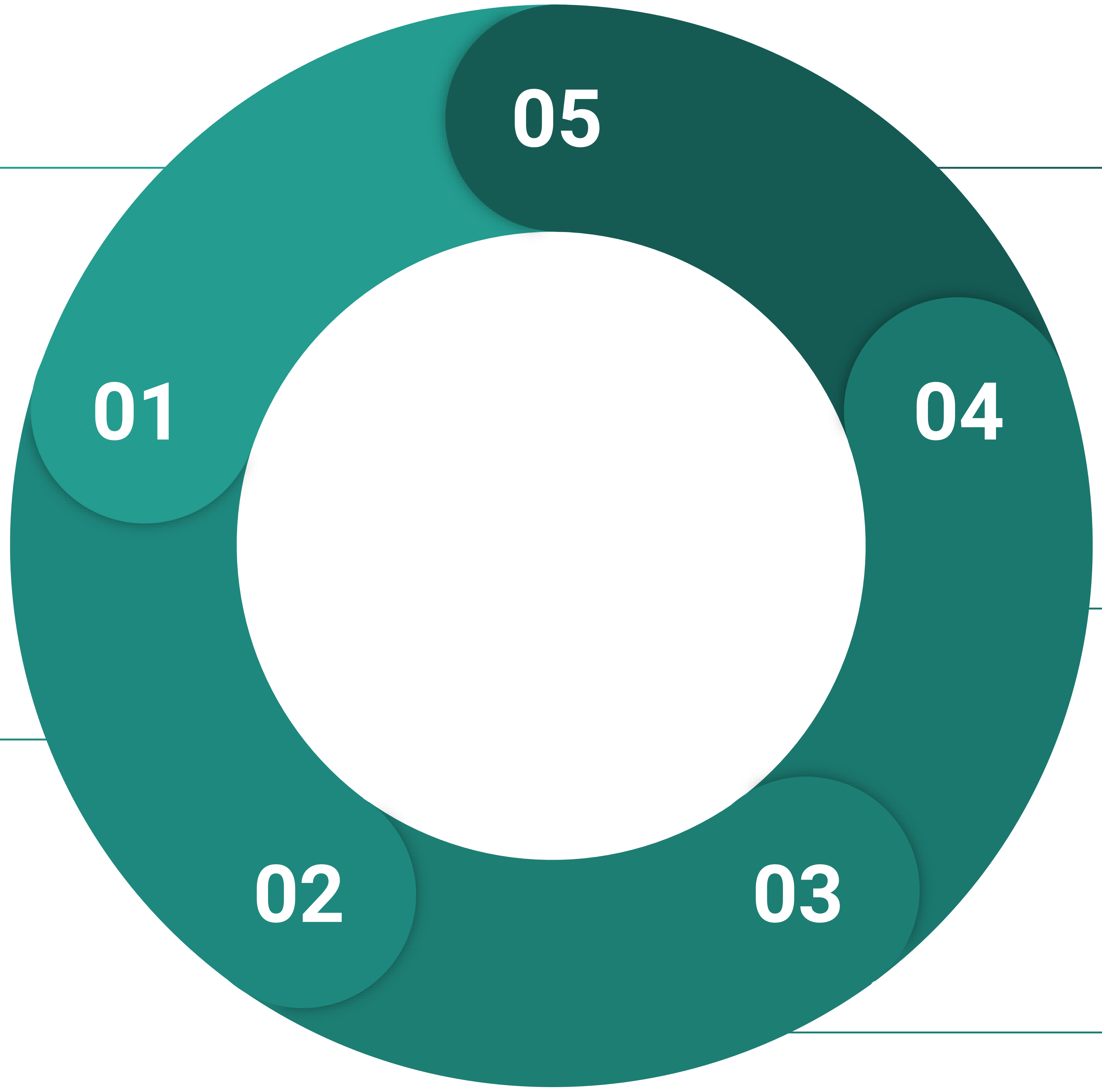
Econometric Model Development - 5 Steps

Define likely explanatory variables

- Customer segmentation defined.
- Develop a list of the major events that cause them not to consume electricity.
- Identify at least 10 variables.

Define functional relationship of explanatory variables and load demand

- Understand key assumptions
- May have lags effects.



Test and validate model

- Determine error and plot forecasts in historical data period.

Perform multiple regression analysis

- Statistically determine which driving variables are retained in the regression.

Research time series of these variables

- Typically data for 20 years back collected to forecast 10 or 15 years into the future.
- Be aware of changed market forces.

Domestic/Residential

Energy Sales $S_{(t)}$, Influenced by

time lagged

- Personal disposable income, *PDI*
- Price of electricity, *P*
- Number of customers, *C*
- Inflation
- People per household
- Air conditioning
- Appliance price index
- Fuel price
- Technology (changes in energy intensity)

