# 9. Advanced Topic in Load forecasting

George Konstantinou, University of Cyprus

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# Content of the lecture

# 1. Introduction

- Nowadays it's quite important to develop accurate and efficient models to predict power load, so that a utility company may operate and plan economically. Load forecasting helps an electric utility to make important decisions on purchasing and generating electric power, load switching, and infrastructure development as well.
- Load forecasts are essential for energy suppliers, financial institutions, ISOs and everyone in general that is involved in electric energy generation, transmission, distribution, and markets.
- Load forecasts fall into three distinct categories: short-term forecasts - from one hour to one week, medium forecasts - from a week to a year, and long-term forecasts which are longer than a year. In addition, forecasts for different time horizons are important for a utility company to schedule its operations correctly.

# 1. Introduction

- Note that, for a certain region, it is possible to predict the next day load with an average accuracy of **1-3%!**
- However, it is not possible to predict the next year peak load with same accuracy since accurate long-term weather forecasts simply do not exist (with current technologies).
- But what about the next year peak forecast? Well, it is possible to provide a probability distribution of the load based only on historical weather observations! It is also possible, make a guess about the weather normalized load, which happens for average annual peak weather conditions or worse than average peak weather conditions for an area.
- ***Weather normalized load:*** load calculated for the (so-called) normal weather conditions which are the average of the weather characteristics for the peak historical loads over a given period of time. The duration of this period varies within different utilities. Most of them take the last 25-30 years of data.

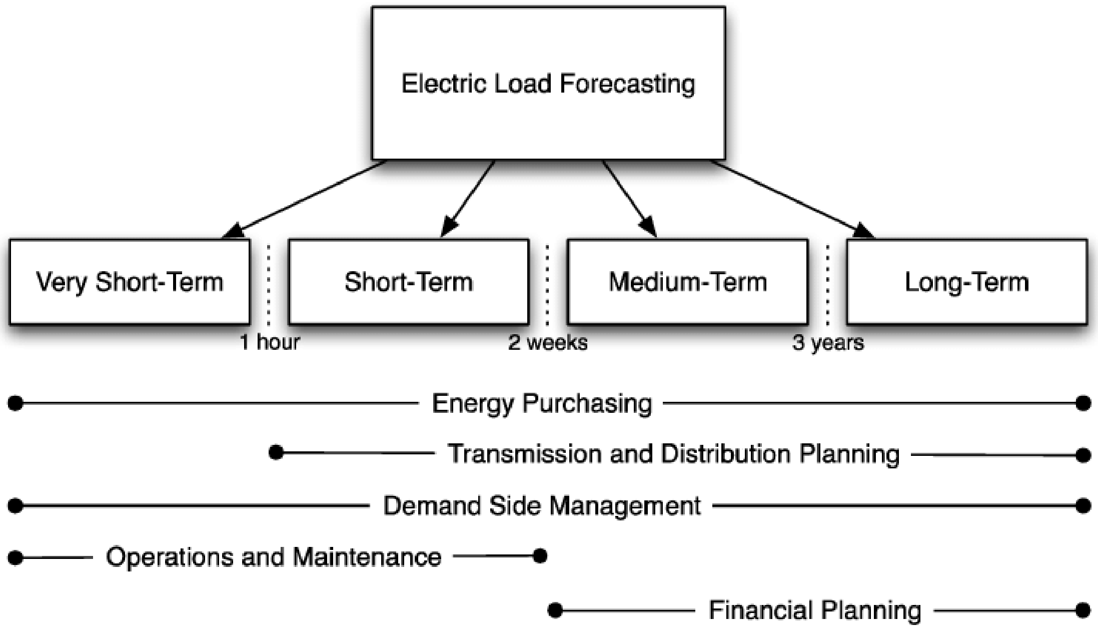
# 1. Introduction

- Load forecasting is the A and the Ω for planning and operational decision done by utility companies. However, with the deregulation of the energy industries, load forecasting is nowadays needed more than ever.
- Given that supply and demand fluctuate with energy prices increasing by a factor of ten (and more!) during peak conditions, load forecasting is extremely important.
- Short-term load forecasting can help quantify load flows and make decisions that can prevent overloading. Timely implementations of such decisions lead to the improvement of network reliability and to the minimization of equipment failures and blackouts.
- Load forecasting is important for evaluations of contracts and various sophisticated financial products on energy pricing offered by the market.

# 1. Introduction

- In the deregulated economy, decisions on capital expenditures based on long-term forecasting are also more important than in a non-deregulated economy when rate increases could be justified by capital expenditure projects.
- Most forecasting methods use statistics (probabilistic) or artificial intelligence algorithms such as neural networks, regression, expert systems and fuzzy logic. Two of the methods, the end-use and econometric approach are widely used for medium- and long- term forecasting.
- A variety of methods, which include the well-known similar day approach, many regression models, neural networks, time series, statistical learning algorithms, fuzzy logic and expert systems, have been especially made for short-term forecasting.

- A variety of mathematical methods and models have been used for the topic of load forecasting.
- The continuous development and improvement of mathematical tools will lead to the development of more accurate load forecasting models.
- The accuracy of a load forecasting model depends not only on the load forecasting techniques, but also on the accuracy of forecasted weather scenarios. So, weather forecasting is also an important topic (which is outside the goals of this chapter).



## 2. Important Factors for Forecasts

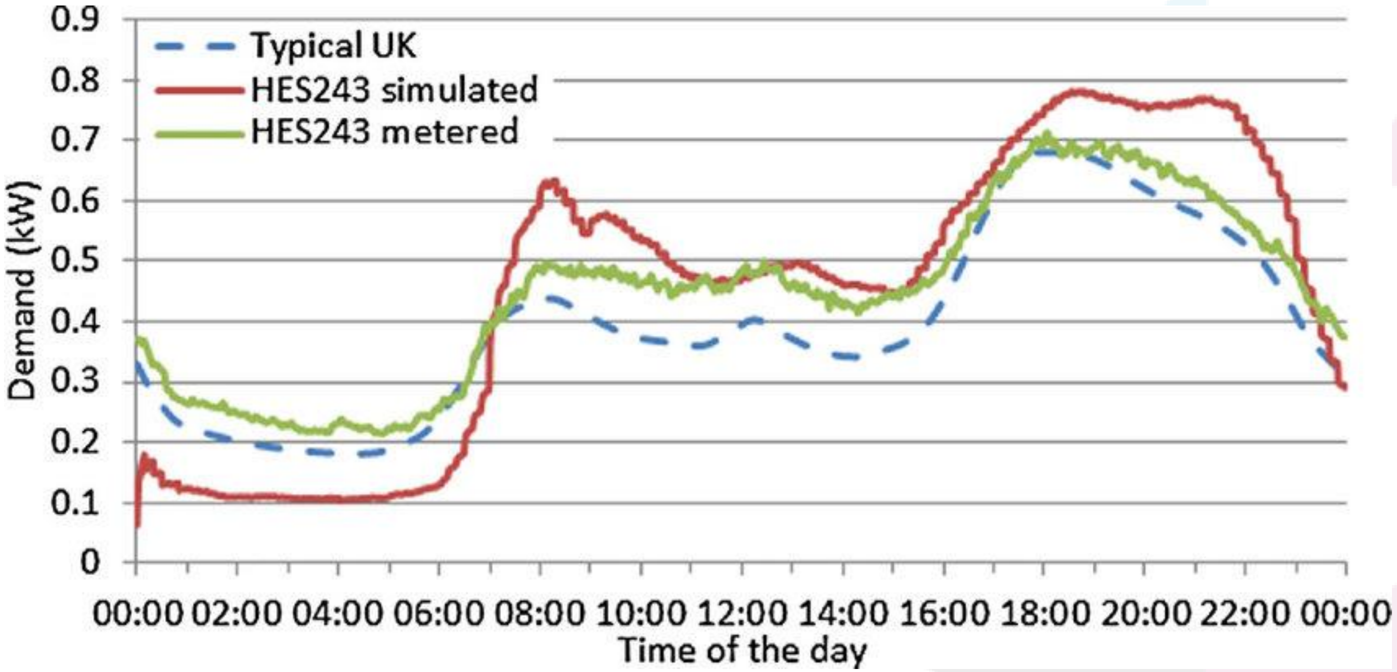
- Several factors should be considered regarding short-term load forecasting, i.e. weather data, time factors, and even possible customers' classes.
- The typical medium- and long- term forecasts consider the historical load and weather data, the number of customers in different classes, the appliances in the area under consideration and their characteristics (including age-working hours), the financial and demographic data and their forecasts, appliance sales data, and other factors as well. The time factors include: time of the year, day of the week, and the hour of the day.
- The load is different for weekdays and weekends. The load on different weekdays can also behave differently. For example, Mondays and Fridays being adjacent to weekends, may have different loads than Tuesday to Thursday. This is true especially in the summer-time. Holidays are more difficult to forecast than working days because of their relative infrequent occurrence.

