Automated machine learning for dynamic energy management using time-series data

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Chapter 2

Preliminaries

2.1 Time-series forecasting

This chapter shows an introduction to the core application domain of this thesis. It covers the basics of time-series forecasting and dynamic energy management.

For single-step time-series forecasting, given a univariate time-series $\mathbf{x} = [x_1, \ldots, x_n]$, consisting of single observations recorded per equally distanced discrete time steps, with $\mathbf{x} \in \mathbb{R}^n$ (where $\mathbb{R}^n$ is the space of possible time-series of length n), we are interested in forecasting each x_i based on the historical data $[x_1, \ldots, x_{i-1}]$. However, not all data points are equally informative for the prediction of x_i. Usually, the points close to x_i are more important than those further away for predicting x_i. The window size w ($w \ll n$) indicates how many previous data points we use to forecast x_i. The time-series forecasting problem we address in this thesis considers pre-observed data points within segments of size w or forecasting a future value of the time-series. Specifically, given a time-series segment $[x_{i-w}, \ldots, x_{i-1}]$, we are interested in forecasting x_i.

For multi-step forecasting, we are interested in forecasting $[x_i, \ldots, x_{i+m}]$. Forecasting window size m indicates we want to forecast the next m values.

2.2 Dynamic energy management

In this chapter, we only discuss the electric load forecasting application. There are similarities between electric load forecasting and other forecasting problems, such as the forecasting of prices of electricity and gas. We hope the review also works for other load forecasting areas.

We typically divide load forecasting problems into four types based on the range: very short term load forecasting, short term load forecasting, medium term load forecasting, and long term load forecasting, with forecasting horizons one day to ten years, and sometimes up to several decades (Hong and Fan, 2016) respectively. In this chapter, we focus on short term load forecasting, with the range between one day to two weeks.

Load forecasting is an active field of research and many papers are published every year on this topic. In this chapter, we provide a review of the preliminary concepts of the short term electricity load forecasting. In Section 2.2.1 we summarize some characteristics of the load data. In Section 2.2.2, we introduce the strategies and techniques for multi-step forecasting and short term electric load forecasting. We introduce the common evaluation measures in Section 2.2.3.

2.2.1 Data characteristics

A number of factors may influence load signals. We examine the characteristics of load data in this section.

Weekend and holiday effects:

On weekends and holidays, many buildings and factories are closed, resulting in less load than on other weekdays. There are also influences on residential buildings - some people wake up later in the morning on weekends and holidays than on weekdays. This behaviour shifts the morning peak a little bit later than normal weekdays. Saturday and Sunday are also different, due to churchgoers on Sunday and different opening hours for shops.

Weekends and holidays also influence the day before and after them. Before weekends and holidays, people usually sleep later than usual. After a weekend, the factories need to consume more energy to restart production. This means that load profiles on different workdays can also be different.

To design the short term load forecasting model, it is better to consider effects from weekends and holidays. To get better performance, short term load forecasting models were developed based on different areas and countries. Different grouping methods are proposed by different researchers.

Here is a list of grouping methods:

1. 2 types of days, Mon —Fri; Sat, Sun. (Chen et al., 1995)

2. 3 types of days, Mon —Fri; Sat; Sun. (Chen et al., 1995)

3. 4 types of days, Mon; Tue —Thu; Fri; Sat, Sun(Methaprayoon et al., 2007)

4. 4 types of days, Mon; Tue —Fri; Sat; Sun (Hsu and Yang, 1991)

5. 4 types of days, Mon —Thu; Fri; Sat; Sun (Amjady, 2001)

6. 5 types of days, Mon; Tue —Thu; Fri; Sat; Sun (Hagan and Behr, 1987)

7. 7 types of days, Mon; Tue; Wed; Thu; Fri; Sat; Sun (Khotanzad et al., 1997)

Weather effects:

In load forecasting, weather conditions have always been an important factor. Most methods in practice require weather information for short term load forecasting. The features regarding weather include temperature, wind speed, and humidity. The most influential and popular factor is temperature, whose measurement is also easier to retrieve. Although humidity has been discussed in the load forecasting literature, it has not been studied as formally as temperature. A recent investigation (Xie et al., 2018) into the effect of relative humidity (RH) on electricity demand shows that adding RH variables improves the forecast accuracy in a case study at a utility in North Carolina. Xie and Hong (2018) used the solar-term calendar, which is based on the zodiac. The results show that the forecast based on the solar-term calendar has higher accuracy than the forecast based on the Gregorian calendar.

2.2.2 Methodology

In the thesis, we aim to resolve address both single-step and multi-step energy load forecasting tasks. We treat the single-step forecasting tasks as a special type of regression problem. In this case, we focus on modeling the relationship between a time-series segment $[x_{i-w}, \ldots, x_{i-1}]$ and x_i. However, multi-step forecasting problems are more complex than multi-step forecasting problems. In this section, we introduce the methodologies that we use to make multi-step forecasting.