Single family, duplex, apartment buildings, townhouses

A real example: Multifactorial Approach | Econometric Model

customer elastic (greatest impact)
most sensitive

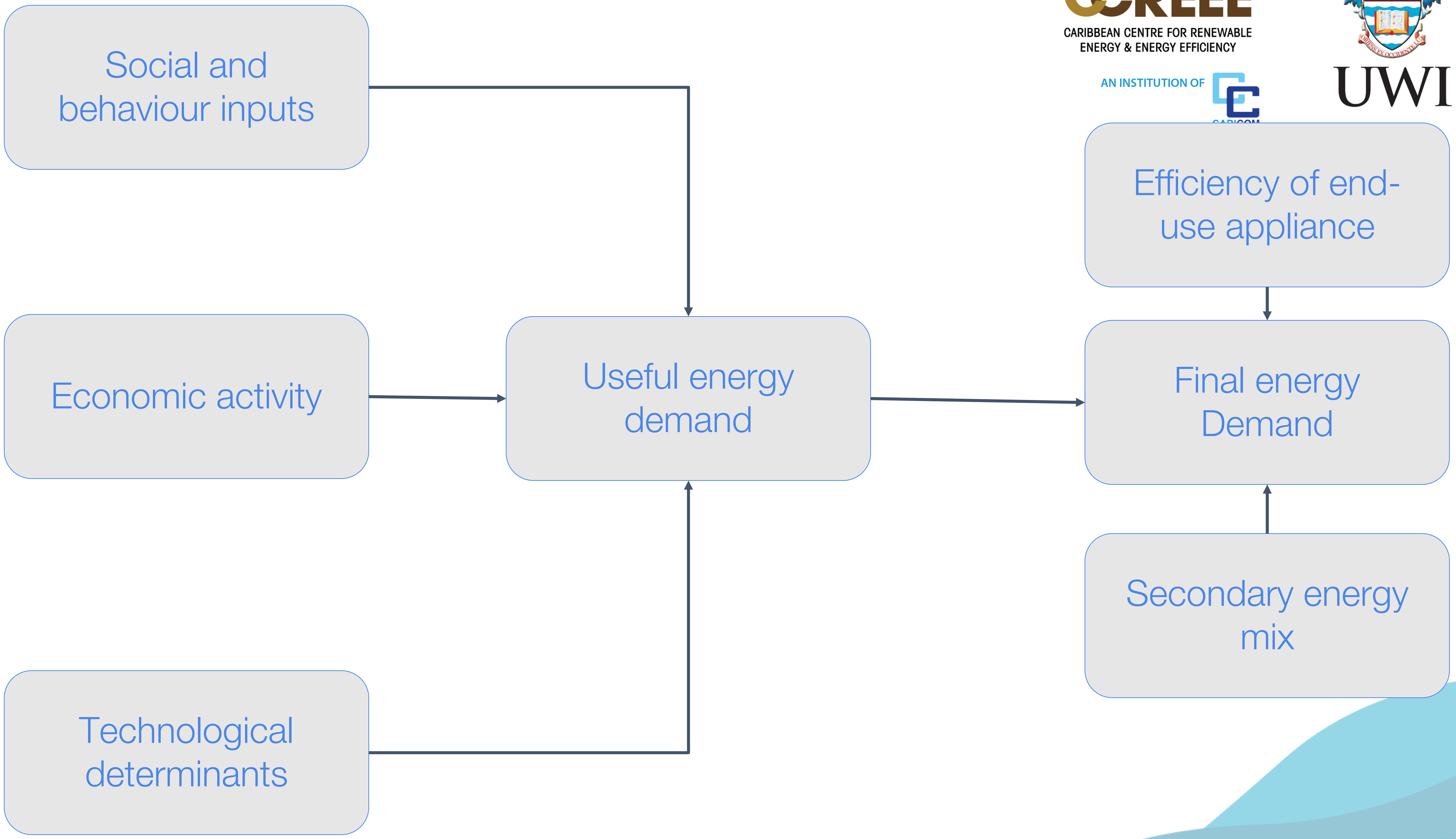
$$\log S_{(t)} = -4.13 + 1.72 \log C_{(t)} - 0.161 \log P_{(t-1)} + 0.363 \log PDI_{(t-1)}$$

least sensitive and negative!

Correlation factor = 0.94
Error = 1.4%

Survey based forecast

End-use forecast



End-Use Model

- AC Saturation (central/distributed)
- AC efficiency
- Thermal efficiency
- Home size
- Income
- Household size
- Price

- Saturation levels (water heater, appliances, lighting densities, plug loads)
- Appliance efficiency
- Income
- Household size
- Price

Cooling Degree Days → *XCool*

XOther ← Billing Days

$$Load_{(t)} = a + b_c{*}XCool_{(t)} + b_o{*}XOther_{(t)} + e_{(t)}$$

XCool and *XOther* are structured variables that account for saturation levels, average efficiency levels, and usage trends of end-use categories in an econometric framework.

Itron white paper: Incorporating DSM into the Load Forecast

Data Requirements

Econometric Models will require:

- Historic and projected GDP
- Projected Electricity Price (usually assumed constant)
- Previous demand (recursive in nature)

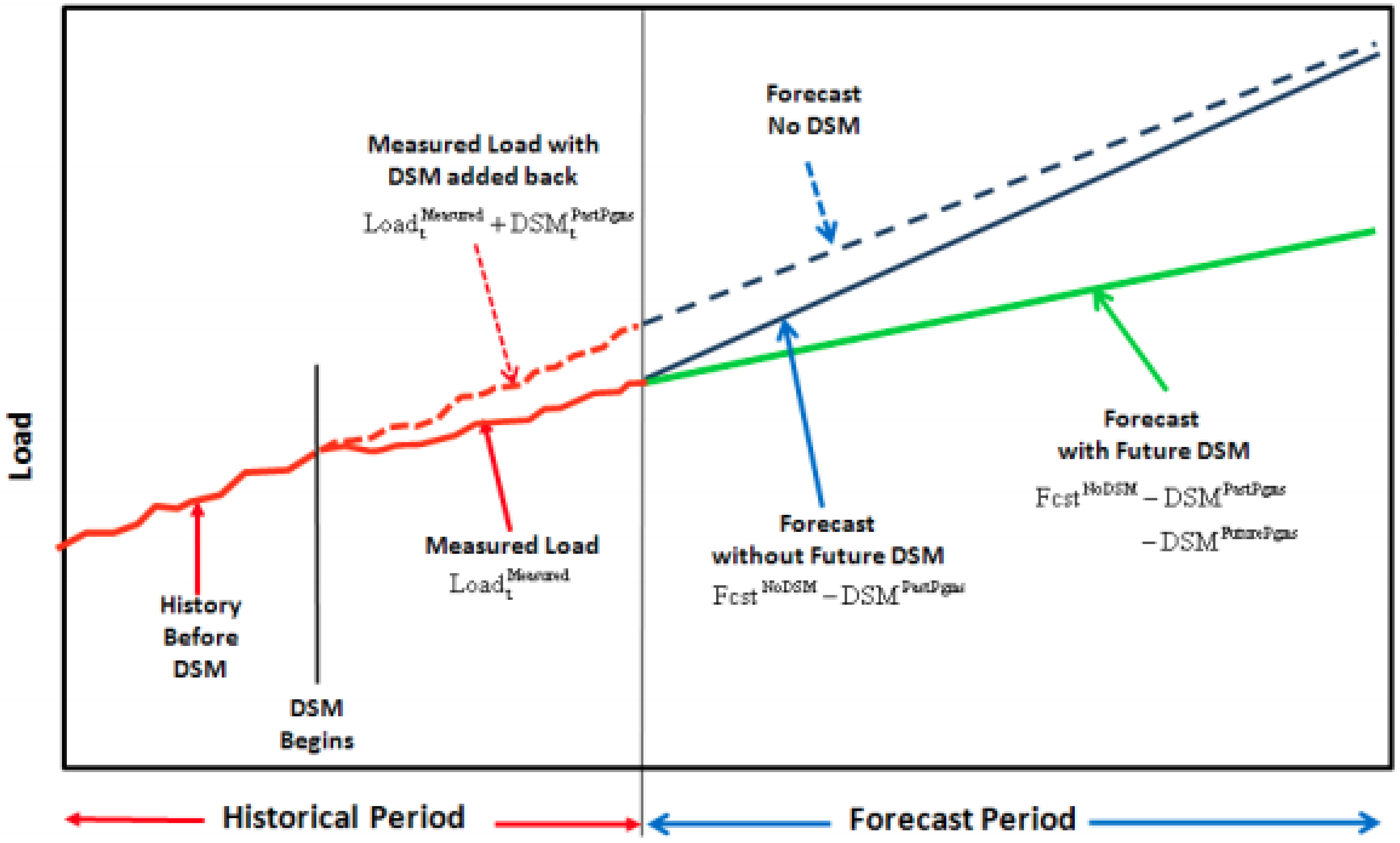
End-user Model:

