

# Load Forecast Methodology Description

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## Model Descriptions

Following the approach used by Hyndman & Fan (2009), the forecasting model consists of two sub-models: **annual** demand growth sub-model based on economic and demographic variables, and **monthly** weather-demand sub-model based on weather variables. The model can be written as follows:

$$\ln(y_{t,p}) = f_p(w_t) + \sum_{j=1}^J C_j Z_{j,t} + n_t \quad (1)$$

Where:

$y_{t,p}$ : monthly electricity load on year  $t$  and month  $p = 1, 2, 3, \dots, 12$

$f_p(w_t)$ : all weather effects

$Z_{j,t}$ : the annual demographic and economic variable at time  $t$  and its impact on monthly demand

$n_t$ : the demand which is left unexplained by the model (the model residuals) at time  $t$

Function(1) can also be written in the form:

$$\ln(y_{t,p}) = \ln(\bar{y}_t) + \ln(\dot{y}_{t,p}) \quad (2)$$

That is:

$$y_{t,p} = \bar{y}_t \cdot \dot{y}_{t,p} \quad (3)$$

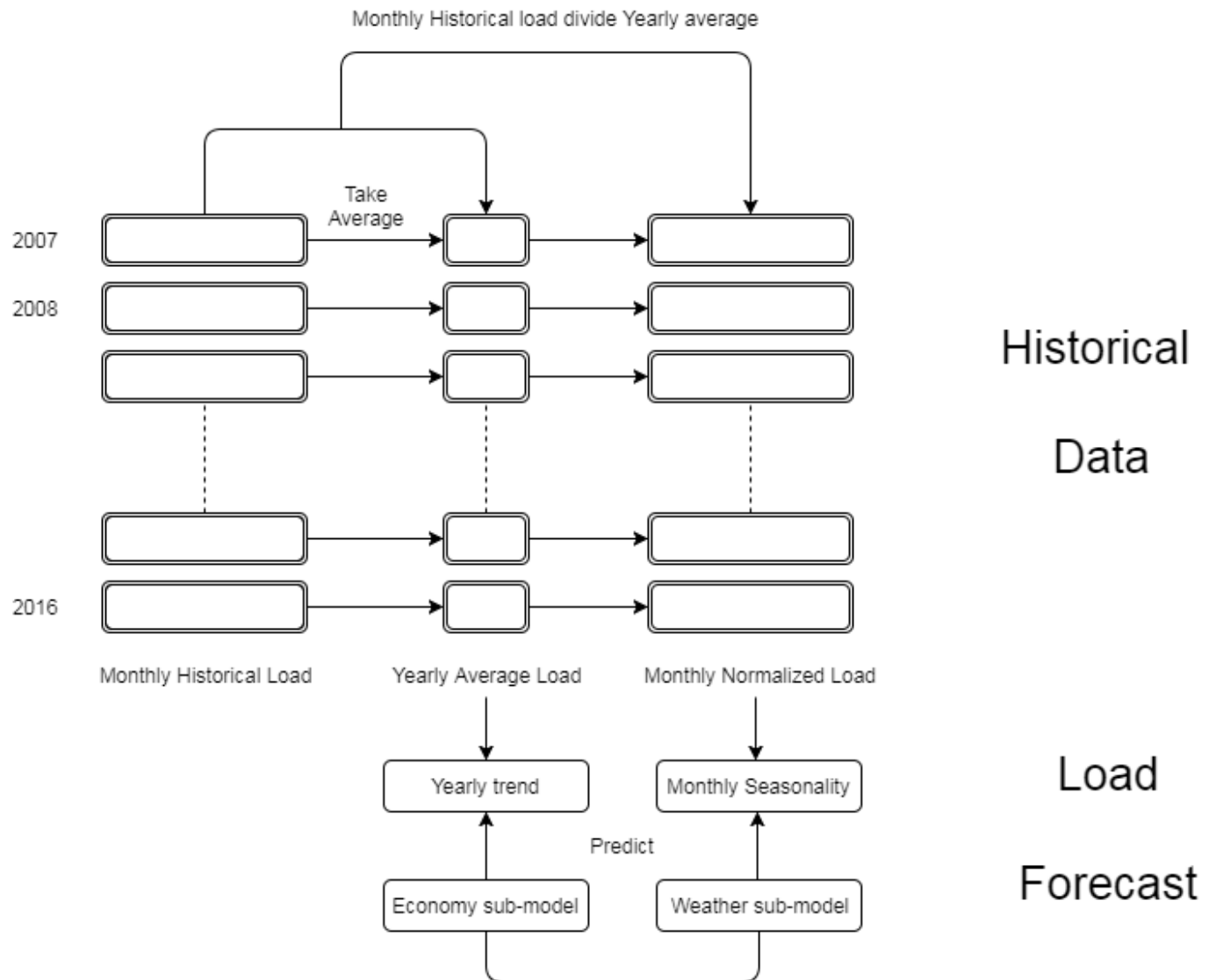
Where:

$\bar{y}_t$ : the annual average electricity sales for year  $t$  in GWh

$\dot{y}_{t,p}$ : the normalized demand for year  $t$  in month  $p$

According to this form, two sub-models were generated in order to estimate  $\bar{y}_{t,p}$  and  $\dot{y}_{t,p}$  separately. Once the estimation of  $\bar{y}_{t,p}$  and  $\dot{y}_{t,p}$  is obtained, their multiplication will be the load forecast we need.

