Load Forecasting

# 1. Introduction

Electricity is one of the driving forces of economic development and is essential to our daily life and wellbeing. Electric load forecasting is a difficult task due to the number of the different random variables that needs to be taken into consideration in order to predict human behavior. People often use electricity at any time that suits their lifestyle, and for the most part we all happen to use electricity at the same time. Most people share a similar lifestyle pattern, from when we wake up, to having a shower, making some breakfast, leaving for work, coming back at night, going to bed, doing our laundry on weekends and so on.

Load forecasting is an integral part in the process of the planning and operation of electric utilities; it has played a vital role in the power industry for over a century. In terms of power supply and demand; for the stable supply of electricity, the reserve power must be prepared. Businesses needs of load forecasting includes power systems planning/operations, revenue projection, rate design, energy trading, and so on. Load forecasting is needed by many business entities other than electric utilities, such as load aggregators, power marketers, independent system operators, regulatory commissions, industrial/commercial companies, banks, trading firms, and insurance companies [1][2]. The demand pattern is very complex due to the deregulation of energy markets; therefore finding an appropriate forecasting model for a specific electricity network is not a trivial task [3]. Electricity demand is accessed by accumulating the consumption periodically; it can be considered for hourly, daily, weekly, monthly, and yearly periods.

The forecasting processes can be grouped into four categories based on their horizons namely: very short term load forecasting (VSTLF), short term load forecasting (STLF), medium term load forecasting (MTLF), and long term load forecasting (LTLF). The cutoff for these categories are, 1 day, 2 weeks, and 3 years respectively. A rougher classification would consider only two categories: STLF and LTLF, with a cutoff at two weeks. Short term load forecasting has been the major point of focus in most literatures [4].

Different factors can affect load forecasting such as, the location of the area, the type of customers in the region, weather factors (temperature, etc.), trend in the data, the time of the day, day of the week, and other unpredictable factors (coronavirus outbreak, etc.).

# 2. Load Forecasting Techniques

The techniques used in load forecasting can be divided in two groups namely; statistical techniques and artificial intelligence (AI) techniques. This section will review some well-known techniques from both categories.

## 2.1 Statistical Techniques

Statistics can be defined as a branch of mathematics that deals with the collection of data, organization, analysis, interpretation and presentation. Statistics can also refer to numbers that can be used to describe data or relationships. Statistical approaches can forecast the current value of a variable through the use of mathematical combination of past historical values of the variable, and previous or current values of other variables [5].

### 2.1.1 The Naïve Approach

The naïve approach is considered to be the most cost-effective forecasting model; it also serves as a benchmark for developing much more sophisticated models. In the naïve approach, the forecast is taken as the previously observed value; this type of forecast is only suitable for time series data. This approach works best if the previous observation has a high similarity with the current; it is sometimes called the similar day approach. If there is seasonality in the time series; the seasonal naïve approach is preferable, because forecasts will be equal to the value from the last season. The seasonal naïve approach is mostly useful when there is very high level of seasonality in the dataset.

The naïve approach, when used as a baseline for other methods; it gives us an understanding about how much value is being added to the current forecasting process. The reason for the benchmarking is because, thou the naïve approach is very simple and straightforward; it performs very well in time series when there is a very high similarity in the data. The formula for the naïve approach, and the seasonal naïve approach are shown below respectively;



Where;  is the time series,  is the forecast horizon, is the seasonal period, and is the integer part of . In summary, the naive formula takes the last observed value as the future value, while the seasonal naive formula takes the value from the previous season.

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# References

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