- Technology based (energy intensity)
- GDP
- Population growth

Improper data selection and poor data analysis lead to low accuracy

DSM Influence

Adjust the load forecast by accounting for the amount and the continuing momentum of the historic DSM contained in the load forecast model



Itron white paper: Incorporating DSM into the Load Forecast

Commercially Available Applications

SAS Energy Forecasting: https://www.sas.com/en_us/software/energy-forecasting.html

ITRON https://www.itron.com/it/solutions/product-catalog/metrixidr-system-operations

LoadSeer http://willdan.com/ServiceBrochures/IA%20Flyer_LoadSEER_v5.pdf

Etap https://etap.com/product/load-forecasting-software

EnFor https://enfor.dk/services/loadfor/

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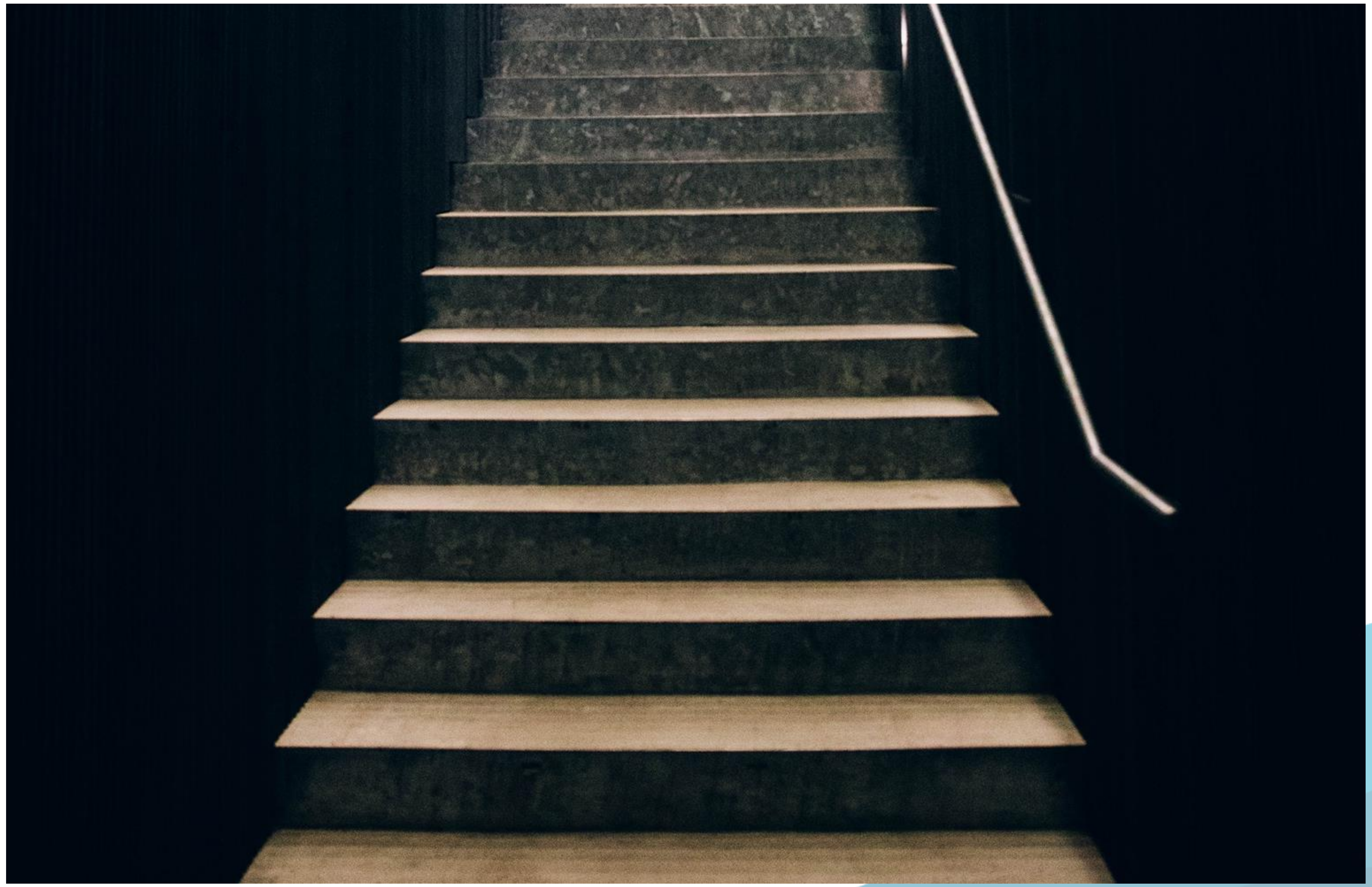
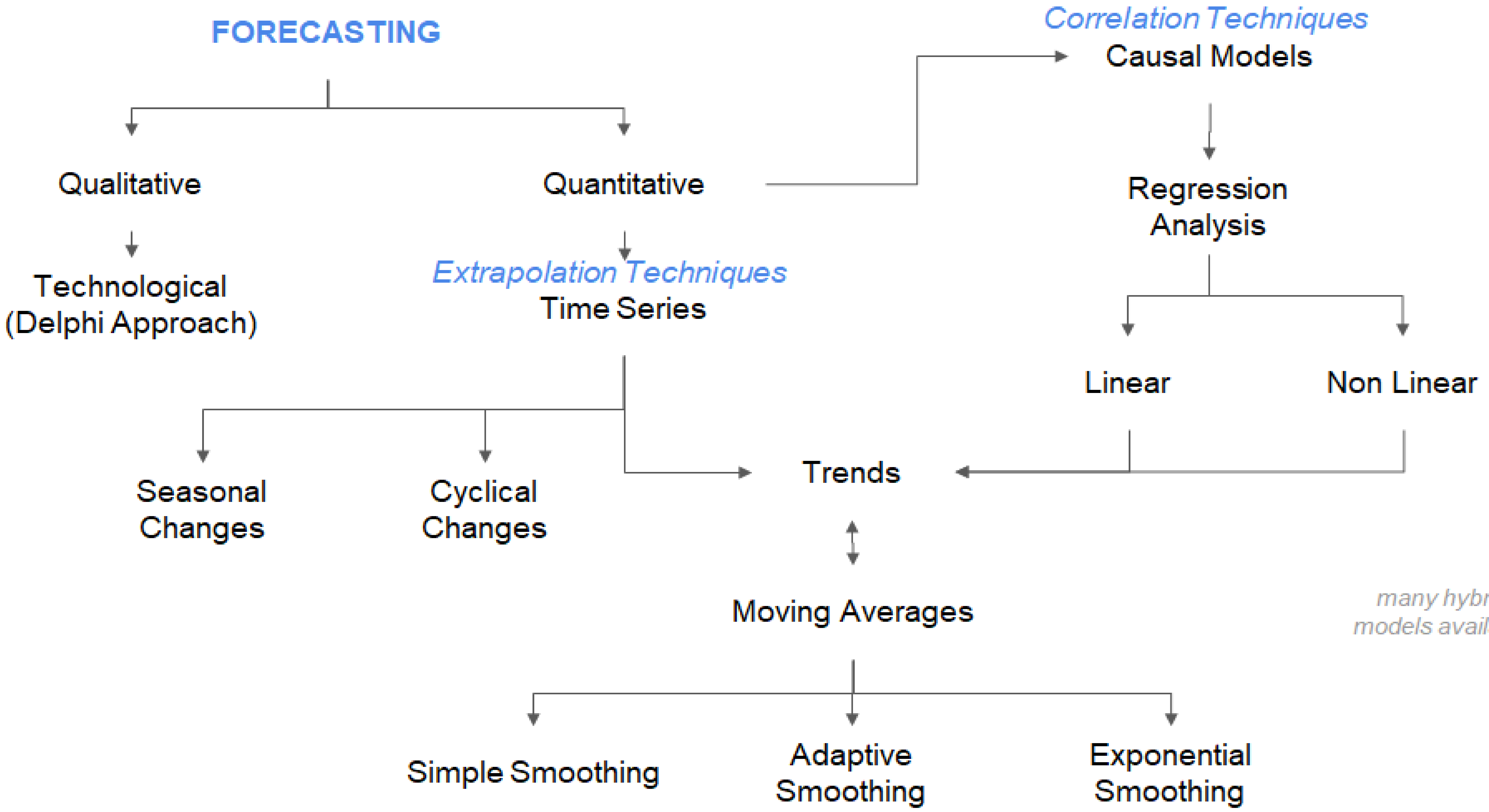
Demand Forecasting Techniques