## General idea of decomposition



## The monthly weather-demand sub-model

This model describes the impact of weather on normalized electricity demand:

$$\ln(\dot{y}_{t,p}) = f_p(w_t) + n_t$$

For the weather factor  $f_p(w_t)$ , we can use the regression model:

$$f_p(w_t) = \beta_0 + \sum_{p=1}^{12} \beta_p W_{p,t}$$

Where:

$W_{p,t}$ : explanatory weather variables which are nonlinear functions of historical weather parameters

$\beta_0$  and  $\beta_p$ : regression coefficients

The explanatory weather variables  $W_{p,t}$  used in this regression model is listed below:

Table 1: Summary of monthly weather-demand sub-model	
Dependent variables	Independent Variables
Monthly normalized Electricity Load	Monthly Maximum Temperature
	Monthly Minimum Temperature
	Monthly Mean Temperature
	Monthly CDD
	Monthly HDD
	Monthly Average Humidity

Heating degree day *HDD* is a measurement designed to quantify the demand for energy needed to heat a building. HDD is derived from measurements of outside air temperature. A similar measurement, cooling degree day *CDD*, reflects the amount of energy used to cool a home or business. The monthly CDD and HDD were computed for the 2007 to 2016 period using the following formulas:

$$HDD = \sum_{0days}^{idays} (T_{ref} - T_{daily\text{mean}})$$

$$CDD = \sum_{0days}^{idays} (T_{daily\text{mean}} - T_{ref})$$

## The annual economic-demand sub-model

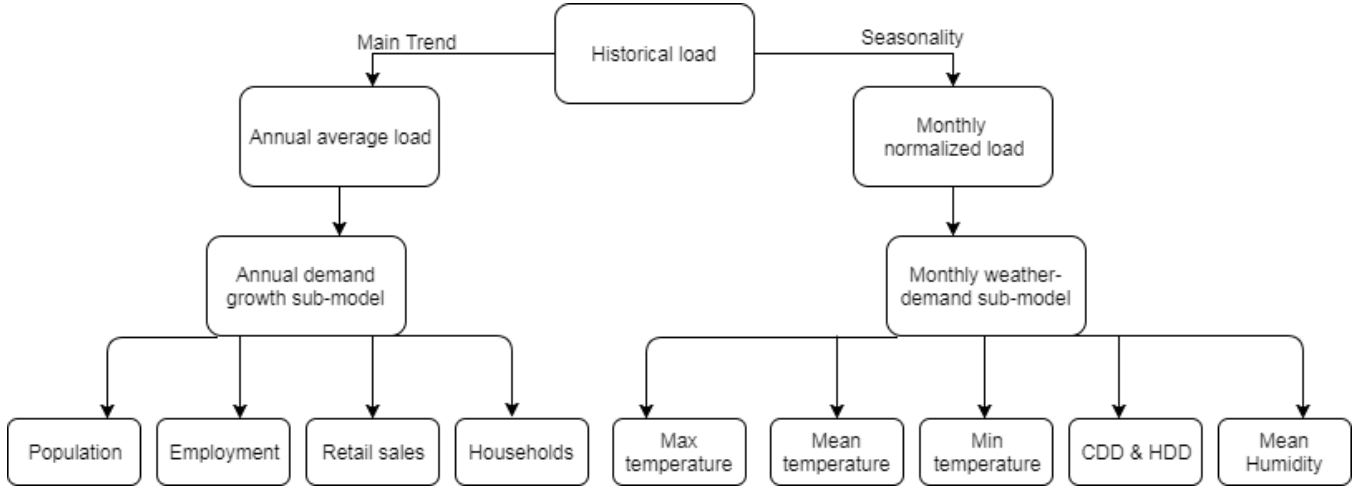
This model describes the impact of economic and demographic on electricity growth:

$$\ln(\bar{y}_t) = \sum_{j=1}^J C_j Z_{j,t}$$

The explanatory economic variables used in this regression model is listed below:

Table 2: Summary of annual demand growth submodel	
Dependent variables	Independent Variables
Annual Average Electricity Load	Total Population
	Total Employment
	Total Households
	Total Retail Sales

## Flow Chart of the methodology



## Model fitting

Historical weather and economic data is used to fit regression models. To find the best combination of independent variables, subset regression method is used.

## Load Forecast

To make prediction with the fitted model, future value of input variables are required, i.e. temperature and economic data. The long-term forecasts for economic data is obtained from Woods and Poole. To simulate the temperatures, we use the normalized weather data to preserve any seasonal or trend patterns.

## Load Forecast Result

Once the new input data is obtained, we can make prediction with the fitted sub-models. By multiplying the obtained results, we can get predicted future value.