## 2. Important Factors for Forecasts

- In addition, weather can influence the load. Specifically, forecasted weather parameters are the most important factors in short-term load forecasts! Various weather variables must be included in load forecasting models.
- Temperature and humidity are the most commonly used load predictors. An electric load prediction survey showed that of the 22 research reports considered, 13 used only temperature, 3 used both temperature and humidity, 3 included additional weather parameters, and 3 used load parameters only.
- Among the weather variables listed above, two composite weather variable functions, the THI (Temperature-Humidity index) and WCI (Wind Chill index), are commonly used by utility companies. THI is a measure of summer heat discomfort and similarly WCI is a cold stress indicator in winter.

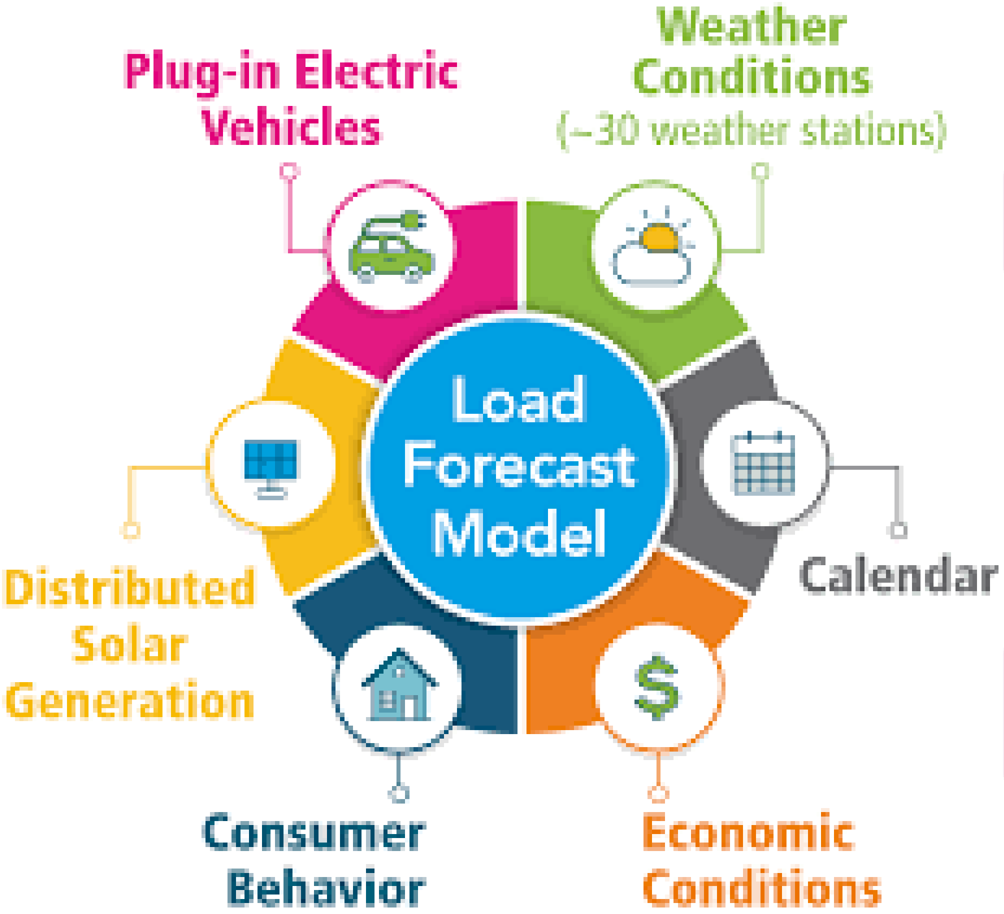
# 2. Important Factors for Forecasts

- Most electric companies serve customers of different classes such as residential, commercial, and industrial.
- Customers that belong to different classes have a different electric usage pattern. Customes from the same class have similar usage.
- Therefore, most utilities distinguish load behavior on a class-by-class basis.



# 3. Forecasting methods

- Over the last few years, several forecasting methods have been developed and implemented. Two of these the end-use and econometric approach are commonly used for medium- and long-term forecasting.
- Other methods, which deal with the similar day approach technique, different regression models, time series, neural networks, expert systems, fuzzy logic, and statistical learning algorithms, are also used for short-term forecasting.
- The development, advances, and researching of the appropriate mathematical tools will lead to the development of more precise load forecasting methods.



# 3. Forecasting methods

- Statistical methods require a mathematical model that express load as function of factors such as time, weather, and even customer class.
- The two important categories of such mathematical models are: additive models and multiplicative models. They differ in whether the forecast load is the sum (additive) of a number of components or the product (multiplicative) of a number of factors. For example, Chen et al. [1] presented an additive model that takes the form of predicting load as the function of four components:

$$L = L_n + L_w + L_s + L_r$$

- where $L$ is the total load, $L_n$ represents the "normal" part of the load, which is a set of standardized load shapes for each "type" of day that has been identified as occurring throughout the year, $L_w$ represents the weather sensitive part of the load, $L_s$ is a special event component that create a substantial deviation from the usual load pattern, and Lr is a completely random term, the noise.

# 3. Forecasting methods

- Chen et al. [1] also suggested electricity pricing as an additional term that can be included in the model. Naturally, price decreases/increases affect electricity consumption. Large cost sensitive industrial and institutional loads can have a significant effect on loads.
- The study in [4] used Pennsylvania-New Jersey-Maryland (PJM) spot price data (as it related to Ontario Hydro load) as a neural network input. The authors report that accurate estimates were achieved more quickly with the inclusion of price data.

## 3. Forecasting methods

- A multiplicative model may be of the form

$$L = L_n \cdot F_w \cdot F_s \cdot F_r,$$

where $L_n$ is the normal (base) load and the correction factors $F_w$, $F_s$, and $F_r$ are positive numbers that can increase or decrease the overall load. These corrections are based on current weather ($F_w$), special events ($F_s$), and random fluctuation ($F_r$).

- Factors such as electricity pricing ($F_p$) and load growth ($F_g$) can also be included.
- Rahman [2] presented a rule based forecast using a multiplicative model. Weather variables and the base load associated with the weather measures were included in the model.

# 4. Medium- and long- term load forecasting methods

- The end-use modeling, econometric modeling, and their combinations are the most often used methods for medium- and long- term load forecasting.
- Descriptions of appliances used by customers, the sizes of the houses, the age of equipment, technology changes, customer behavior, and population dynamics are usually included in the statistical and simulation models based on the so-called end-use approach.
- In addition, economic factors such as per capita incomes, employment levels, and electricity prices are included in econometric models. These models are often used in combination with the end-use approach.
- Long-term forecasts include the forecasts on the population changes, economic development, industrial construction, and technology development.

# 4. Medium- and long- term load forecasting methods

- **End-use models:** The end-use approach directly estimates energy consumption by using extensive information on end use and end users, such as appliances, the customer use, their age, sizes of houses, and so on.
- Statistical information about customers along with dynamics of change is the basis for the forecast. End-use models focus on the various uses of electricity in the residential, commercial, and industrial sector. These models are based on the principle that electricity demand is derived from customer's demand for light, cooling, heating, refrigeration, etc.
- Thus, end-use models explain energy demand as a function of the number of appliances in the market [3]. However, it is sensitive to the amount and quality of end-use data. For example, in this method the distribution of equipment age is important for particular types of appliances. End-use forecast requires less historical data but more information about customers and their equipment.