Steps in Demand Forecasting

- Determine the use of the forecast
- Select the items to be forecast
- Determine the time horizon of the forecast
- Select the forecasting model(s)
- Gather the data
- Make the forecast
- Validate and implement results

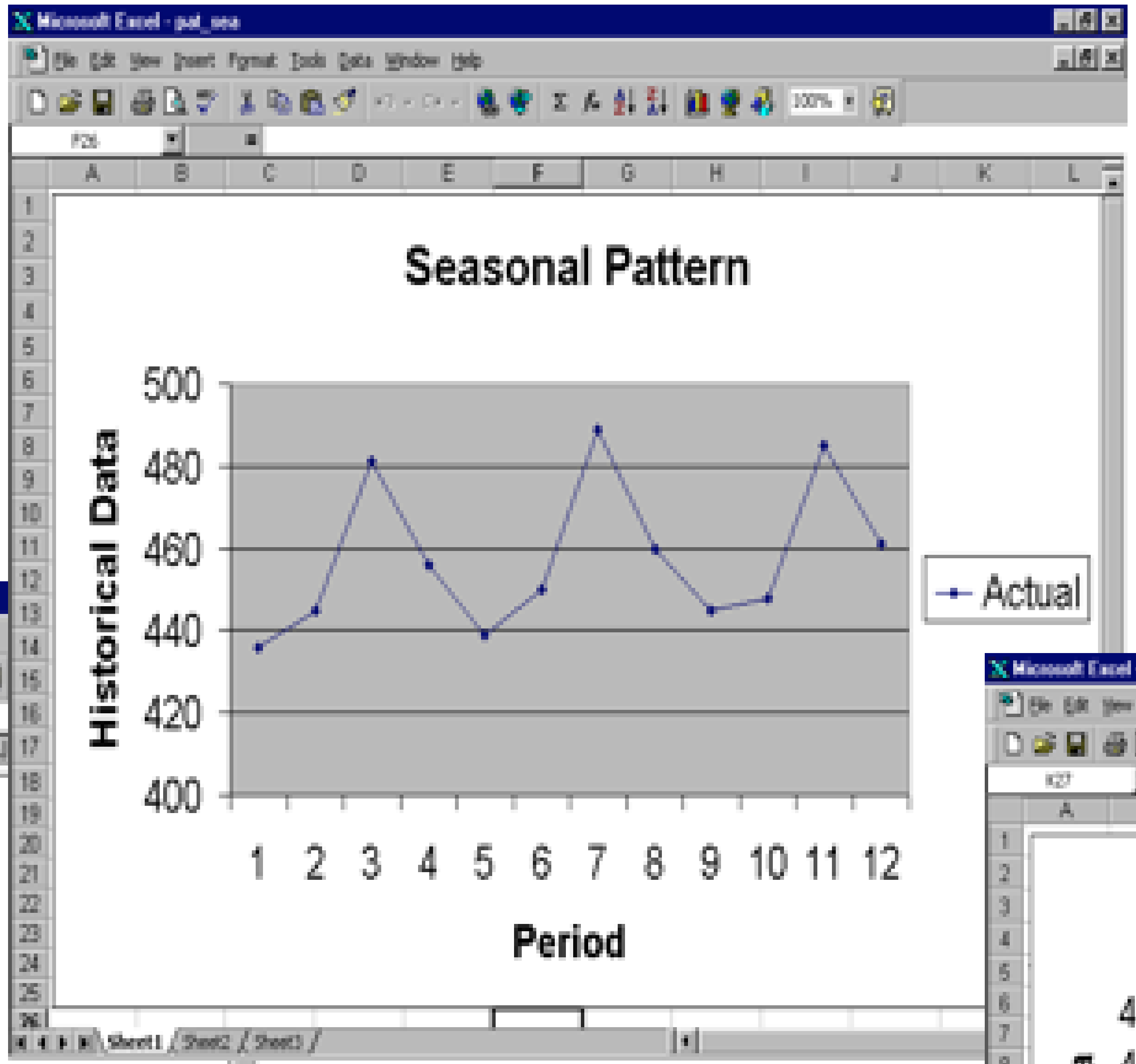


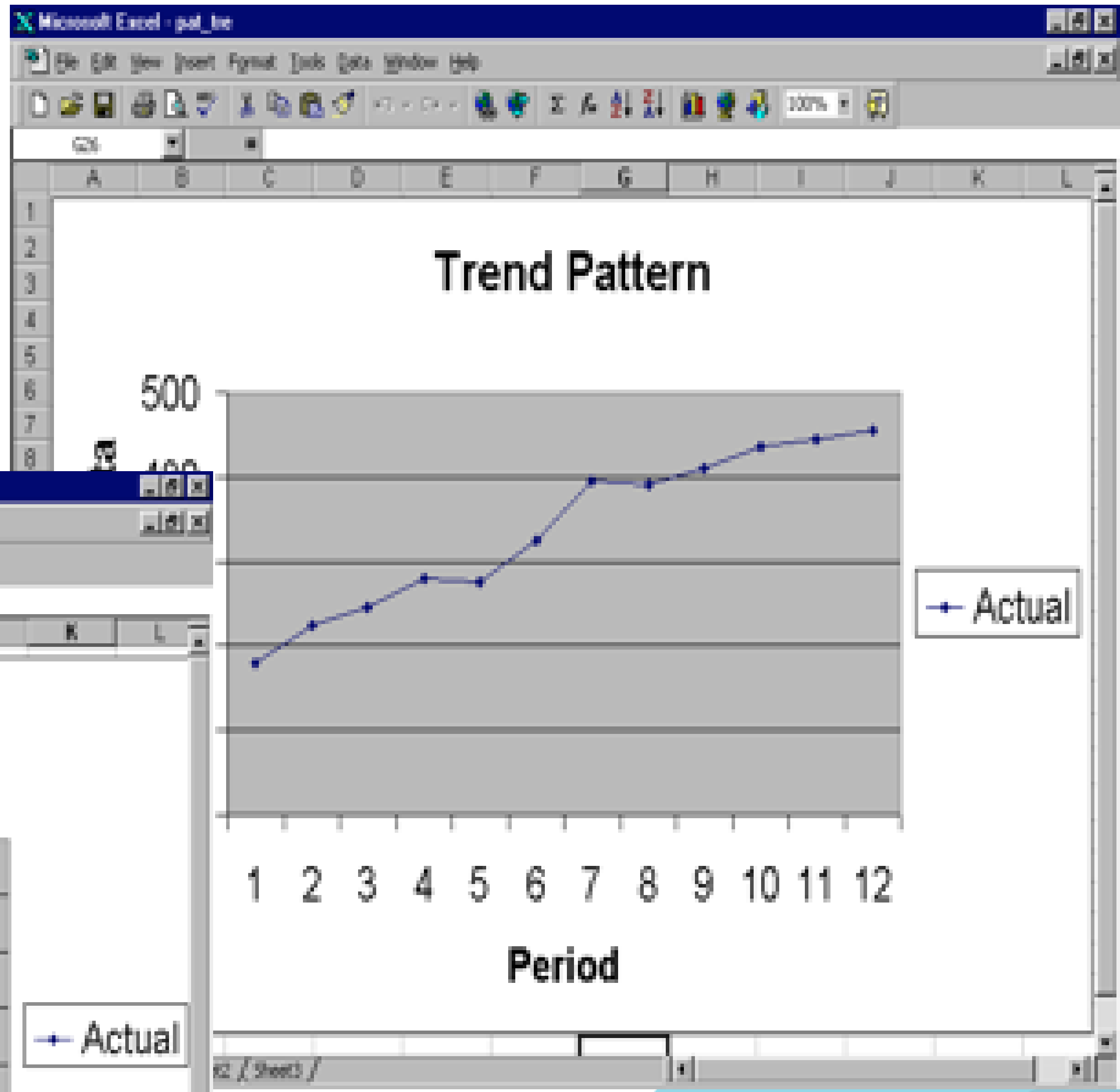
Forecasting Methods

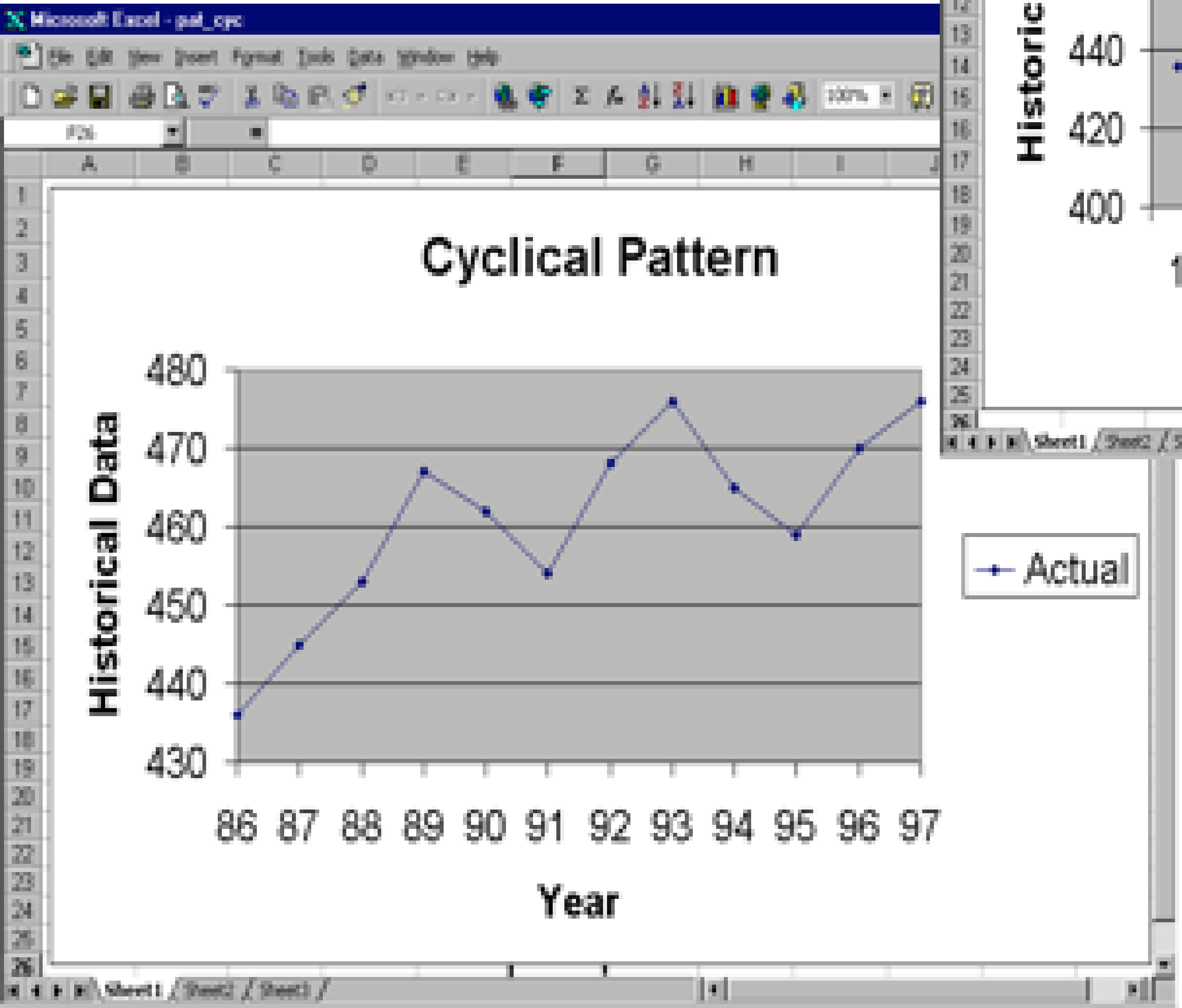


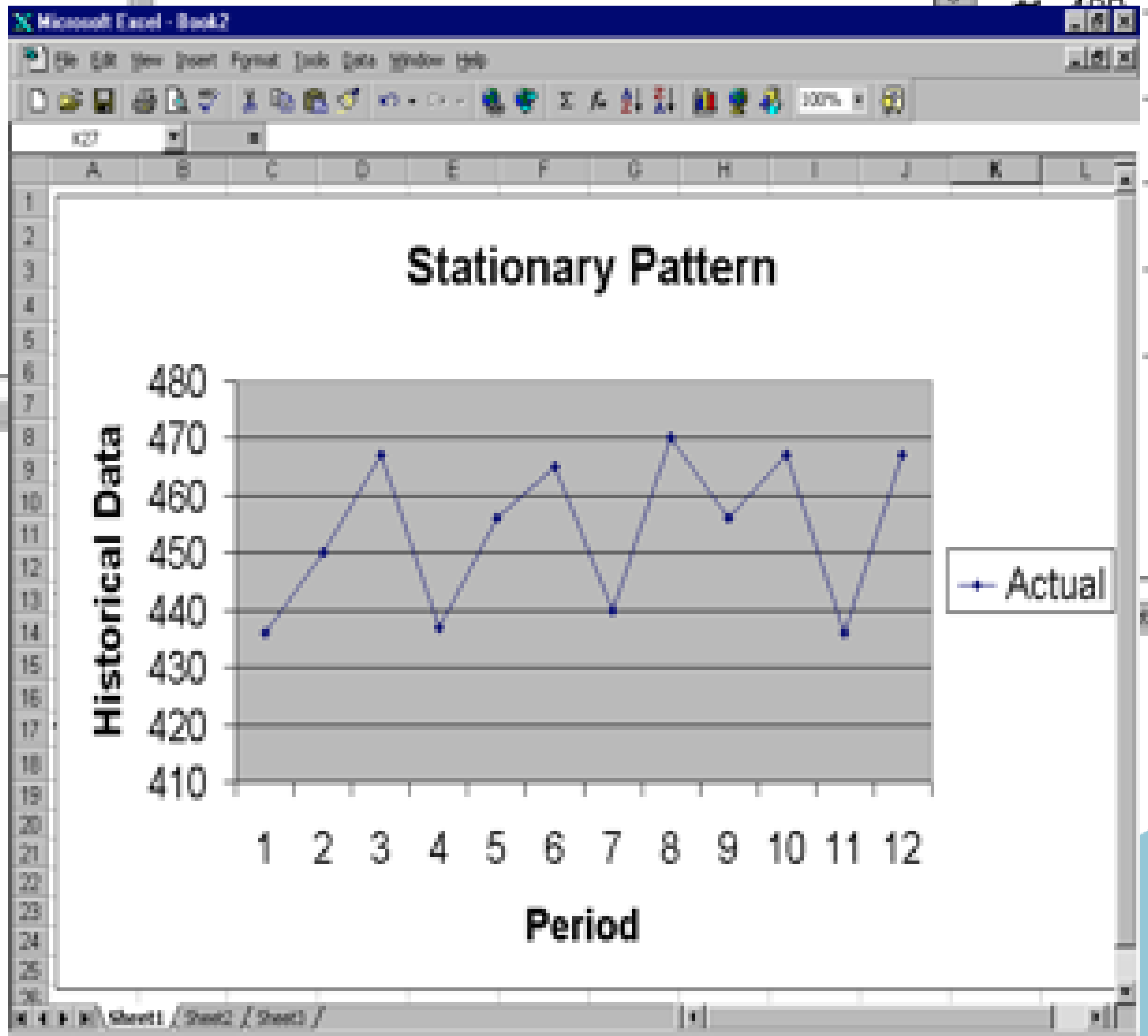
many hybrid models available

Quantitative Methods









Let's try an example - Moving Average

You're a manager of a shop that sells preserved fruit. You wish to forecast the sales of red mango for 2009 using a 3 year moving average.

$$\frac{\sum Demand\ in\ the\ previous\ N\ years}{N}$$

2004	6
2005	4
2006	5
2007	7
2008	9
2009	?