Multi-step forecasting strategies:

A multi-step ahead time-series forecasting task consists of predicting the next m values $[x_i, \cdots, x_{i+m}]$ of a historical time-series $[x_1, \cdots, x_{i-1}]$ composed of $i-1$ observations, where $m > 1$ is the forecasting horizon. In this section, we introduce a few existing strategies for multi-step ahead forecasting and compare them in theory.

Recursive strategy: In this strategy, a single model f is trained to perform a one-step-ahead forecast:

$$\hat{x}_i = f(x_{i-w}, ..., x_{i-1}) \tag{2.1}$$

In this strategy, given a univariate time-series $\mathbf{x} = [x_1, \ldots, x_n]$ composed of n observations, a model f is trained to perform a single-step ahead forecast:

$$\hat{x}_i = f(x_{i-w}, ..., x_{i-1}), i \in \{w+1, ..., n\} \tag{2.2}$$

Then we use $\hat{x}_{i+1}$ as an input to predict x_{i+2}.

$$\hat{x}_{i+1} = f(x_{i-w+1}, ..., x_i, \hat{x}_i), i \in \{w+1, ..., n\} \tag{2.3}$$

We continue recursively, making new predictions in this manner until we forecast x_{i+m}.

Direct strategy: In this approach, m models $f_1, \cdots, f_m$ are learned to perform a single-step ahead forecast for each horizon. For example, the first two models are:

$$\hat{x}_i = f_1(x_{i-w}, ..., x_{i-1}) \tag{2.4}$$

$$\hat{x}_{i+2} = f_2(x_{i-w}, ..., x_{i-1}) \tag{2.5}$$

MIMO strategy: A group of researchers (Taieb and Bontempi, 2011) also proposed a Multi-Input Multi-Output (MIMO) strategy. This strategy learns one multiple-output model f from the time-series $[x_1, ..., x_n]$ where

$$\hat{x}_i, ..., \hat{x}_{i+m} = f(x_{i-w}, ..., x_{i-1}) \tag{2.6}$$

2.2.3 Evaluation measures

Many measures have been developed for judging the similarity of time-series data. Due to the fact that each error measure has disadvantages that can lead to inaccurate evaluation of the forecasting results, it is impossible to choose only one measure (Mahmoud, 1984), and the most appropriate error measure depends on the particular situation. In this section, we introduce a couple of the most common approaches used for measuring load forecasting accuracy.

MAE: In statistics, mean absolute error (MAE) is a measure of the difference between two continuous variables. Mean Absolute Error is the average distance between the predicted value and the real value. MAE is unable to indicate large relative differences or even wrong signs around 0. We define x'_t as the predicted value at timestamp

t, with $e_t = x_t - x'_t$ defined as the error between x_t and x'_t. For a time-series of length n, MAE is calculated as

$$\text{MAE} = \frac{\sum_{t=1}^{n} |e_t|}{n} \tag{2.7}$$

MAPE: The mean absolute percentage error (MAPE) expresses accuracy as a percentage. MAPE is defined as:

$$\text{MAPE} = \frac{100\%}{n} \sum_{t=1}^{n} \left| \frac{e_t}{x_t} \right| \tag{2.8}$$

The difference e_t between x_t and x'_t is divided by the actual value x_t again. Multiplying by 100% makes it a percentage error. MAPE cannot be used if x_t is 0.

RMSE: RMSE is the square root of the average of squared errors. The effect of each error on RMSE is proportional to the size of the squared error; thus larger errors have a disproportionately large effect on RMSE, and it is sensitive to outliers. As it is scale-dependent, RMSE is a measure of accuracy to compare forecasting errors of different models for a particular data set, and not between data sets. RMSE is given by

$$RMSE = \sqrt{\frac{1}{n} \sum_{t=1}^{n} e_t^2} \tag{2.9}$$

$\mathbf{R^2}$: R^2 is the coefficient of determination. R^2 measures the degree to which the dependent variable of a given effect is determined by the independent variables. R^2 is more informative than MAE, RMSE in regression analysis evaluation (Chicco et al., 2021). R^2 is defined as:

$$R^2 = 1 - \frac{\sum_{t=1}^{n} {e_t}^2}{\sum_{t=1}^{n} (x_t - \bar{x})^2} \tag{2.10}$$

It is the proportion of the variance in x'_t that is predictable from the input variables.

2.2.4 Conclusions

In this chapter, we provide an overview of short term electric load forecasting, which is a classical branch of the load forecasting problem and show a few preliminary concepts about energy load forecasting. We first introduced some characteristics of electrical load data and methods to incorporate these effects. We then reviewed general forecasting strategies for these time-series and their relative strengths, followed by specific techniques used to model electrical load. Lastly, we discussed some evaluation measures of these models ranging from the simple MAE to the R^2. Once again, it is important to note that there are pros and cons to every metric, and the best measure is always specific to the specific situation.

We hope that this chapter not only offers insights for researchers and practitioners in the area of load forecasting to assist in further development of useful models and methodologies, but also provides the broader scientific community with enough background knowledge and good reference sources, so that more researchers can contribute to this new, challenging and important area of load forecasting.