# 4. Medium- and long- term load forecasting methods

- **Econometric models.** The econometric approach combines economic theory and statistical techniques for forecasting electricity demand. The approach estimates the relationships between energy consumption (dependent variables) and factors influencing consumption. The relationships are estimated by the least-squares method or time series methods.
- One of the options in this framework is to aggregate the econometric approach, when consumption in different sectors (residential, commercial, industrial, etc.) is calculated as a function of weather, economic and other variables, and then estimates are assembled using recent historical data. Integration of the econometric approach into the end-use approach introduces behavioral components into the end-use equations.

# 4. Medium- and long- term load forecasting methods

- **Statistical model-based learning.** The end-use and econometric methods require a large amount of information relevant to appliances, customers, economics, etc. Their application is complicated and requires human participation.
- In addition, such information is often not available regarding particular customers and a utility keeps and supports a profile of an "average" customer or average customers for different type of customers. The problem arises if the utility wants to conduct next-year forecasts for sub-areas, which are often called load pockets.
- In this case, the amount of the work that should be performed increases proportionally with the number of load pockets. In addition, end-use profiles and econometric data for different load pockets are typically different. The characteristics for particular areas may be different from the average characteristics for the utility and may not be available.

# 4. Medium- and long- term load forecasting methods

- In order to simplify the medium-term forecasts, make them more accurate, and avoid the use of the unavailable information, Feinberg et al. ([4], [5]) developed a statistical model that learns the load model parameters from the historical data.
- Feinberg et al.([4], [5]) studied load data sets provided by a utility company in Northeastern US. The focus of the study was summer data. Several load models were compared and it was concluded that the following multiplicative model is the most accurate:

$$L(t) = F(d(t), h(t)) \cdot f(w(t)) + R(t)$$

- where ***L(t)*** is the actual load at time ***t***, ***d(t)*** is the day of the week, ***h(t)*** is the hour of the day, ***F(d,h)*** is the daily and hourly component, ***w(t)*** is the weather data that include the temperature and humidity, ***f(w)*** is the weather factor, and ***R(t)*** is a random error.

# 4. Medium- and long- term load forecasting methods

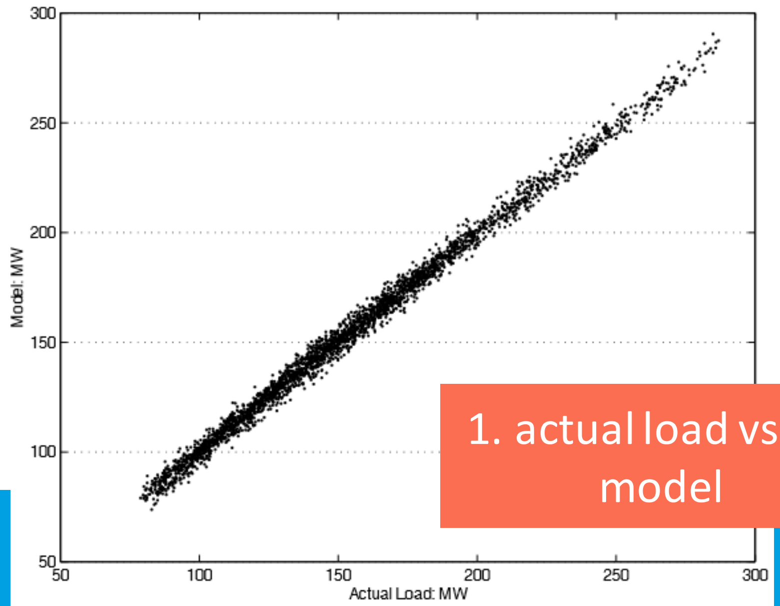
- In fact, w(t) is a vector that consists of the current and lagged weather variables. This reflects the fact that electric load depends not only on the current weather conditions but also on the weather during the previous hours and days. In particular, the well-known effect of the so-called heat waves is that the use of air conditioners increases when the hot weather continues for several days.
- To estimate the weather factor *f(w),* we used the regression model

$$f(w) = \beta_0 + \sum \beta_j X_j$$

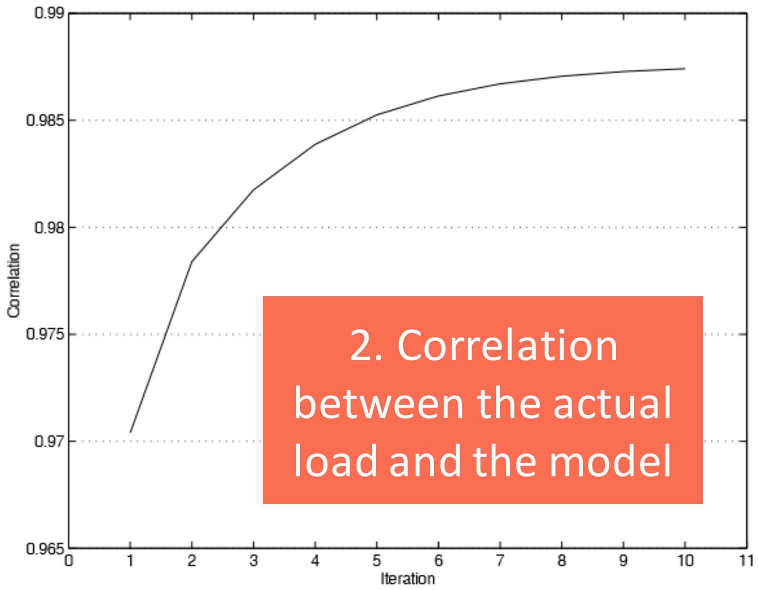
- where $X_j$ are explanatory variables which are nonlinear functions of current and past weather parameters and $\beta_0$, $\beta_j$ are the regression coefficients.
- The parameters of the model can be calculated iteratively. We start with $F = 1$. Then we use the above regression model to estimate $f$. Then we estimate $F$, and so on.

# 4. Medium- and long- term load forecasting methods

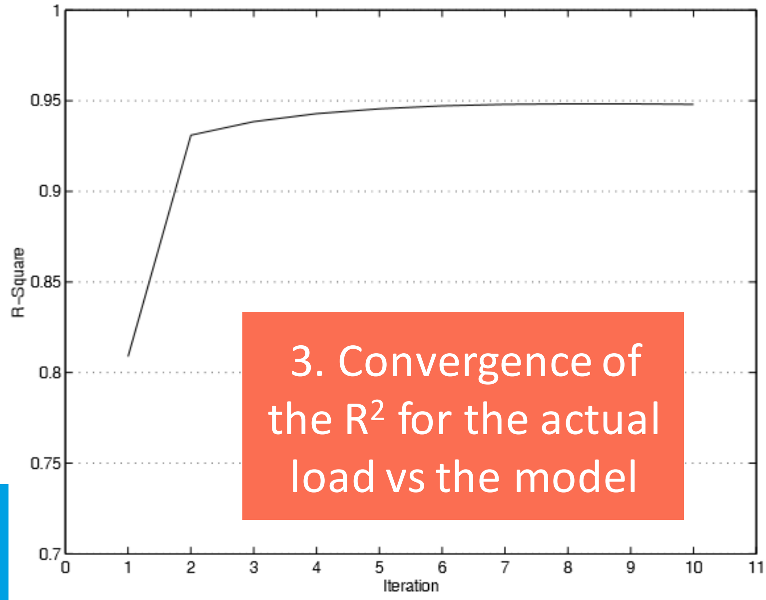
- The described algorithm demonstrated rapid convergence on historical hourly load and weather data. We have applied it to many areas with population between 50,000 and 250,000 customers. Figure 1 below presents an example of a scatter plot that compares the model and real parameters. Figure 2 demonstrates the convergence of the correlation between the actual load and the model for the iteration process. Figure 3 demonstrates the convergence of the linear regression procedures in the algorithm.