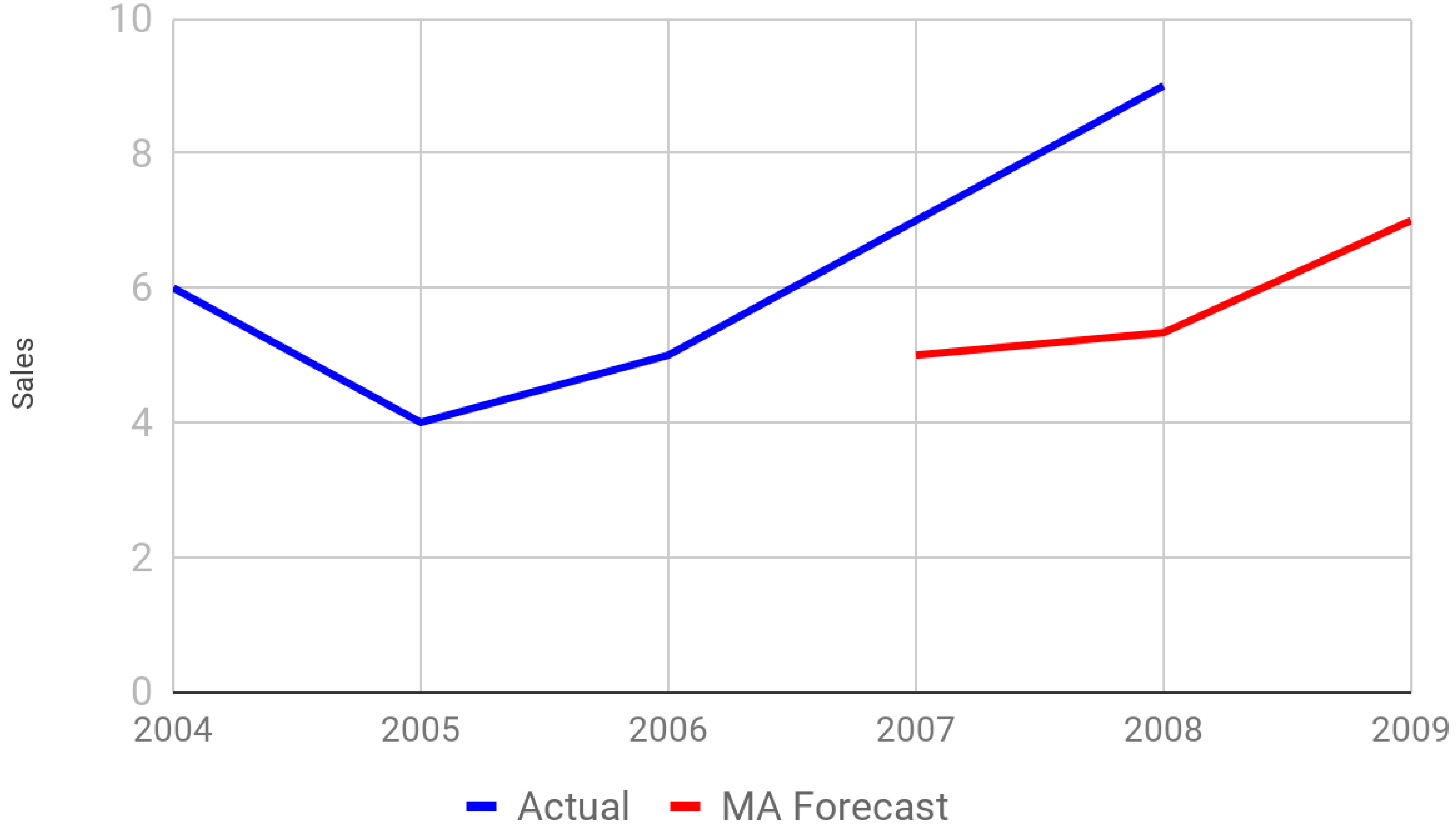
Example - Moving Average

Year	Actual	Moving Total (n=3)	Moving Averge (n=3)
2004	6	n/a	n/a
2005	4	n/a	n/a
2006	5	n/a	n/a
2007	7	6+4+5 =15	15/3=5
2008	9		
2009	n/a		

Year	Actual	Moving Total (n=3)	Moving Averge (n=3)
2004	6	n/a	n/a
2005	4	n/a	n/a
2006	5	n/a	n/a
2007	7	6+4+5 =15	15/3=5
2008	9	4+5+7 = 16	16/3 = 5.333
2009	n/a		

Example - Moving Average

Year	Actual	Moving Total (n=3)	Moving Averge (n=3)
2004	6	n/a	n/a
2005	4	n/a	n/a
2006	5	n/a	n/a
2007	7	6+4+5 =15	15/3=5
2008	9	4+5+7 = 16	16/3 = 5.333
2009	n/a	5+7+9 = 21	21/3 = 7



Can add weights based on intuition to produce the weight moving average.

Disadvantages - Moving Average

- Increasing *N* makes forecast less sensitive to changes
- Do not forecast trend well due to the delay between actual outcome and forecast
- Difficult to trace seasonal and cyclical patterns
- Require much historical data
- Weighted Moving Average may perform better