1. actual load vs the model




2. Correlation between the actual load and the model




3. Convergence of the $R^2$ for the actual load vs the model

# 4. Medium- and long- term load forecasting methods

- The software generates several important characteristics. For example, for each load pocket and for the system, it calculates a weather normalization factor that is a ratio of the peak load to the load that would be observed under average peak conditions. It also produces probability distributions for the next year peaks.
- The described methods can be applied to both medium- and long-term forecasting. However, the long-term forecasts should incorporate economic and population dynamic forecasts as input parameters.

# 5. Short-term load forecasting methods

- A large variety of statistical and artificial intelligence techniques have been developed for short-term load forecasting.
- **Similar-day approach.** This approach is based on searching historical data for days within one, two, or three years with similar characteristics to the forecast day. Similar characteristics include weather, day of the week, and the date.
- The load of a similar day is considered as a forecast. Instead of a single similar day load, the forecast can be a linear combination or regression procedure that can include several similar days. The trend coefficients can be used for similar days in the previous years.

# 5. Short-term load forecasting methods

- **Regression methods.** Regression is one of most widely used statistical techniques. For electric load forecasting regression methods are usually used to model the relationship of load consumption and other factors such as weather, day type, and customer class.
- Engle et al. [6] presented several regression models for the next day peak forecasting. Their models incorporate deterministic influences such as holidays, stochastic influences such as average loads, and exogenous influences such as weather.

# 5. Short-term load forecasting methods

- **Multiple linear regression (MLR):** The MLR method calculates the electric load at a specified time t using explanatory weather and non-weather variables that are known to have some influence on the electric load. These variables are identified by correlation analysis with the load. The variables are multiplied by regression coefficients that are found using the least square estimation technique.
- The MLR electrical load model has the following form:

$$y(t) = a_0 + a_1 x_1(t) + \ldots + a_n x_n(t) + a(t)$$

where $y(t)$ = electrical load, $x_1(t) \ldots x_n(t)$ explanatory variables correlated with $y(t)$, $a(t)$ = a random variable with zero mean and constant variance, $a0$, $a1$, … , $an$ = regression coefficients.

# 5. Short-term load forecasting methods

- **Time series.** Time series methods are based on the assumption that the data have an internal structure, such as autocorrelation, trend, or seasonal variation. Time series forecasting methods detect and explore such a structure.
- Time series have been used for decades in such fields as economics, digital signal processing, as well as electric load forecasting. In particular, ARMA (autoregressive moving average), ARIMA (autoregressive integrated moving average), ARMAX (autoregressive moving average with exogenous variables), and ARIMAX (autoregressive integrated moving average with exogenous variables) are the most often used classical time series methods.
- ARMA models are usually used for stationary processes while ARIMA is an extension of ARMA to nonstationary processes. ARMA and ARIMA use the time and load as the only input parameters. Since load generally depends on the weather and time of the day, ARIMAX is the most natural tool for load forecasting among the classical time series models.

# 5. Short-term load forecasting methods

- The electric load $y(t)$ is modeled as the output of a linear filter with a random input $a(t)$. This method uses historical load information to forecast the future load. The Autoregressive (AR) process defines the forecasted electric load, $y(t)$, in terms of the previous loads and a random noise signal $a(t)$.

$$y(t) = \phi_1 y(t-1) + \phi_2 y(t-2) + \ldots + \phi_p y(t-p) + a(t)$$

- The Moving-Average (MA) process defines the forecasted electric load in terms of the current and previous random noise signals. The noise series is constructed from the previous forecast errors.

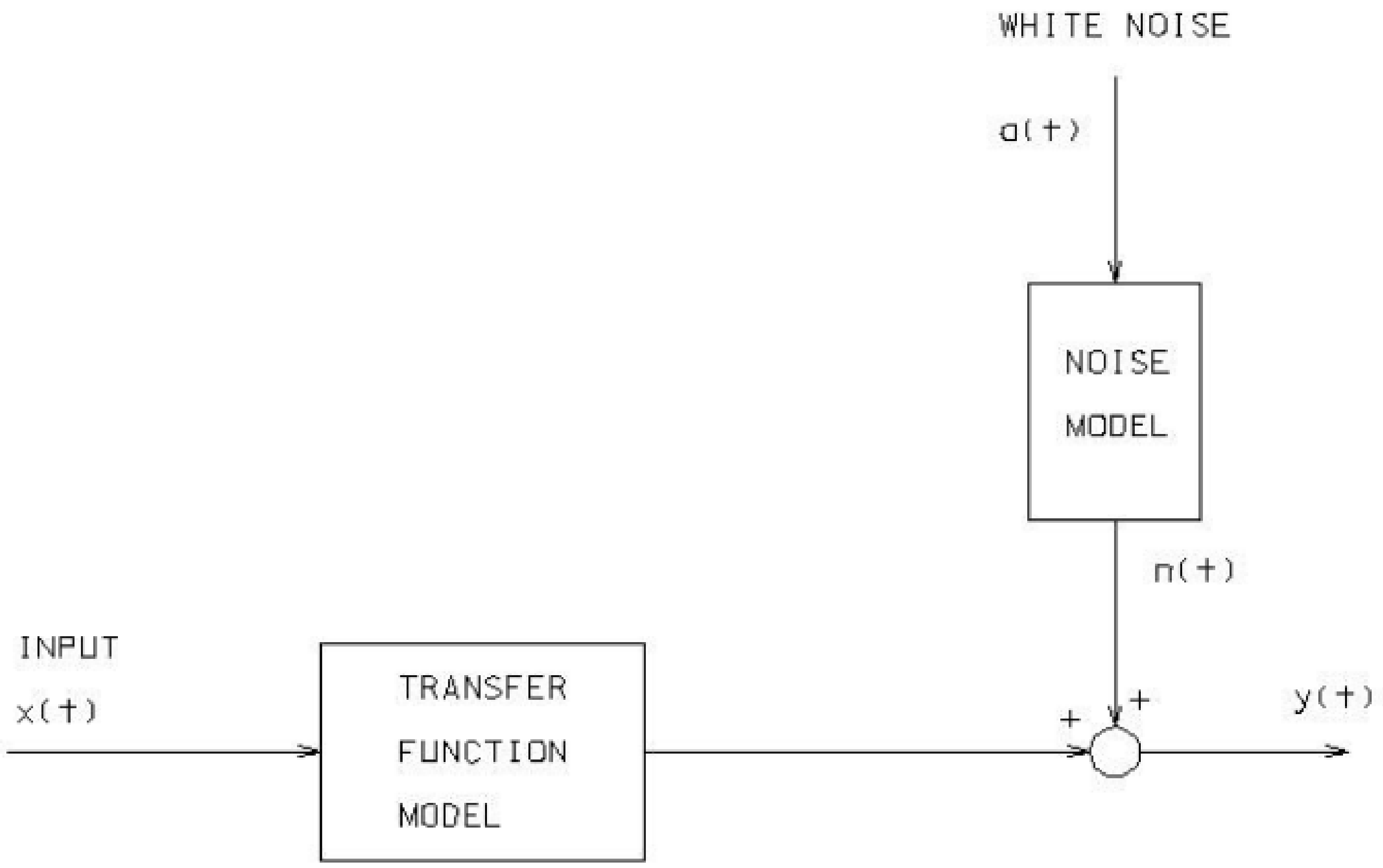
$$y(t) = a(t) - \Theta_1 a(t-1) - \Theta_2 a(t-2) - \ldots - \Theta_{q1} a(t-q)$$

- The Autoregressive Moving-Average (ARMA) process defines the forecasted load using a combination of the AR and MA processes

$$y(t) = \phi_1 y(t-1) + \phi_2 y(t-2) + \ldots + \phi_p y(t-p) + a(t) - \Theta_1 a(t-1) - \Theta_2 a(t-2) - \ldots - \Theta_{q1} a(t-q)$$

# 5. Short-term load forecasting methods

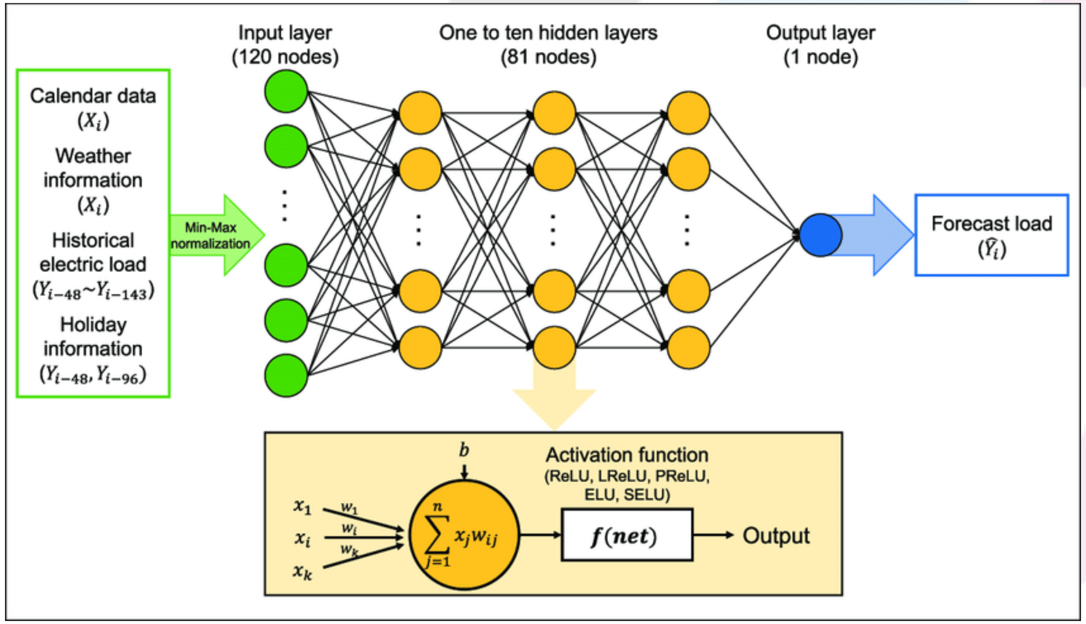
- The model for the ARMA process can be modified to perform forecasting for a time series with a non-stationary mean by a differencing process. This method is known as the Autoregressive Integrated Moving-Average (ARIMA) process.
- Some time series have periodic behaviors that are due to hourly, daily, weekly, monthly, yearly, or other periodicities. Models for these types of time series are known as seasonal processes. Multiple periodicities, such as hourly and daily cycles, can be modeled with the seasonal process, however, the order of the model increases with each additional period. The seasonal process model is a modification of the AR, MA, ARMA, or ARIMA process.
- The Transfer Function (TF) model utilizes one of the previously discussed models to represent historical load and a white noise term with one or more other variables that affect the load such as temperature or humidity. The effects of these other variables can be modeled using a transfer function as shown in the next Fig.




Transfer Function (TF) model

## 5. Short-term load forecasting methods

- **Neural networks.** The use of artificial neural networks (ANN or simply NN) has been a widely studied electric load forecasting technique since 1990 (see [7]). Neural networks are essentially non-linear circuits that have the demonstrated capability to do non-linear curve fitting.
- The outputs of an artificial NN are some linear or nonlinear mathematical function of its inputs. The inputs may be the outputs of other network elements as well as actual network inputs.
- In practice network elements are arranged in a relatively small number of connected layers of elements between network inputs and outputs. Feedback paths are sometimes used.



# 5. Short-term load forecasting methods

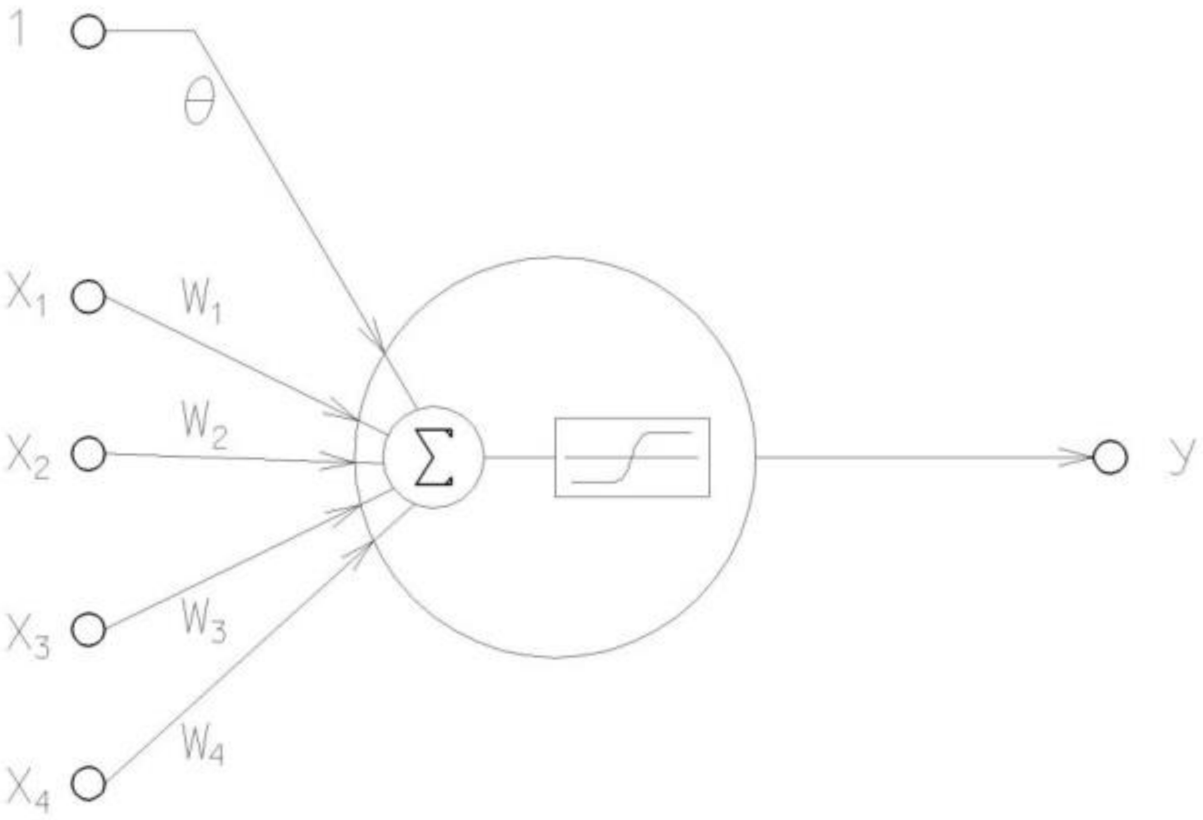
- In applying a neural network to electric load forecasting, one must select one of a number of architectures (e.g. Hopfield, back propagation, Boltzmann machine), the number and connectivity of layers and elements, use of bi-directional or uni-directional links, and the number format (e.g. binary or continuous) to be used by inputs and outputs, and internally.
- The most popular artificial neural network architecture for electric load forecasting is back propagation. Back propagation neural networks use continuously valued functions and supervised learning. That is, under supervised learning, the actual numerical weights assigned to element inputs are determined by matching historical data (such as time and weather) to desired outputs (such as historical electric loads) in a pre-operational “training session”.
- Artificial neural networks with unsupervised learning do not require pre-operational training.

# 5. Short-term load forecasting methods

- Bakirtzis et al. [8] developed an ANN based short-term load forecasting model for the Energy Control Center of the Greek Public Power Corporation. In the development they used a fully connected three-layer feedforward ANN and for training they used back propagation algorithm.
- Input variables include historical hourly load data, temperature, and the day of the week. The model can forecast load profiles from one to seven days.
- Also, Papalexopoulos et al. [9] developed and implemented a multi-layered feed forward ANN for short-term system load forecasting. In the model three types of variables are used as inputs to the neural network: season related inputs, weather related inputs, and historical loads.

# 5. Short-term load forecasting methods

- Khotanzad et al. [20] described a load forecasting system known as ANNSTLF. ANNSTLF is based on multiple ANN strategies that capture various trends in the data. In the development they used a multilayer perceptron trained with the error back propagation algorithm.
- ANNSTLF can consider the effect of temperature and relative humidity on the load. It also contains forecasters that can generate the hourly temperature and relative humidity forecasts needed by the system.
- In the new generation, ANNSTLF includes two ANN forecasters, one predicts the base load and the other forecasts the change in load. The final forecast is computed by an adaptive combination of these forecasts. The effects of humidity and wind speed are considered through a linear transformation of temperature.