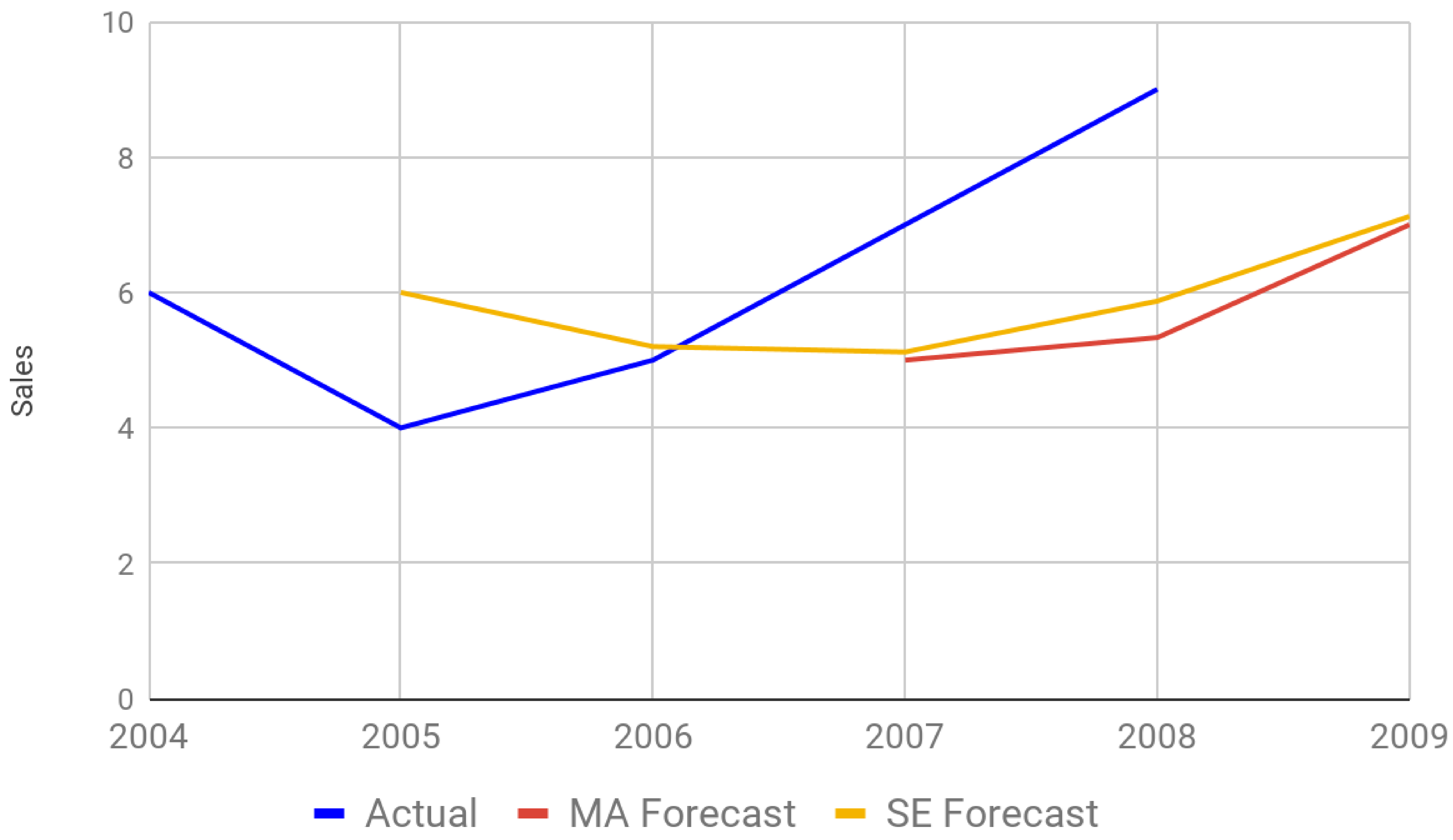
An Example - Exponential Smoothing

You're a manager of a shop that sells preserved fruit. You wish to forecast the sales of red mango for 2009 using single exponential smoothing $\boldsymbol{\alpha} = 0.4$.

2004	6
2005	4
2006	5
2007	7
2008	9
2009	?

Example - Single Exponential Smoothing

Year	Actual	Prediction	
2004	6		
2005	4	6	
2006	5	5.2	6 + (4-6)*0.4
2007	7	5.12	5.2 + (5-5.2)*0.4
2008	9	5.87	5.12 + (7-5.12)*0.4
2009	n/a	7.13	5.87 + (9-5.87)*0.4



Growth Rate

Projected Demand → $D_t = D_0(1+g)^t$

Historic Demand Data

Year	Energy (GWh)
2019	1279.07
2018	1218.16
2017	1160.15
2016	1104.91
2015	1052.29
2014	1002.18
2013	954.46
2012	909.01
2011	865.73
2010	824.50

Compound Annual Growth Rate (CAGR)

$$g = \left(\frac{D_t}{D_0}\right)^{\frac{1}{t}} - 1 = 5\%$$

Projected Demand

Year	Energy (GWh)
2029	2083.47
2028	1984.26
2027	1889.77
2026	1799.78
2025	1714.08
2024	1632.45
2023	1554.72
2022	1480.68
2021	1410.17
2020	1343.02

Elasticity

Elasticity Based → $$\varepsilon_{elasticity} = \frac{\%\ Change\ kWh}{\%\ Change\ GDP}$$

Historic Energy Sales and GDP Data

Year	Energy (GWh)	GDP/Capita (USD)	Elasticity
2017	2827.7	16,050.00	0.71
2016	2810.7	15,914.29	- 0.38
2015	2697.9	17,900.00	- 0.37
2014	2608.9	19,728.57	1.22
2013	2568.8	19,478.57	0.84
2012	2447.9	18,400.00	3.14
2011	2352.1	18,164.29	0.24
2010	2271.1	15,828.57	0.62
2009	2071.2	13,692.86	0.44
2008	2398.3	19,907.14	0.83

Average Elasticity 0.73 →

Projected Energy Sales from GDP data

Year	GDP/Capita (USD Billion)	Energy (GWh)
2025	18,653.25	3,156.36
2024	18,269.55	3,108.74
2023	17,892.68	3,061.71
2022	17,450.39	3,006.14
2021	17,276.43	2,984.22
2020	17,130.24	2,965.76
2019	16,621.96	2,901.06
2018	16,197.20	2,846.61

Models

MODELS	TIME - SERIES?	PROS	CONS
LOG -LOG	No	Allows for more data volatility, suitable for emerging economies.	Relies on the accuracy of exogenous forecast
ARIMA	Yes	Allows for more data volatility, suitable for emerging economies.	Only historical evolution, lacks expectation
ARIMAX	Yes	Allows for events that did not happen before by including exogenous variables.	Relies on the accuracy of exogenous forecast
VAR	Yes	Multi-variate, allows for cross-variable dynamics.	Only historical evolution, lacks expectation
ETS (EXPONENTIAL SMOOTHING)	Yes	Allows non-linearity in the construction of parameters, and non-stationarity.	Only historical evolution, lacks expectation
ANN (NEURAL NETWORK)	Yes	Allows for non-linearity in parameters, perform better with multicollinearity.	Relies on the accuracy of exogenous forecast

Which method do I choose?

- Depends on how expert one is in that method (time series analysis, expert systems and artificial intelligence).
- Optimum forecast performance
  - Applicability and accuracy
  - Availability of data
  - Size of population

Closing Remarks

Facts in Forecasting

CARIBBEAN CENTRE FOR RENEWABLE ENERGY & ENERGY EFFICIENCY
AN INSTITUTION OF CARICOM
UWI

- Main assumption: Past pattern repeats itself into the future.
- Forecasts are rarely perfect: Don't expect forecasts to be exactly equal to the actual data.
- The science and art of forecasting try to minimize, but not to eliminate, forecast errors. Forecast errors mean the difference between actual and forecasted values.
- No forecasting method is effective in all situations.
- Good judgment, intuition, commercial knowledge and experience to make a forecasting method effective.

General Takeaways (1)

- Load forecasting is key for utility planning and financial survival.
- Ever changing risks including generation resource mix, environmental regulation, aging assets and infrastructure, the projected low cost of natural gas, decreasing costs of renewable technologies, new electric appliances.
- Accurate (as possible) load forecasts for resource planning, rate cases, designing rate structures and financial planning are required.

General Takeaways (2)

- Installed smart grid technologies now contribute to granular big data.
- Many factors influence and each model is tailored for each utility, each year.
- Errors exist.

Sources of Errors

- Data sources.
- Key information (usually about loads) not considered.
- Forecasts yield higher than physical limit of the end use.

Forecasting Evolution

	HISTORICAL CONTEXT	CURRENT CONTEXT	FUTURE CONTEXT
DRIVERS	» Generation capacity planning » EE and traditional load management	» T&D planning » Strategic R&D » Rise of solar PV, EV, storage	» Grid management » Large-scale DER integration » Climate change
DATA SOURCES	» Monthly bills » Ad hoc end-use data » Load research studies » EM&V studies	» AMI data » Comprehensive end-use data » DER performance data	» Big data
MODELING FRAMEWORK	» Total annual consumption » System coincident peak demand	» Total hourly demand	» Locational hourly demand

Thank You

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