An artificial neuron model

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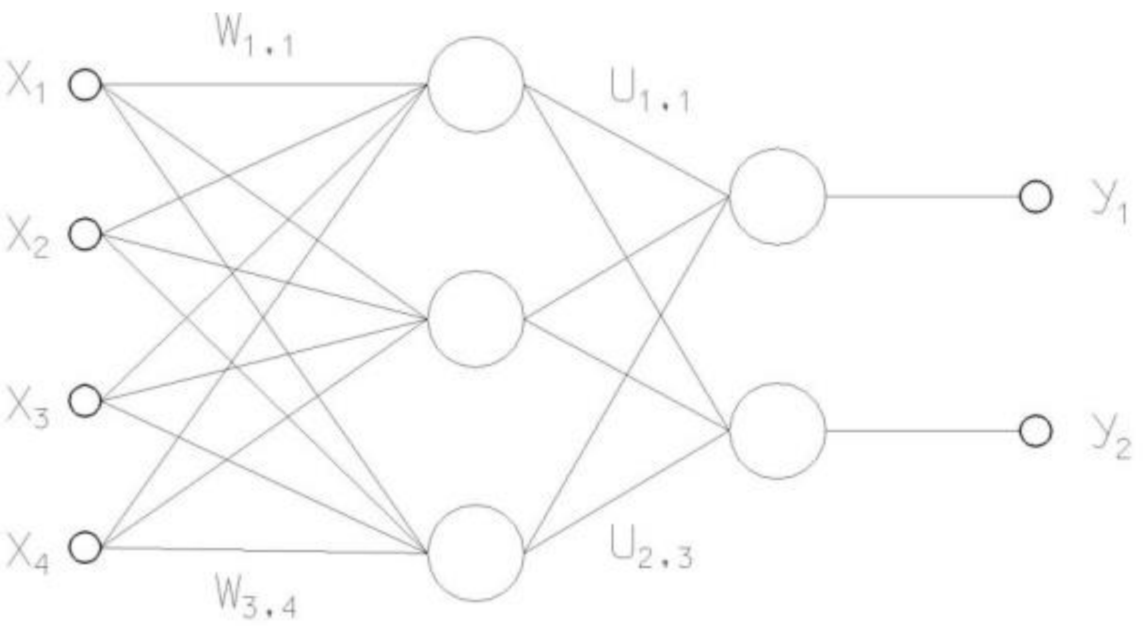
# 5. Short-term load forecasting methods

- The neuron model consists of the linear combination of one or multiple numerical inputs (represented by $X_i$ in the previous Fig.) and a constant input term (represented as an input of 1). Each variable input $X_i$ is adjusted by a unique weight, $w_i$, and the constant input of 1 is adjusted by a variable bias, Θ.
- The linear combination of these inputs and bias are input to a nonlinear activation function whose output is the output of the neuron. The training of ANNs requires the activation function to be nondecreasing and differentiable.
- The most common activation functions used in ANNs are the linear function $y = x$, or some variation of the bounded sigmoid function such as the logistic function $y = 1/(1 + e^{-x})$.
- The architecture of ANNs can vary, but the most commonly used is the multilayer perceptron (MLP)

# 5. Short-term load forecasting methods




Two-layer, feed-forward, neural network

Fig. shows an ANN that consists of two layers, an output layer (to which the output nodes are connected), and a hidden layer (located between the inputs nodes and output layer)

# 5. Short-term load forecasting methods

- The neurons in a layer can share inputs, but they are not connected to one another. If the ANN is a feed-forward network, then the outputs of one layer are connected as the inputs to the next layer. Often, one hidden layer is adequate to approximate any continuous function. Depending on the network topology, the ANN can have multiple outputs.
- Previous Fig. can be represented mathematically as follows if the hidden layer neurons' activation functions are logistic, and the output layer neurons' activation functions are linear:

$$y_k = \sum_{j=1}^{3}\left(u_{kj} \times \frac{1}{1+exp\left(-\sum_{i=1}^{4} w_{ji}x_i+\Theta_j\right)}\right) + \Theta_k$$

## 5. Short-term load forecasting methods

- **Expert systems.** Rule based forecasting makes use of rules, which are often heuristic in nature, to do accurate forecasting. Expert systems, incorporate rules and procedures used by human experts in the field of interest into software that is then able to automatically make forecasts without human assistance.
- Expert system use began in the 1960’s for such applications as geological prospecting and computer design. Expert systems work best when a human expert is available to work with software developers for a considerable amount of time in imparting the expert’s knowledge to the expert system software.
- Also, an expert’s knowledge must be appropriate for codification into software rules (i.e. the expert must be able to explain his/her decision process to programmers).
- An expert system may codify up to hundreds or thousands of production rules.

- **Fuzzy logic.** Fuzzy logic is a generalization of the usual Boolean logic used for digital circuit design. An input under Boolean logic takes on a truth value of “0” or “1”.
- Under fuzzy logic an input has associated with it a certain qualitative ranges. For instance, a transformer load may be “low”, “medium” and “high”. Fuzzy logic allows one to (logically) deduce outputs from fuzzy inputs.
- In this sense fuzzy logic is one of a number of techniques for mapping inputs to outputs (i.e. curve fitting). Among the advantages of fuzzy logic are the absence of a need for a mathematical model mapping inputs to outputs and the absence of a need for precise (or even noise free) inputs. With such generic conditioning rules, properly designed fuzzy logic systems can be very robust when used for forecasting. Of course in many situations an exact output (e.g. the precise 12PM load) is needed. After the logical processing of fuzzy inputs, a “defuzzification” process can be used to produce such precise outputs [11].

# 5. Short-term load forecasting methods

- **Support vector machines.** Support Vector Machines (SVMs) are a more recent powerful technique for solving classification and regression problems. This approach was originated from Vapnik's statistical learning theory.
- Unlike neural networks, which try to define complex functions of the input feature space, support vector machines perform a nonlinear mapping (by using so-called kernel functions) of the data into a high dimensional (feature) space.
- Then support vector machines use simple linear functions to create linear decision boundaries in the new space. The problem of choosing an architecture for a neural network is replaced here by the problem of choosing a suitable kernel for the support vector machine [12].

# 5. Short-term load forecasting methods

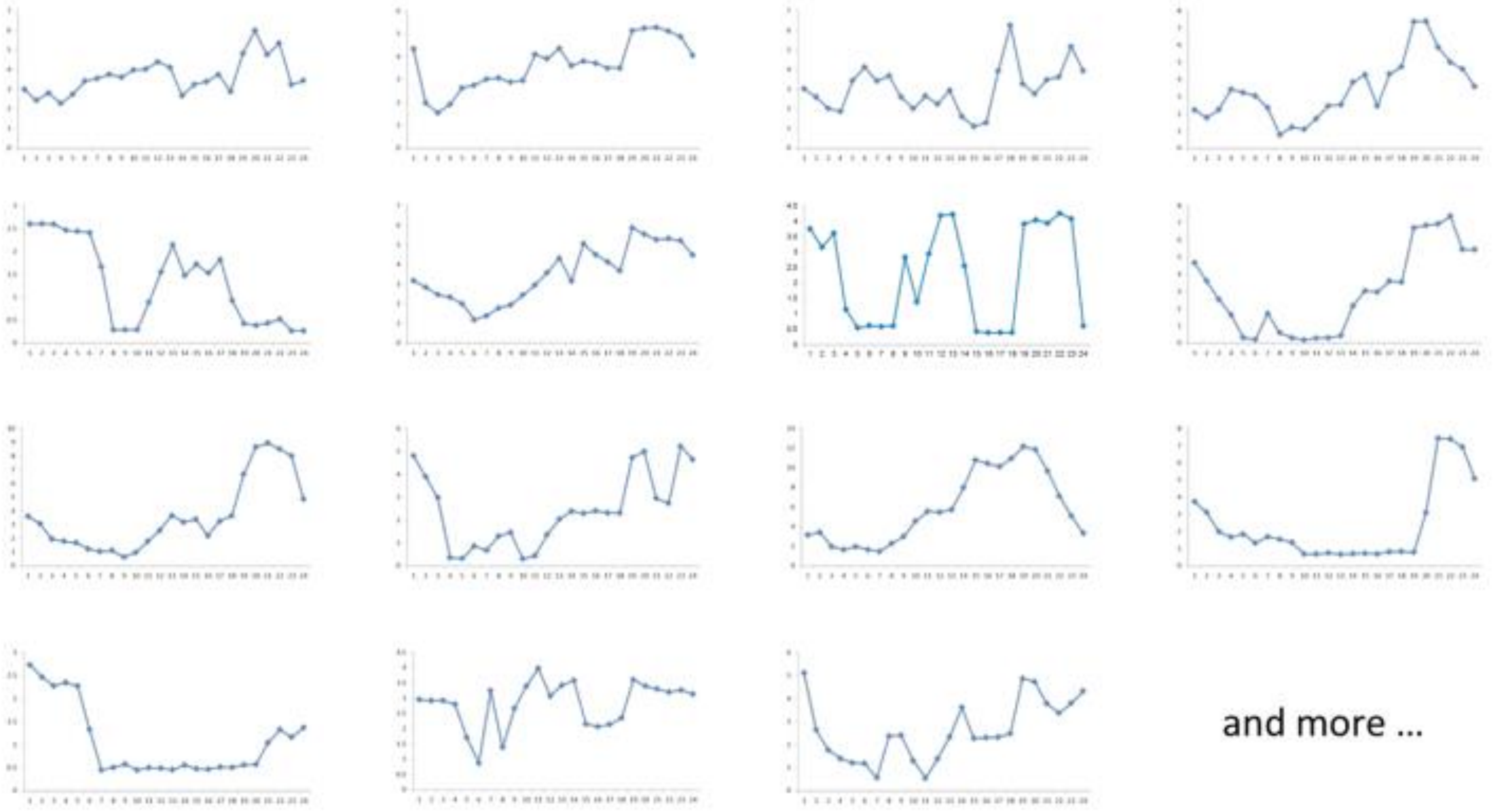
- Mohandes [13] applied the method of support vector machines for short-term electrical load forecasting. The author compares its performance with the autoregressive method. The results indicate that SVMs compare favorably against the autoregressive method.

## Residential Load Forecasting

- Residential customers include private households that use energy for heating, cooling, cooking, lighting, small appliances. Among all customer classes, residential customers have the most weather responsive electricity consumption behavior. Although the load of an individual residential customer can be quite stochastic, residential load aggregated to the revenue class level is more predictable than the loads of other customer classes.
- Therefore, we usually apply advanced statistical models for residential load forecasting. A residential load forecasting model typically includes many variables such as weather, calendar, and population.

## Residential Load Forecasting

Diverse daily residential load profiles



and more ...

# 6. Types of load forecasting

## Residential Load Forecasting

- Before the smart grid era, most meters were being read once a month. The energy usage of most residential customers was in monthly load series.
- Because the meters were not read at the same time, load forecasters had to first convert thousands of load series from billing month to calendar month. This task required load profiles at hourly or daily interval. To develop these load profiles, a utility had to install a small sample of interval meters taking daily or hourly readings. The number of interval meters had to be large enough to be used to infer the load profiles of all residential customers.
- The process of using  readings from a small number of interval meters to develop load profiles of all residential customers is called load profiling.

## 6. Types of load forecasting

- Another important aspect of residential load forecasting is appliance saturation survey, which requests households to provide information on appliances, equipment, and general consumption patterns.
- The survey usually results in the number of households with end-use saturation. Such information is very important in estimating the peaks.
- For instance, without the constraints of end-use saturation, the demand would grow at the same rate as the temperature increases during hot summer days, which may lead to over-forecast of the peak load. Other than the saturation factor, the efficiency of air conditioning systems and differences in individual’s temperature preferences are also important outcomes of the survey studies.

# 6. Types of load forecasting

## Commercial Load Forecasting

- Commercial customers such as retail stores, restaurants, hotels, and educational institutions are those customers not involved in manufacturing. Commercial customers can be roughly divided into two sub-classes, small commercial and large commercial customers. The cut-off is generally based on the peak load of 50 kW during any 12-month period.
- Load forecasting for small commercial customers is similar to residential load forecasting, because small commercial customers usually have close response to weather. Load forecasting for large commercial customers requires customized efforts depending upon the type of business. In addition to weather, most large commercial loads are significantly affected by the business schedules. Some of them have strong seasonal patterns.

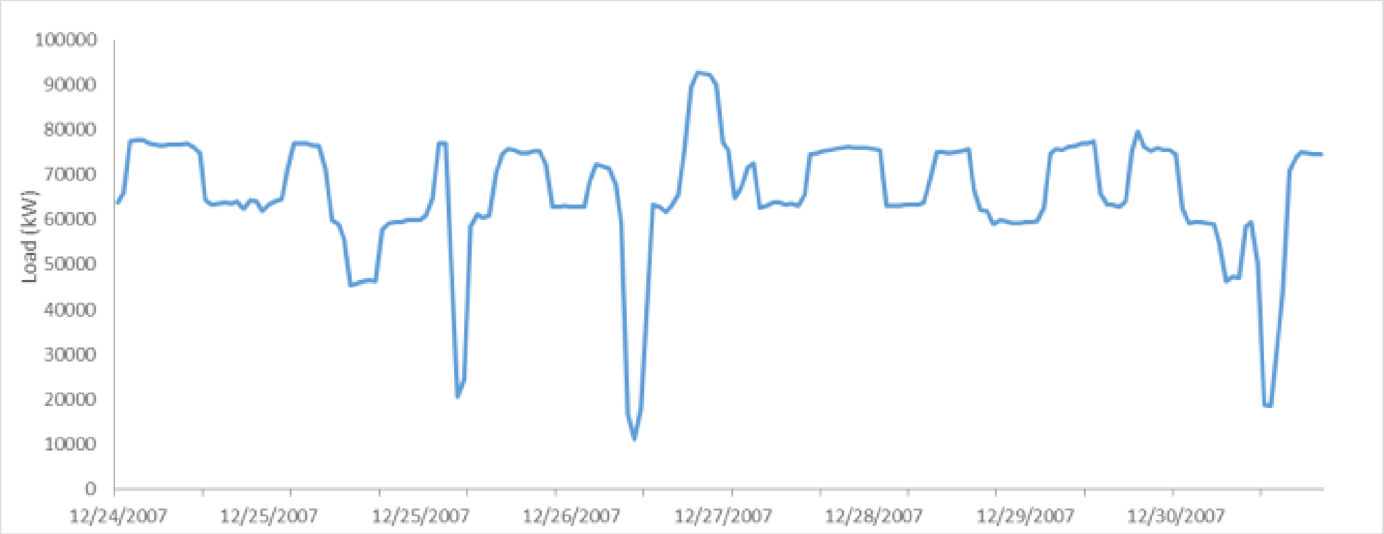
## Commercial Load Forecasting

- The load of education institutions also has its own characteristics. The daily schedule of students is different from working professionals. For instance, many students stay up late. Therefore, daily peaks of student dorms often occur close to midnight.
- At annual level, education institutions follow academic calendars. The load level is low during academic holidays.
- Another special load is from agriculture customers, who need to pump water for irrigation, keep the animals warm during extreme cold periods, and dry grain. Since time of the day may not be critical to some of these agriculture needs, farmers given enough incentives can schedule some activities to a period designated by the utility. For agriculture load forecasting, detailed information about the type of farming or dairy operations in addition to historical load and weather information is needed.

# 6. Types of load forecasting

## Industrial Load Forecasting

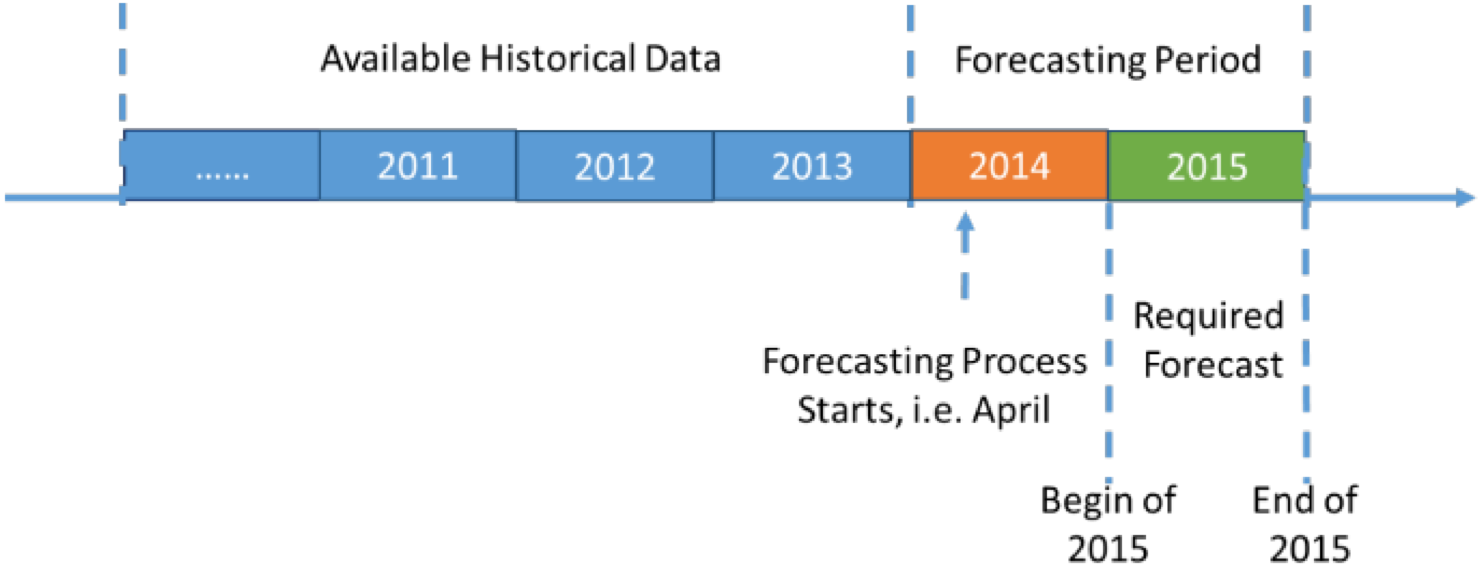
- There are several factors affecting the load of an industrial customer, such as facilities, business types, production levels, electricity rates, customer-owned generation, and production schedule.
- Since there are not only one or two major driving factors highly correlated with the load, the industrial load is very unpredictable. Industrial load forecasting can be performed based on the end use of industrial subclasses.




Hourly load profile of an industrial customer

# 7. Selection of load forecasting horizon

- Forecast origin is the last available point in the historical data. Forecast horizon is the distance between the forecast origin and the furthest point that is being forecasted. Figure below depicts a one-year ahead load forecasting process. At the beginning of spring 2014, the data up to end of year 2013 is available for load forecasting. Although the forecast is for the 12 months of 2015, the forecast horizon is in fact 2 years.



# 7. Selection of load forecasting horizon

- The forecast horizon should cover the planning horizon. The planning horizon has to be longer than the lead time.
- Lead time is the time between the initiation and completion of a process. For instance, the lead time between the decision of replacing a 4kV service transformer and commissioning of a new transformer can be anywhere between a few weeks and two or three months, depending upon the urgency, availability of personnel, equipment supplies, and so forth.
- For the purpose of building a transmission substation, the lead time can be anywhere between three to five years. If the time to secure the land ahead of time is counted, the lead time can be up to 10 years.

# 7. Selection of load forecasting horizon

- In many utility applications, the planning horizon can be beyond 20 years. To cover such a long planning horizon, the forecasting horizon would be 20 years or longer. It should be recognized that the longer the forecast horizon, the more unpredictable the load is. There are many factors affecting the predictability through the forecast horizon. An important one is the length of data history.
- There are several aspects of the relationship between data history and forecast horizon:

*1) The business cycle should repeat itself at least two times. To forecast the load of one year, at least two years of history is needed.*

*2) The data history should be two to three times of the forecast horizon. In other words, to forecast 20 years ahead, 40 to 60 years of history is ideal.*

## 7. Selection of load forecasting horizon

- In reality, access to longer than 30 years of load history is rarely available. Even if the load data is available with long history, the very old data may not be useful. This is because the electricity consumption pattern has changed dramatically over the past few decades.
- In the U.S., forecasters have access to 10 to 15 years of high quality load data, and 30 to 40 years of high quality weather and economy data. These are good enough for 5 years ahead load forecasting, but not really sufficient for the forecast horizon beyond 20 years.
- 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, i.e., 5 years. 2) Develop probabilistic load forecasts, to better describe the uncertainty associated with the load in the long term.

# 8. Forecasting Horizons for Utility Applications

- Load forecast for financial planning is usually updated every 1 to 5 years with a forecast horizon of 1 to 20 years.
- For generation and transmission planning, the forecast horizon could be 5 to 30 years as new generators or transmission lines require a long lead time (e.g., over 5 years).
- The update of load forecast for generation and transmission planning is usually done every 1 to 2 years. The updating cycle and forecast horizon for distribution planning are similar to those for generation and transmission planning, except that the forecast horizon could be as short as 1 year since the lead time for equipment on the distribution level is generally much shorter than that on the transmission level. Load forecast for renewable energy planning has a similar updating cycle and forecast horizon to distribution planning but could have a forecast horizon of up to 30 years, which is typically the life cycle of a renewable energy project.

# 8. Forecasting Horizons for Utility Applications

| | Updating Cycle | Forecast Horizon |
|---|---|---|
| **Financial Planning** | 1 – 5 years | 1 – 20 years |
| **Generation Planning** | 1 – 2 years | 5 – 30 years |
| **Transmission Planning** | 1 – 2 years | 5 – 30 years |
| **Distribution Planning** | 1 – 2 years | 1 – 20 years |
| **Integrated Resource Planning** | 3 – 10 years | 10 – 50 years |
| **Renewable Energy Planning** | 1 – 2 years | 1 – 30 years |

Forecasting horizon and updating cycle of representative utility applications

# 8.1 Data Requirements for Supporting New Load Forecasting Models

- New load forecasting models in the smart grid era should take advantage of modern automatic metering infrastructure, information technology, and advancements in atmospheric science. The following data sources are useful in supporting the new load forecasting models:

1. Load: hourly load history at end user level; hourly load history at distribution substation and transmission substation level; hourly wholesale load history.
2. Weather: hourly weather history at weather stations within and surround the services territory.
3. End use and appliance survey results.
4. Demographic and economy information.

# 8.1 Data Requirements for Supporting New Load Forecasting Models

5. Hierarchical information: connections among substations and meters; breakdowns of revenue classes; breakdowns of rate classes; billing group mapping; industry code mapping.
6. Outage logs: record of all outages including location, customers affected, and duration.
7. Demand response and energy efficiency programs: start and end time of all demand response programs, illustrations of all types of energy efficiency programs and implementation date.
8. Negative demand: metered customer-owned generation history.
9. System loss information: estimated transmission and distribution losses.

## 6. Summary

- In this chapter we have discussed several statistical and artificial intelligence techniques that have been developed for short-, medium-, and long-term electric load forecasting.
- Several statistical models and algorithms that have been developed though, are operating ad hoc. The accuracy of the forecasts could be improved, if one would study these statistical models and develop the mathematical theory that explains the convergence of these algorithms.
- Researchers should also investigate the boundaries of applicability of the developed models and algorithms. So far, there is no single model or algorithm that is superior for all utilities. The reason is that utility service areas vary in differing mixtures of industrial, commercial, and residential customers. They also vary in geographic, climatologic, economic, and social characteristics

# 6. Summary

- As mentioned before, weather is an important factor that influences the load. The usual approach to short-term load forecasting uses the forecasted weather scenario as an input. However, one of the most important recent developments in weather forecasting is the so-called ensemble approach which consists of computing multiple forecasts. Then probability weights can be assigned to these ensembles.
- Instead of using the single weather forecast, weather ensemble predictions can be used as multiple inputs for load forecasts. These inputs generate multiple load forecasts.

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